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RESEARCH ARTICLE

Thresholds of knowledge development in complex problem solving: a multiple-case study of advanced learners' cognitive processes

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Abstract This multiple-case study examined how advanced learners solved a complex problem, focusing on how their frequency and application of cognitive processes contributed to differences in performance outcomes, and developing a mental model of a problem. Fifteen graduate students with backgrounds related to the problem context participated in the study. Data sources included direct observation of solution operations, participants' think aloud and stimulated recalls as they solved the problem, as well as solution scores indicating how well each participant solved the problem. A grounded theory approach was used to analyze stimulated recall and think aloud data. A set of thirteen cognitive processes emerged in the coding and were tallied for each participant. Individual cases were then grouped into clusters that shared similar frequencies of prior knowledge activation, performance outcomes, and tool use behaviors. Each cluster was profiled from least to most successful with descriptive accounts of each cluster's approach to solving the problem. A cross cluster analysis indicated how learners' cognitive processes corresponded with problem solving operations that revealed thresholds of knowledge development and formed an integrated mental model of the problem. The findings suggested that mastering problem solving operations within each threshold enhanced the learners' conceptual awareness of where to apply cognitive processes and increased the combinations of cognitive processes they activated at higher thresholds of knowledge development. The findings have implications for anticipating where novices need support within each threshold of knowledge development during complex problem solving.

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Introduction

Problem solving is cognitive processing aimed at accomplishing certain goals when the solution is unknown (Mayer and Wittrock 1996). Early models of problem solving described an iterative cycle of representing the problem, searching for a solution, and implementing a solution strategy (Foshay and Kirkley 1998). Bransford and Stein (1984), for example, proposed that an IDEAL problem solver should have the ability to identify the problem, define the problem, explore possible strategies, act on these strategies, and look at the effects. When an unknown obstructs the initial solution path, the problem solver initiates a new cycle and repeats the steps until a solution is reached. This and similar models of problem solving have foregrounded an information processing approach without taking into consideration how complexity impacts cognitive demands or the spectrum of cognitive processes that underlie solution operations (Iiyoshi et al. 2005; Kim and Reeves 2007; Lajoie 2008; Merriënboer and Stoyanov 2008).

Traditional instructional design models, which remain the norm in formal educational settings, have similar limitations when it comes to addressing problem complexity, primarily because these models are predicated on mapping a pre-specified cognitive process to a pre-determined learning outcome or solution. The Revised Bloom's Taxonomy of Educational Objectives (Anderson and Krathwohl 2001; Bloom et al. 1956), for example, sequenced six categories of cognitive processes along a hierarchy of knowledge development: Remember, Understand, Apply, Analyze, Evaluate, and Create. Each cognitive process category was associated with four dimensions of knowledge: factual knowledge, conceptual knowledge, procedural knowledge, and metacognitive knowledge. The taxonomy made it possible to associate cognitive processes with the depth of content knowledge a learner needed to master a pre-determined learning outcome for well-structured problems (Krathwohl 2002). Mastery of such problems requires application of a limited number of concepts, rules, and principles. All elements of the problem are given and there is just one correct answer (Jonassen 2000).

Although information processing models and taxonomies of cognitive processes have proved helpful for the design of well-structured problems, they do not approximate the complexity of problem solving that characterizes work and learning in the 21st Century (Jonassen 2000; Mayer 1998). The current shift in instructional design from learning objectives to authentic reference situations (Merriënboer and Stoyanov 2008) necessitates the need for more robust models of problem solving that account for how a problem's complexity, structure, and context impact a learner's ability to manage multiple and competing cognitive demands. The social and cultural skills required within workplaces, alongside the dynamic, technology-infused task environments in which knowledge is now produced and distributed, have increased the need for technology scaffolds to help learners construct, represent, and apply knowledge just in time.

When technology-based tools serve as scaffolds in learning environments, they are often called cognitive tools. According to Jonassen (1996), cognitive tools are "computer-based tools and learning environments that have been adapted or developed to function as intellectual partners with the learner in order to engage and facilitate critical thinking and higher order learning" (p. 9). Research has shown that cognitive tools have the potential to facilitate knowledge construction, support conceptual understanding, and scaffold higher-order cognitive tasks within complex learning environments (Jonassen 2006; Pea 1985; Salomon et al. 1991). In particular, tools are needed to help learners enact a "well-planned, prioritized, set of cognitions and actions" (Funke and Frensch 1995) toward the development of a mental model of the problem. Mental models are the "rich, complex, interconnected, interdependent, multi-modal representations of what someone or some group knows" (Jonassen and Strobel 2006, p. 4), and they "are generally created in response to challenging problem situations" (Spector 2010, p. 27). When learners begin to externalize a mental model through external knowledge representations brought about by use of tools in the problem environment, these mental models can serve as an index for knowledge development, providing a window into how a learner is thinking and reasoning about the problem (Kim 2012; Spector 2010).

In this multiple-case study (Kluwe 1995; Stake 2006; Yin 2003), we examined advanced learners' (i.e., graduate students) cognitive processes as they solved a complex problem in a problem-based, digital learning environment that provided a collection of technology-enriched cognitive tools to assist students' problem solving. The goal of this research is to understand how frequency and application of cognitive processes when solving a complex problem contributed to knowledge development and the overall quality of solution operations.

Theoretical framework

Characteristics of complex problems

Complex problems contain multiple, interrelated components that are unclear or implicitly represented and are open to multiple approaches and solution paths (Spector 2010). They typically occur within dynamic task environments that are information-rich. As circumstances change, the learner must take new information into consideration, adjust his or her representation of the problem, and devise new plans (Kluwe 1995). Limited or missing information about the factors impacting the situation create multiple subproblems—"clusters of interrelated problems related to the same work activities" (Jonassen 2000, p. 81).

The more complex the problem, the less top-down guidance learners have for acquiring and applying relevant knowledge (Funke and Frensch 1995; Spiro et al. 1988). When elements that relate to the problem are far apart, the problem is said to be ill-structured. These problems have unclear goals, missing elements, multiple solution paths, and sometimes no solution at all (Funke and Frensch 1995; Jonassen 2003, 2000). The more distance there is between the learner and the task, the more ill-structured the problem becomes, and cognitive demands increase. The learner must give the problem form by bringing together components perceived as relevant to its solution, which requires recognizing the problem, expressing personal opinions and beliefs about it, devising arguments for its solution, and keeping track of progress (Belland 2010; Belland et al. 2011; Cho and Jonassen 2002; Dunkle et al. 1995; Larkin 1983).

Cognitive demands are further exacerbated by the prevalence of non-recurring tasks. Irregularities occur in the task environment that rarely fit preformed schema (Spiro et al. 1988), requiring the learner to adapt or tailor a concept to fit the situation at hand (Spector 2008). The "mobilization of potential knowledge" (Spiro et al. 1988, p. 8) is far more useful for managing complexity in the task environment than the application of fixed concepts and knowledge structures. Solutions often require novel approaches that integrate cross-disciplinary knowledge (Spector 2008).

Cognitive tools as scaffolds for problem solving

Solving complex problems is challenging for novices because they are most accustomed to solving well-structured problems (Jonassen 2000) and lack well-developed mental models of the task environment in which complex problems occur. Despite these challenges, an underlying assumption of instructional design is that learners are not necessarily limited to any particular level of cognitive development. Given appropriate scaffolding, learners can not only work within a zone of proximal development but also can go beyond their current limitations when they make use of the affordances within the immediate environment to externalize thinking (Vygotsky 1978).

From the perspective of distributed cognition (Henning 2004), knowledge develops through interactions between internal and external representations in the task environment. Zhang and Norman (1994) theorized external and internal representations as “equal partners” during problem solving, with external representation activating perceptual processes and internal representations activating cognitive processes. In their view, high-level cognitive functions result from the learner’s internalization of information in the environment and the externalization of internal representations (Zhang and Norman 1994). Knowledge and intelligence develop through interactions between external objects, such as tools in the task environment, and the learner’s prior knowledge (Zhang 1997). Both external and internal representations work together to anchor and structure cognitive behavior and, in the process, each transforms the other (Zhang 1997).

Because novices “lack perquisite knowledge and capacities for the subject domain” (Mayer 1989, p. 44), they are the most likely to benefit from tools that can serve as external knowledge representations that guide and direct the application of cognitive processes; in turn, these external representations develop the learners’ internal representation of the problem (Zhang and Norman 1994). Cognitive tools can provide scaffolding in various ways: (1) sharing part of the cognitive load so that learners can work on higher-order tasks; (2) representing abstract concepts in meaningful and concrete ways; (3) modeling effective cognitive strategies or techniques; (4) guiding learners through cognitive tasks using expert or cognitive tutoring systems; (5) supporting metacognitive and self-regulation tasks; and (6) challenging learners’ knowledge and beliefs (Liu et al. 2013a; Jonassen 2006; Lajoie 1993). The external demands of the problem become less complex as the learner uses tools to build an internal representation, or mental model, of the problem from which they can construct an external representation that can structure the application of cognitive processes.

Construction of mental models during problem solving

Learners develop mental models through activities in the task environment with the goal of understanding a phenomenon, often mediated through use of cognitive tools (Derry 1996). Mental models are defined as “the knowledge and structure in memory, as propositions, productions, schemas, neural networks, or other forms” (Zhang 1997, p. 180). They are situational understandings of a system, containing “the essential parts, states, or actions of the system as well as the essential relations among them, so that the learner can be able to see how the systems works” (Mayer 1989, p. 59). Unlike schema, which is knowledge stored in the head and divorced from context and situation, a mental model consists of knowledge that is situationally and contextually bound (Derry 1996). A mental model is an internal representation of a system that the learner brings to bear in a problem-solving situation (Jonassen 2003; van Gog et al. 2005). It is developed through the application of different cognitive processes such as "constructing, testing, and adjusting a mental representation of a complex problem or situation" (Derry 1996, p. 168). Jonassen (2005) identified "planning, data collecting, collaborating, accessing information, data visualizing, modeling, and reporting" (2005, p. 91) as processes learners apply toward the development of mental models. Through time, experience, and reflection on learning in the problem space, mental models gain strength, coherence, and conceptual complexity (Jonassen and Strobel 2006; Kim 2012).

Once constructed, a mental model becomes a "building block" for further reasoning about the problem but is always subject to further adjustment based on the outcomes of problem solving (Derry 1996). A well-developed mental model integrates different kinds of knowledge. Jonassen and Strobel (2006) identified six interrelated features of well-formed mental models. They include structural knowledge (the structure of concepts in a domain), procedural knowledge (the plan for solving the problem), image of system (mental images of the system being explored), metaphors (associations), executive knowledge (i.e., knowing when to activate mental models), and beliefs (assumptions about the problem).

Building mental models has many benefits for solving complex problems. Well-developed mental models reduce cognitive demands by extending the capacity of working knowledge. The information load, shifting dynamics, and unclear task characteristics of a complex problem evoke cognitive demands that exceed the limitations of working knowledge, making it difficult to attend to all the components of the problem (Funke and Frensch 1995; Spiro et al. 1988). Novices recall discrete, isolated bits of information that quickly exceed the capacity of working memory, which is fleeting (Anderson 2009; Kluwe 1995; Miller 1956). They may employ a backward reasoning approach, working from a hypothesis regarding the unknown back to the given facts through trial and error, requiring them to track multiple sub-goals and tasks related to solving the problem (Patel and Groen 1991). A problem that is ill-structured for a novice may be a well-structured, routine problem for an expert. Experts can recognize routine tasks and apply procedural knowledge without exceeding the limitations of their working memory (Charness 1976; Chase and Ericsson 1982; Ericsson and Staszewsli 1989). They apply a top-down or forward cognitive processing approach by working from the known facts to the unknown.

Having well developed mental models also assists with recalling relevant knowledge. Knowledge is more accessible when mental models are structured and integrated. Novices may have stored knowledge of procedures, rules, and formulas, but without sufficiently integrated sets of mental models, they fail to recognize what conditions warrant the application of this knowledge or why it is relevant (Bransford et al. 2000). Expert knowledge is more thoroughly integrated into a coherent mental model that includes specifications of when, where, and why to use their knowledge (Bransford et al. 2000); that is, expert knowledge is organized in condition-action form, increasing speed and accuracy during problem solving.

In addition, the development of mental models increases perceptions of what information is most relevant in the task environment. Experts can perceive recurring patterns of information that are undetectable to the novice, and they use this information to make accurate predictions of solution procedures (Chase and Simon 1973; Livingston and Borko 1989). Their perceptual awareness of relevant information is usually a consequence of having a well-developed mental model. Experts, for example, can classify and externally represent problems in their field by concepts, principles, big ideas, or laws; novices, on the other hand, work on the basis of surface features (Chi and Bassock 1991; Chi et al. 1981; Savelsbergh et al. 1998). They neither recognize nor understand the underlying systems. Consequently, they solve the problem in a foreshortened way, relying on surface characteristics and superficial understandings (Chi and Bassock 1991; Chi et al. 1981; Glaser 1989).

Much of what is known about the structure of mental models is inferred from external knowledge representations that reveal how the learner conceptualized the problem (Spector 2008; Zhang 1997). External representations guide the learner's perception of what information is relevant, and help to "organize information around coherent explanations" (Mayer 1989, p. 46). They can take different forms—numerical, verbal, or pictorial—and may be organized in groups, hierarchies, or other meaningful patterns and sequences (Kleinmuntz and Schkade 1993). Some examples include diagrams, graphs, annotated concept maps, texts, and tables. Externalizing representations of problems have numerous benefits for helping novices to manage problem complexity such as limiting abstraction, aiding interpretation of information, recognizing invariant information, seeing a situation from different perspectives, and making inferences (Spiro et al. 1988; Zhang 1997). Furthermore, they can be used to extend working memory, store information, and share knowledge (Zhang 1997).

By examining the structure of external representations, it is possible to judge the progress the learner is making in developing knowledge, how the individual is reasoning about the problem, where there are misconceptions, and where support is likely to be needed (Kim 2012; Spector 2008). Kim (2012) provided a stage-sequential model of learning progress by measuring the surface, structure, and semantic features of external representations. Presumably, mental models become more integrated and conceptually complex as the learner progresses through stages of knowledge development: novice, advanced beginner, competent learner, proficient learner, and intuitive experts (Dreyfus and Dreyfus 1986; Kim 2012). At each stage, the learners' mental models, as assessed through external knowledge representations, reveal features that are more connected and semantically complex.

Additional insight into how mental models develop can be inferred from how strategically an individual interacts with and thinks across multiple knowledge representations tools. Novices, for example, tend to work from a single representation, and depend on fixed knowledge structures rather than adapting them based on information in the problem (Spiro et al. 1988). Experts, however, think across multiple knowledge displays to plan and carry out goals and strategies, make connections across multiple representations, and negotiate a shared understanding with others (Henning 2004; Jonassen and Strobel 2006; Kozma 2003). Regulating these processes involves "switching attention between internal and external representations, integrating internal and external information, and coordinating perceptual and cognitive operations" (Zhang 1997, p 186).

Given the critical role mental models play in problem solving, it is important that technology learning environments provide scaffolds that support the construction of mental models, which requires "engaging learners in using a variety of tools for constructing physical, visual, logical, or computation models of the phenomena" (Jonassen and Strobel 2006, p. 8). Schkade and Kleinmuntz (1994) found that abilities in acquiring information was strongly influenced by the organization of information, and skill in combining and evaluating information was strongly influenced by the form a representation took. They concluded that the way information is externally represented impacts decision-making and the ease of carrying out decision-making operations. In other words, cognitive tools, when strategically employed, can help the learner develop and coordinate between the inner and outer representations of problems to enhance, guide, and manage cognitive processes.

Metacognition and self-regulation

Skill in metacognition and self-regulation supports the development of mental models and the fidelity of external knowledge representations (Kim 2012; Zimmerman and Campillo 2003). Metacognition, originally defined as thinking about one's own thinking (Flavell 1971), involves self-awareness of cognitive processes, but may also include "affective and motivational components that can energize or hinder use of a strategy or skill on a transfer task" (Borkowski et al. 1987). Self-regulation refers to the control learners have over "setting goals, selecting appropriate learning strategies, maintaining motivation, and monitoring and evaluating academic progress" (Ramdass and Zimmerman 2011, p. 196). Increasing metacognitive and self-regulation activities has been shown to lead to higher recall and retention (Lee et al. 2010; Poitras et al. 2011) and deeper understanding (Bannert and Reimann 2011) as learners become more aware of and take charge of forming their conceptualizations of problems.

Studies on expert-novice differences suggest self-regulation is improved as mental models grow to include procedural knowledge of strategies. Learning a problem solving strategy can lead to better problem representations, and problem representations can lead to better use of strategies (Alibali et al. 2009). Because experts have developed mental models in condition-action form (Bransford et al. 2000), they know when to switch strategies in response to changing variables in the task environment. They balance the cost and benefits of a new strategy by assessing the level of cognitive effort required, and the effectiveness of a strategy to bring about a desired outcome based on prior experiences (Kleinmuntz and Schkade 1993). They are accurate at judging problem difficulty, aware of the appropriateness of solutions attempted (Chi et al. 1982), are conscious of the errors they make, can accurately analyze the reasons why they fail, and take corrective action when needed (Chi and Bassock 1991; Chi et al. 1981; de Jong and Ferguson-Hessler 1991; Dunkle et al. 1995; Jonassen 2003; Larkin 1983). They are known to have cognitive flexibility (Spiro et al. 1988), which involves switching between tasks in response to shifting variables, and adopting new procedures in response to a new rule. Cognitive flexibility has also been described as divergent thinking—the ability to bring multiple perspectives to the task at hand, and is necessary for finding new solutions, and creating new knowledge and tools (Ionescu 2012).

Cognitive tools can support self-regulation by helping novices attend consciously to what they know, bring awareness of knowledge gaps, and strategize courses of action (Prawat 1989). By representing the features of a problem, learners can assesses outcomes, recognize a need for a new strategies, and change plans. Cognitive tools can also support metacognition through structuring the learning experience, providing scaffolds (e.g., prompts and feedback) to support the development of mental models, and guiding students toward self-regulation activities (Bannert and Reimann 2011; Efklides 2008; Lee et al. 2010) and dynamic information processing—cognitive strategies, monitoring, and evaluation (Funke and Frensch 1995).

Purpose of the study

In this study, we sought to better understand the connection between cognitive processes, performance outcomes, and the efficacy of operations for the development of mental models. We used a multiple case method to examine advanced learners' (i.e., graduate students) (Kluwe 1995; Stake 2006; Yin 2003) problem solving operations, focusing on the how the frequency and application of cognitive processes contribute to the development of mental models and differences in performance outcomes. Case study allows for a process analysis of complex problem solving through a descriptive account of think-aloud data and solution operations of advanced learners. We assumed that the performance of advanced learners would provide insight into cognitive processes underlying successful problem solving, and have implications for designing cognitive tools that support development of mental models for novices.

Our inquiry built upon previous research using the same learning environment (see description below) to examine the interplay between the use of built-in cognitive tools and learners' cognitive processes. Liu and Bera (2005) found that the use of different types of tools was associated with different stages of problem solving and the students increasingly used multiple tools in the later stages of their problem solving process. The results of the second study showed different types of cognitive tools were used for different types of cognitive processes; a connection was established between cognitive tool use and cognitive processes (Liu et al. 2004). In a third study, results confirmed the findings from previous two studies with sixth graders (the target audience of the learning environment) to further exhibit strong connections between cognitive processes and cognitive tool use (Liu et al. 2009). The findings of these three studies provided empirical evidence to support the theoretical notion that technology-based cognitive tools play an important role in assisting students' problem solving and activating cognitive processes necessary for constructing knowledge and active learning (Jonassen and Reeves 1996).

The current study examines how application of cognitive process contributed to performance outcomes and the development of mental models. Our research question was: How does the frequency and application of cognitive processes during problem solving contribute to differences in performance outcomes and operations in the development of mental models?

Method

Participants

Fifteen graduate students from a large research university in the southwestern United States agreed to participate in this study. These students were recruited from Astronomy ($n = 5$), Educational Psychology (learning and cognition program area, $n = 3$), Instructional Technology (IT) ($n = 4$, two of them had a background in math and science education) and Science Education ($n = 3$, all were middle school science teachers). We chose a group of advanced learners as the participants because we intended to use simulated recall interviews to explore in-depth learners' thinking processes. Our past experience told us that it was very difficult for sixth graders (the target audience of the technology environment) to articulate their thought processes in an explicit and detailed way. Because we selected participants from areas related to the technology environment—content knowledge, technology, and how to learn—we assumed that, compared to sixth graders, these graduate students would have more familiarity of the knowledge and skills for solving the problem strategically, and would apply advanced forms of reasoning typical of their respective disciplines (Mayer 1998, 1989). Because it takes 10,000 h, or 10 years of deliberate practice to be a true expert in a domain (Ericsson et al. 2007), we did not view these learners as experts, but we did hypothesize that they would demonstrate strategic application of cognitive processes toward the development of mental models, and that more frequent activation of higher-order processes occur among successful problem solvers. More information about each participant is presented in Table 1.

The technology environment

The same learning environment, Alien Rescue, was used for the present study as well as the prior studies. Alien Rescue (Liu et al. 2013a, http://alienrescue.edb.utexas.edu/) is a multimedia problem-based learning (PBL) environment designed for sixth-grade space science. Its goal is to engage sixth-grade students in solving a complex problem that requires them to use the tools, procedures, and knowledge of space and planetary science to learn about our solar system and processes of scientific inquiry. Students are asked to find a suitable relocation site for six alien species whose homes were destroyed. Students, enacting the role of scientists, conduct investigations of the aliens and our solar system to decide which planets and moons are most habitable for each species. In doing so, they identify and gather missing data, acquire and apply various science concepts, build probes to prospective planets and moons, and interpret data to find a home for each alien. Students convert temperature, interpret spectra, and decipher periodic tables and apply other skills such as managing budgets and costs of missions as they work toward a solution.

However, factors impacting the solution are not readily transparent and new information that learners discover in the course of solving the problem requires them to develop new solution plans and contingencies. Typical of complex problems, multiple solution paths are possible, and many sub-problems arise involving case-analysis, decision-making, strategic performance, dilemmas, argumentation, and composition (Jonassen 2000). We further increased complexity for the participants by imposing a time limit. The technology environment is designed for fifteen 45-min class sessions for sixth graders, and a total of six alien species need new homes, but we gave each participant 90 min to find a home for the same alien species, the Jakla-Tay, which included time for thinking aloud and

Table 1 Characteristics of participants

	Name	Gender	# of problems solved	Solution correct	Subject matter area
1	Jay	M	1	No	Astronomy
2	Parker	M	1	Yes	Astronomy
3	Quinn	F	2	Yes	Astronomy
4	Liam	M	1	Yes	Astronomy
5	Tad	M	1	Yes	Astronomy
6	Iris	F	1	No	Science education
7	Brooke	F	1	Yes	Science education
8	Jacey	F	1	No	Science education
9	Kyle	M	1	Yes	IT w. Math/science background
10	Ian	M	2	Yes	IT w. Math/science background
11	Carlton	M	1	No	IT
12	Noah	M	1	No	IT
13	Jodie	F	2	Yes	Learning and cognition
14	Erin	F	1	Yes	Learning and cognition
15	Seth	M	1	Yes	Learning and cognition

composing a solution. Participants who solved the problem in less than an hour were asked to find a home for a second alien species, the Akona. These conditions kept the problem sufficiently complex for the advanced learners.

To assist the students, a set of cognitive tools is provided to scaffold students' problem solving (Liu et al. 2013b). Table 2 provides a summary of the functions of each tool. The tools can be divided into the four categories of cognitive tools identified by Lajoie (1993, 2000): Tools sharing the cognitive overload, supporting cognitive processes, supporting activities otherwise out-of-reach, and supporting hypothesis testing.

Procedure

Each participant solved the problem individually in a lab setting on different days. The researcher provided a brief introduction to logging in and navigating through the program. Each participant watched the opening video scenario, which provided the context and described the problem, and then worked on the problem independently at the participant's own computer. The participants received no guidance in terms of the use of each tool, the sequence of tool use, or proceeding through the program. Rather, the PBL program

Table 2 Categories and descriptions of cognitive tools in alien rescue

Category	Functions
Category 1: Tools sharing cognitive overload	
Alien Database[a]	Provides information on the aliens' home worlds, their story, and their characteristics and habitat requirements
Solar System Database	Provides information on the characteristics of selected worlds within the solar system
Missions Database	Provides information on selected NASA missions
Concepts Database	Provides instructional modules on various scientific concepts
Spectral Database	Allows students to interpret spectra found in the Alien Database
Periodic Table	Allows students to look up information on the elements
Category 2: Tools supporting cognitive process	
Notebook	Allows students to generate and store notes on their research findings
Category 3: Tools supporting otherwise out-of-reach activities	
Probe Design Center	Provides information on real scientific equipment used in both past and future probe missions. Students construct probes by deciding probe type, communication, power source, and instruments
Launch Center	Provides an interface for launching probes. Students review the probes built in Probe Design, and decide which probe(s) to launch considering the budget
Category 4: Tools supporting hypothesis testing	
Mission Status Center	Allows students to view data retrieved by probes. Students must interpret this data in order to turn it into information that the students can use in developing the solution. Malfunctions are possible, and poor planning can result in mission failure and wasted budgetary expenditures
Message Tool	Serves as a repository of text messages sent to the student during problem solving
Solution Form	Allows students to submit solutions and rationales for the problem that can be reviewed and critiqued by the teacher

[a] Also called Research Room

encouraged the learners to freely establish and implement their own course of action. An essential goal of the program is that learners engage in planning, decision-making, and determining the best use of the program's affordances to reach the optimal solution. After 90 min, each participant was asked to stop working and to write a solution recommendation for the home(s) they selected and the rationale.

Data sources

To allow triangulation (Creswell 2009), data were collected from three sources: stimulated recall interviews, thinking aloud processes, and students' solution scores.

Stimulated recall interviews and thinking aloud processes

We asked participants to verbalize their thoughts during task completion (Ericsson and Simon 1993) using a think-aloud and stimulated recall procedure as they solved the problem. The stimulated recall technique is "a valuable tool for investigating cognitive processes in a naturalistic context" (Lyle 2003, p. 861). According to Spector (2010), "It is what the person is thinking and how that person is thinking about the problem situation that is very likely correlated with the quality of the solution that is developed and implemented" (p. 32). The stimulated recall procedure involves an observer making careful notes while the participant works through a problem, asking probing questions using the observational notes as stimulus (Calderhead 1981; Lyle 2003). In this study, the researcher asked each participant to explain what he/she was thinking immediately after he/she activated cognitive tools in the environment rather than after he/she had solved the problem. Two example questions are: "I see you found the alien database. What were you thinking that made you want to go into there?" and "I noticed you recorded several pieces of information in your notebook as you read through the solar database. Why did you do that?" Each participant was asked what he/she was thinking after he/she clicked a tool, so there was only a few seconds delay between the action and participant's recall. Stimulated recall allows researchers to capture the link between the learner's abstract understanding of the task requirements and the actual behaviors the learner engaged in. It also makes it possible to measure cognitive activities and motivation strategies to look for similarities in perception of task requirements across the entire problem solving process and to record the learners' idiosyncratic knowledge and personalized routines.

Solution score

The participants' performance outcome was measured by how well they were able to draft a well-supported recommendation for the home they selected. Evaluation of the students' recommendations focused on how well they analyzed and synthesized data to support their solution and advance an argument for the home they selected. Scores, ranging from 1 to 8 on a rubric, were determined by three key criteria: (1) The feasibility of homes they selected (certain home(s) are good while other(s) are poor choices given the characteristics of the alien species and the planets), (2) The number of reasons they used to substantiate their choice, and (3) The number of limitations of the proposed home or gave consideration to how its constraints might be overcome. A rationale received a higher score when it not only selected a good choice for home and provided several justifiable reasons, but also indicated limitation(s) of the chosen home.

Data analysis

The data analysis used a multiple-level scheme, following the guidelines by Miles and Huberman (1994) for the development of a grounded theory (Corbin and Strauss 2008). First, the participants' thinking aloud and stimulated recalls were audio recorded and transcribed. In this step, we took an inductive approach by using open coding and constant comparison. Data were coded to identify the cognitive processes the participants enacted while solving the problem and using different cognitive tools. Five researchers were engaged in the coding process. To identify the codes, initially, the five researchers read through the transcripts from two participants and identified the cognitive processes independently. Then the research team met to discuss each code that surfaced and develop a definition of each code to reach a consensus on how to identify the cognitive processes. Transcripts were re-coded based upon the defined categories of cognitive processes that emerged from the initial coding. Through this iterative process of discussion and re-checking, a set of thirteen codes were generalized and agreed upon by the research team (see Table 5 Appendix for a list of the codes and their definitions). These codes described what cognitive processes the participants said they were doing, not what outcomes these processes may lead to. For example, even though we may assign the code of planning and strategizing, or synthesizing to an action, it does not mean that the participant was planning effectively or synthesizing the right information. It simply means that the code described the behaviors that corresponded with these processes as articulated by the participants in their recall interviews. As a second step, using this coding scheme, each transcript was then coded by one researcher and verified and checked by a second researcher. Any disagreement in coding was discussed and resolved until 100 % inter-rater reliability was achieved.

As a third step, all identified cognitive processes were tallied and examined for emergent patterns. In order to identify patterns across participants, in addition to presenting the frequency of codes for each participant (see column 1 in Table 3), we also calculated the percentage of each code with its relation to the total number of codes (see column 2), by dividing the frequency for each code with the total number of codes. By doing so, we attempted to eliminate the effect caused by the difference in the length of participants' stimulated recall, which may lead to a difference in the raw frequency numbers.

We examined the patterns based upon the use of tools, and the frequency and percentage of prior knowledge (code #5 in Table 3) the participants activated during the stimulated recall protocol. The code prior knowledge activation indicates the participant already had some prior knowledge and used that knowledge as a base to solve the problem. Given the focus of this study, we wanted to see how these advanced learners utilized their prior knowledge in their problem solving process. We examined the code of activating prior knowledge to explore the patterns revealed across the participants. To assign a behavior as activating prior knowledge, typically such verbs or phrases were used by the participants: recalling, thinking of, I have the knowledge, and I knew. For example, Quinn said: "After reading the type of atmosphere that their planet had, I had immediately thought of Io" and "I think a lot of it is just simply because I kind of have some prior knowledge of the different planets and moons, but I don't remember all of them." Frequency of prior knowledge activation was not an indicator of how much prior knowledge one actually had, but rather how often they activated it.

Finally, we examined the participants' performance across several measures: the number of problems they solved, the number of cycles they took to solve the problem, the number of probes they launched (a key cognitive tool use), the cost effectiveness of their missions (the total cost of all probes sent to collect data), the percentage of activating prior

Table 3 Frequency and percentage of cognitive codes

Cluster	Cluster 1								Cluster 2					
Participants	Carlton		Seth		Jacey		Noah		Liam		Tad		Iris	
Codes	#	%	#	%	#	%	#	%	#	%	#	%	#	%
1-Seeking information	12	19.67	13	17.57	9	16.36	12	20.34	19	20.88	11	14.47	13	20.00
2-Comparing	5	8.20	5	6.76	3	5.45	8	13.56	15	16.48	9	11.84	7	10.77
3-Confirming	6	9.84	9	12.16	0	0.00	4	6.78	9	9.89	7	9.21	5	7.69
4-Generating hypothesis	5	8.20	4	5.41	7	12.73	6	10.17	3	3.30	6	7.89	5	7.69
5-Activating prior knowledge	2	3.28	0	0.00	0	0.00	4	6.78	5	5.49	7	9.21	3	4.62
6-Evaluating and synthesizing	5	8.20	7	9.46	8	14.55	7	11.86	10	10.99	15	19.74	11	16.92
7-Testing hypothesis	3	4.92	3	4.05	2	3.64	2	3.39	4	4.40	13	17.11	4	6.15
8-Planning and strategizing	12	19.67	12	16.22	14	25.45	4	6.78	9	9.89	5	6.58	8	12.31
9-Just-in time learning	0	0.00	1	1.35	2	3.64	0	0.00	0	0.00	0	0.00	1	1.54
10-Organizing	6	9.84	1	1.35	1	1.82	4	6.78	7	7.69	1	1.32	2	3.08
11-State of mind (curiosity, confusion,…)	2	3.28	12	16.22	5	9.09	4	6.78	5	5.49	0	0.00	4	6.15
12-Orienting: browsing, scoping	1	1.64	3	4.05	1	1.82	1	1.69	0	0.00	0	0.00	0	0.00
13-Metacognition	2	3.28	4	5.41	3	5.45	3	5.08	5	5.49	2	2.63	2	3.08
Total	61	100	74	100	55	100	59	100	91	100	76	100	65	100

Cluster	Cluster 3								Cluster 4							
Participants	Parker		Erin		Kyle		Jay		Jodie		Quinn		Ian		Brooke	
Codes	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%
1-Seeking information	8	17.39	20	34.48	10	18.52	9	18.00	13	19.40	7	16.28	19	18.10	8	21.62
2-Comparing	6	13.04	6	10.34	7	12.96	10	20.00	8	11.94	7	16.28	12	11.43	4	10.81
3-Confirming	0	0.00	5	8.62	3	5.56	1	2.00	2	2.99	2	4.65	5	4.76	3	8.11
4-Generating hypothesis	5	10.87	3	5.17	3	5.56	5	10.00	4	5.97	6	13.95	11	10.48	4	10.81

Table 3 Frequency and percentage of cognitive codes

Cluster	Cluster 3								Cluster 4							
Participants	Parker		Erin		Kyle		Jay		Jodie		Quinn		Ian		Brooke	
Codes	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%
5-Activating prior knowledge	2	4.35	0	0.00	3	5.56	1	2.00	5	7.46	4	9.30	12	11.43	2	5.41
6-Evaluating and synthesizing	5	10.87	8	13.79	6	11.11	8	16.00	5	7.46	6	13.95	7	6.67	2	5.41
7-Testing hypothesis	4	8.70	4	6.90	1	1.85	2	4.00	6	8.96	1	2.33	4	3.81	5	13.51
8-Planning and strategizing	5	10.87	2	3.45	7	12.96	8	16.00	5	7.46	6	13.95	16	15.24	4	10.81
9-Just-in time learning	1	2.17	0	0.00	2	3.70	1	2.00	4	5.97	1	2.33	3	2.86	0	0.00
10-Organizing	3	6.52	1	1.72	2	3.70	1	2.00	8	11.94	0	0.00	7	6.67	3	8.11
11-State of mind (curiosity, confusion,…)	4	8.70	7	12.07	5	9.26	2	4.00	1	1.49	2	4.65	6	5.71	0	0.00
12-Orienting: browsing, scoping	2	4.35	0	0.00	2	3.70	0	0.00	1	1.49	0	0.00	2	1.90	1	2.70
13-Metacognition	1	2.17	2	3.45	3	5.56	2	4.00	5	7.46	1	2.33	1	0.95	1	2.70
Total	46	100	58	100	54	100	50	100	67	100	43	100	105	100	37	100

Table 4 Profiles of learner clusters

Profile	Number of problems attempted	Average number of problem solving cycles (total cycles)	Average number of probes launched (total probes)	Developed a cost effective solution	Average percentage of activating prior knowledge	Argued a viable solution	Average solution score
Cluster 1 ($n = 4$): low prior knowledge, unsuccessful	1	4.25 (17)	3 (12)	No	2.51	No	1
Cluster 2 ($n = 3$): medium prior knowledge, successful	1	6.33 (19)	6 (18)	No	6.44	Yes	5
Cluster 3 ($n = 4$): low prior knowledge, highly successful	1	4.25 (17)	2.75 (11)	Yes	2.98	Yes	7
Cluster 4 ($n = 4$): high prior knowledge, highly successful	2	2 (8)	1.75 (7)	Yes	8.40	Yes	6

knowledge (the frequency of activating prior knowledge [code #5] divided with the total occurrences of cognitive codes), and their solution score. Participants who shared similar results across these factors were grouped together into clusters (see Table 4). As a result, four profiles of problem solving performance emerged.

Findings and discussion

Multiple factors underlie success at solving a complex problem, and various scaffolds for activating cognitive processes can be used more or less effectively toward deriving effective solutions (Bixler and Land 2010; Puntambekar and Hübscher 2005; Simons and Klein 2007). Thus, in the findings, we begin by describing performance trends and cognitive processes operations that characterized each cluster (See Figs. 1, 2, 3, 4). We discuss clusters from least to most successful in solving the problem to show a progression of complex problem solving ability. Next, we provide a cross cluster analysis to show differences in how learners applied cognitive processes to develop facets of problem representation, or thresholds of knowledge development (see Fig. 5) as learners applied cognitive processes toward the development of mental models during the problem solving process. Finally, we discuss cognitive process associated with self-regulation, and suggest some directions for designing cognitive tools.

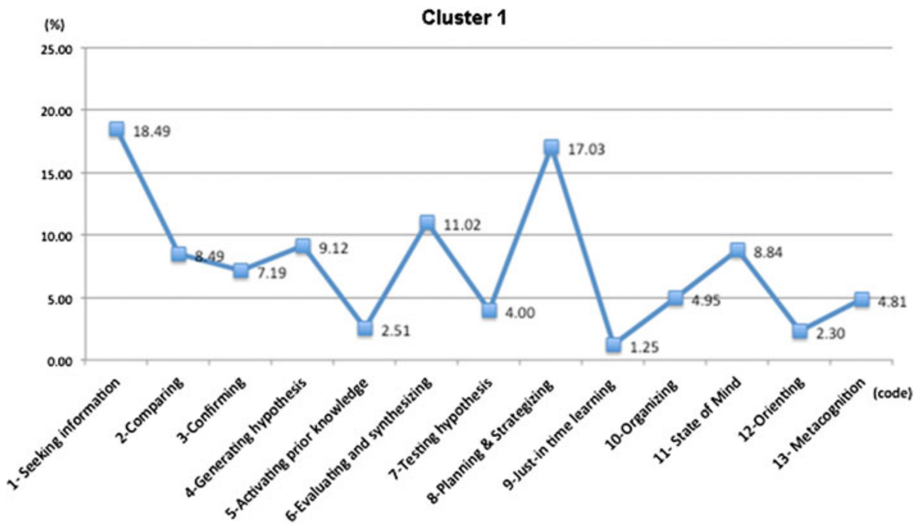

Fig. 1 Distribution of codes in cluster one

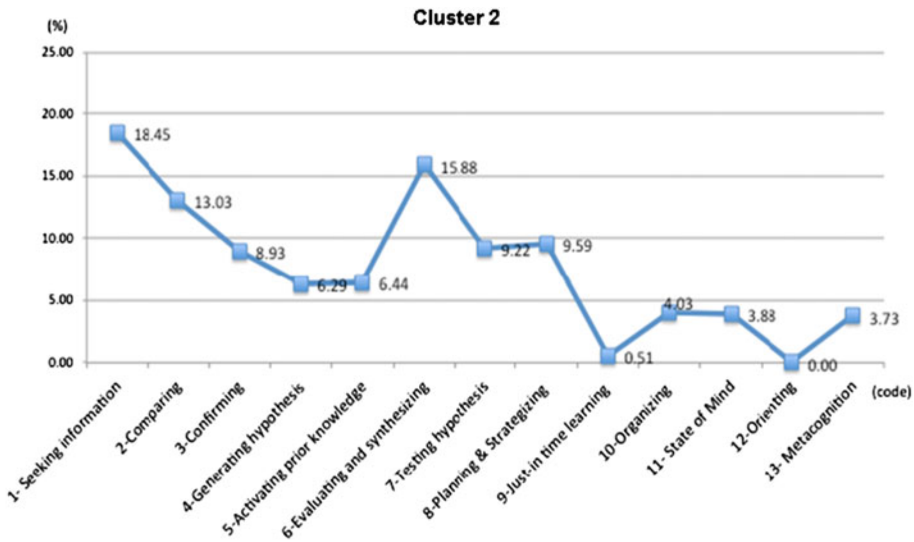

Fig. 2 Distribution of codes in cluster two

Profiles of complex problem solving

Cluster 1: low prior knowledge activation, unsuccessful

The four advanced learners we placed in Cluster 1 came from IT, Learning and Cognition, and Science Education programs. Together, they averaged 4.25 problem solving cycles and sent an average of three probes (see Table 4). Figure 1 presents the distribution of cognitive codes for this group. Their low activation of prior knowledge suggested that they had low domain

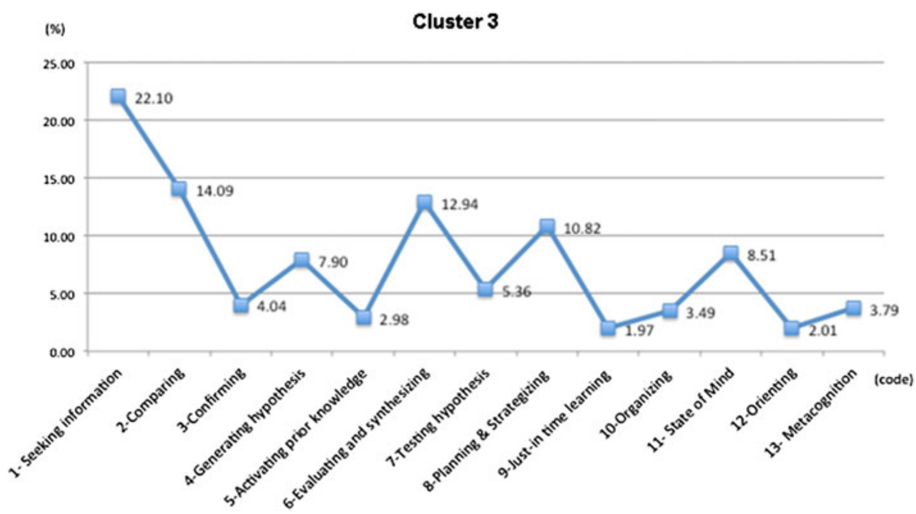

Fig. 3 Distribution of codes in cluster three

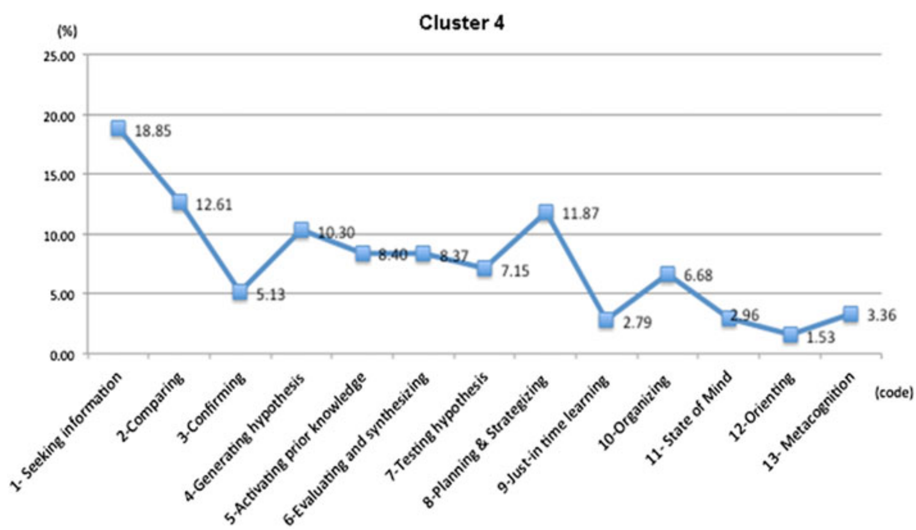

Fig. 4 Distribution of codes in cluster four

knowledge, or that their knowledge was inert. As shown in Table 3, Seth and Jacey did not activate prior knowledge (code #5) during their stimulated recall. Carlton also had a low degree of activating prior knowledge (ranked as the 11th highest among the fifteen participants), and Noah was ranked in the middle among the fifteen participants. Ultimately, they were unsuccessful solving the problem. In the following, we discuss aspects of their performance that led to unsuccessful outcomes.

Ineffective operations for building structural knowledge Although seeking information (code 1) was the top ranked code for this cluster (code 1, 18.49 %), they had formed ineffective procedural operations for building domain knowledge. First, when compared to the other more successful clusters, these learners seldom compared data (code 2, 8.49 %) when seeking information, which compromised their ability to make connections and build conceptual knowledge. They often used tools that were inappropriate for the stage of problem solving they were in and the cognitive processes they wanted to enact. For example, during the research stage, both Jacey and Carlton used hypothesis testing tools (probe builder and launcher) to seek information without having an actual hypothesis. Jacey said, “I guess I am just going to randomly send probes to these different planets to collect data. Then I’ll observe the data and see which [planets] I can eliminate.” They sent probes with the intention of seeking information rather than testing specific hypotheses. Failure to associate their cognitive processes with the right tool at the right time (i.e., stage of problem solving) and their difficulty with making connections among the information they processed exacerbated backward reasoning processes (Chi and Bassock 1991; Glaser 1989) and compromised development of structural knowledge.

Inadequate self-regulation Cluster 1 learners engaged metacognitive processes (code 13, 4.81 %) and had high frequencies of planning and strategizing (code 8, 17.03 %). However, often they carried out plans and applied strategies before considering their appropriateness or alternative courses of action. They focused more on finding shortcuts than on building knowledge of concepts and identifying all the factors impacting the problem. They often disregarded prompts for specifying the purpose for their missions, and built probes without consideration of costs or feasibility. Carlton said, “Since I have an unlimited budget, I may as well make the Cadillac of all probes and send it to every planet I think might fit… there is no rationale, for not including an instrument.” They went through several cycles before formulating a specific research question. Because their research questions were too broad, they had difficulty gathering relevant information and building domain knowledge of concepts central to the problem. When things were not working, they were inflexible changing their plans until they encountered excessive setbacks. Jacey underwent five cycles before self-regulating, which was essential for revising her representation of the problem and developing more effective operations for building structural knowledge of the domain:

> I need to be more specific about where I want to send this probe and what I want it to do, but I really don’t have enough information on all these different planets. Maybe I can eliminate them in another way, so I may have to go into the solar system database and research individual planets. Maybe there is already information about the atmosphere without sending a probe. So I am going to eliminate by the information that is already known without spending a lot of money.

Once they began associating the tools with the cognitive function they wanted to enact, as Jacey did above, they grew more proficient at developing more effective plans and strategies for building structural knowledge and generating hypotheses.

Setbacks elicited negative emotions State of mind (code 11, 8.84 %) was highest among Cluster 1 learners. Feelings of frustration and uncertainty in the wake of setbacks corresponded with task avoidance and foreshortened conclusions. They demonstrated behaviors typical of performance learning orientations, as characterized by “focusing on avoiding inferiority, not looking stupid or dumb in comparison to others” (Pintrich 2000, p. 99). Carlton said: “I feel like I have a high self-concept and so I feel like finishing quickly is important to me, and that I can show others that I can finish quickly.” Seth oscillated between building background knowledge and “just getting done.” He said: “I want to do it quick and like perform well or something." The emphasis they placed on speed as a measure of ability contributed to ineffective procedural operations such as inconsistent use of tools and frequent disregard for self-regulatory cues within the problem space. Performance orientation behaviors, which focused on maintaining one's self-efficacy as a capable problem solver through external validation, did not regard setbacks as feedback for revising problem representation, but as threats to their sense of self as capable problem solvers. At the same time, they cared about being successful and were concerned when setbacks inhibited progress.

Having trouble with integrating meaningful information In contrast to the other clusters, these learners had low occurrence of comparing (code 2, 8.49 %). They did not have a systematic procedure for comparing across data representations to make connections between isolated facts. Although they had recorded life-supporting requirements of the alien species in the notebook tool, they failed to discern how requirements interacted to sustain life and had trouble prioritizing requirements when examining the affordances and constraints of a potential home. Lack of an integrated conceptual knowledge base made it difficult for them to perceive what factors were most important when evaluating results from problems. In the end, they drew conclusions from a limited set of data. Their failed solutions resulted from inadequate procedures for developing structural knowledge, ineffective operations for self-regulating, frustration and anxiety in response to setbacks, and difficulty bringing together relevant data to evaluate outcomes.

Cluster 2: medium to high prior knowledge activation, somewhat successful

Cluster 2 was comprised of three learners whose stimulated recall responses revealed a medium to high activation of prior knowledge of planetary science, and averaged a solution score of 5 points. Liam and Tad were doctoral students in Astronomy, and Iris was a master student in science education. As shown in Table 3, Liam's percentage of activating prior knowledge was 5.49 %, which was ranked as the seventh among the fifteen participants. Iris' 4.62 % of prior knowledge code was ranked as the ninth. Tad's activation of prior knowledge accounted for 9.21 % of his total occurrences of cognitive codes, which was the third highest among the fifteen participants. Despite their advanced knowledge, they took an average of 6.33 of cycles to solve the problem and accrued excessive project costs. In the following, we describe the performance trends across their cases.

Reliance on structural knowledge Cluster 2 learners identified a suitable habitat for the alien species within three cycles, acting on an intuitive leap or hunch. Relying on their advanced knowledge of the domain, they made accurate forward inferences (Chase and Simon 1973; Livingston and Borko 1989) by comparing, confirming, and synthesizing data when seeking information. For example, while reading that the alien species need for sulfur to grow their crops, Tad immediately sent a probe to Titian, a moon of Jupiter, claiming, "…there is atmospheric nitrogen present for their plants and there is atmospheric methane present. Usually where there is methane there is sulfur—they tend to go hand and hand a lot of times." Having prior domain knowledge increased the diversity of cognitive processes and knowledge construction processes when seeking information. However, they had neglected orienting (code 12, 0 %) to the full range of tools available to the problem space and enacted operations for hypotheses development and testing before gathering contextual knowledge about the alien's characteristics and other factors that can affect the alien's ability to adapt to an imperfect but otherwise habitable environment.

Inert argumentation Cluster 2 learners worked from limited data, and looked for a perfect match rather than argue for how the aliens could overcome the limitations of a feasible environment. Information seeking, comparing, and confirming were the dominant processes they used to evaluate probe results when operations for synthesizing data were necessary for building an argument and generating a solution. A pattern of rapid dismissal of strong candidates emerged. For example, after checking the data from his probe, Liam abruptly ruled out Io, a good match, as being appropriate for the species: "…I just noticed that it [Io] doesn't have nitrogen in its atmosphere based on the results, so I am going to scrap that idea." Liam did not argue how the species could use their farming and engineering abilities to manufacture nitrogen from Io's natural resources. Developing the argument would have required synthesizing their prior knowledge with the data they obtained from the probes, and the information about the alien's needs and characteristics. Operations for these processes remained inert until they had formed a better conception of the task and developed an awareness of all the factors impacting the situation.

Delayed self-regulation They averaged sending six probes before generating a solution. Having ruled-out the best homes during the initial cycles, they sent probes to unlikely candidates based on overly complicated rationales. Cluster 2 engaged planning and strategizing (code #8) processes, but they did not reevaluate their approach until they had exasperated resources of time, money, and mental stamina. Few remaining options caused them to reexamine their initial hypotheses. For example, Liam stated:

> It seems kind of strange to go full circle and come back to Io which looked pretty good from the start. I sort of ruled it out because of its lack of nitrogen. But after going through all the other possibilities it is becoming clear to me I was trying to find a perfect match. I am not finding one.

Recognizing how multiple factors impacted solution procedures was critical to their reevaluation of the problem, and enhanced solution generation procedures to include synthesis and evaluation of multiple data to build arguments. Tad, for example, reviewed his probe results from Venus after having eliminated the planet several cycles earlier having decided Venus' surface temperature was too hot. This time, however, he synthesized knowledge of the aliens with his conceptual knowledge of the domain to build an argument: "The temperature is high, but they are a subterranean species, they live mostly below the surface, so that may not affect them as much." Bringing related factors together to build arguments remained inert until they had formed an accurate perception of the task's complexity.

For Cluster 2 learners, prior knowledge facilitated rapid development of hypotheses yet caused them to activate solution generation procedures before they had understood the complexity of the task or the types of data they would need. This left their representation of the problem underdeveloped for many cycles. Inconsistent self-regulation kept them from reforming their representation of the problem and activating operations for argumentation until they had no other recourses but to make something work from the mass of data they had collected.

Cluster 3: low-medium prior knowledge activation, highly successful

Cluster 3 included four advanced learners. Jay and Parker were doctoral students in Astronomy. Kyle was a Master's student in IT, and Erin was a doctoral candidate in Learning and Cognition. As shown in Table 3, these four learners had low frequencies of prior knowledge codes. This was the case even for Jay and Parker who were doctoral students in astronomy. Parker's percentage of activating prior knowledge was 4.35 %, which was ranked as the tenth and Jay's 2 % ranked as the 12th among the fifteen participants. Kyle's activation of prior knowledge accounted for 5.56 %, which was ranked in the middle of using prior knowledge as compared with other participants. Erin never activated prior knowledge during the stimulated recall. Even so, this cluster had the highest solution scores (see Table 4). We examine the performance traits that made them highly successful problem solvers in the following.

Methodological use of tools to develop domain knowledge These learners developed domain knowledge by comparing data representations and forming connections between isolated facts as they sought information. They averaged the highest levels of comparing (Code 2, 14.09 %) of all the clusters. They initially worked on the basis of surface characteristics (Bransford et al. 2000; Chi and Bassock 1991; Glaser 1989). Kyle, for example, searched for a planet or moon that matched the color of the aliens' skin: "They [the aliens] talked about how they were the same color as that planet, so I figured it might be an adaptation of theirs; so, they might want to be on a planet that is the same color as them." Such logical approximations involved comparing data and perceiving meaningful patterns, but lacked a thorough knowledge base with which to derive immediate breakthroughs. They gradually grew from superficial surface comparisons toward organizing their operations around concepts underlying the problem. They used the notebook tool to externalize conceptual knowledge, keep track of unknown information, and pose questions around knowledge gaps. Parker, through use of the notebook tool, combined geological, physical, biological, and atmospheric knowledge he had formed to set boundaries around his search:

> As a first cut I am looking for red planets and red moons because they need these heavy metals, and it seems a significant fact that they use red and orange bricks in building their homes. Like Mars I am saying that it might be a possibility, but there are a few questions that I have about its atmosphere like 'Does it have nitrogen and sulfur?'

Recognizing and isolating unknown information was necessary for formulating research questions that guided the development of structural knowledge, and compelled these learners to use tools methodologically for resolving unknowns. Just in time learning (Code 9, 1.97 %) was a skill they applied when encountering a knowledge constraint that inhibited progress. Kyle, for example, used the concepts database tool whenever new factors emerged and obstructed his initial path:

> I didn't know anything about the probes, so I want to learn about those. At the same time, I've been wondering about converting temperature, so it was good that I found it [concept database] in there. So I have to go back and read this because honestly I didn't remember much about Kelvin, so I need to look at that again.

They recognized the need to convert temperature scales, distinguish between probes types, and interpret spectra, but had to relearn the concepts so they could execute these operations toward their larger goal. Their search of the research databases was sustained by self-generated questions and learning goals that if proved unsuccessful could still produce insights about the problem and bring them closer toward a solution.

Productive response to failure These learners responded to failure productively (Kapur and Rummel 2012; Kapur 2008) by identifying the underlying issue and determining new solution paths. Setbacks triggered appraisal of outcomes and development of new goals. Their formative response to setbacks was indicative of a mastery learning behavior (Pintrich 2000). They were driven more out of curiosity than by external validation, and embraced uncertainties. For example, when studying the alien species, Erin stated: "I am a social scientist…when I don't know, I go and find out." They embraced the role of scientist with a genuine concern for the species, taking care to balance the alien's needs with perceived wants, and inferring how these factors could help them adapt to an imperfect home. Parker said: "I am looking for things that might make them comfortable, like they need heavy metals because they know how to work with them and they seem to like digging the tunnels." In this regard, enacting the role of scientists on a mission to save endangered species was the locus of their attention, rather than external perceptions of themselves as problem solvers.

High self-regulation Figure 3 shows that the average percentage of planning and strategizing (code 8, 10.82 %) was the fourth most applied process for this cluster, and metacognition (code 12, 3.79 %) was the tenth most activated processes. Cluster 3 focused on self-regulating the efficacy of their procedures for building domain knowledge. Being self-regulative of procedural operations provided a more strategic and defined focus, especially when planning missions for testing hypothesis. As shown in Fig. 3, information seeking (#1), evaluating and synthesizing (#6), comparing data, and generating hypothesis peaked in their frequency distribution of cognitive codes. The sequence of these processes—seek, compare, plan, and evaluate—indicated that they had formed a predictable pattern for managing the problem and evaluating progress. They were cognizant of why they needed the information they gathered, how they would apply it, and why the application mattered. Parker's response was typical: "I only have one question about the planets, so I chose the mass spectrometer. I already know there is volcanic activity on the planet and I don't think I really need the radar. I don't think that is relevant." They waited to test hypotheses until they had exhausted all information resources, were functioning at the cusp of their knowledge, and could neither dismiss a home from consideration nor affirm its suitability.

Strategic use of tools to support decision-making As Cluster 3 built domain knowledge, they became strategic with using multiple tools simultaneously to support synthesis and evaluation processes prior to generating a solution. As shown in Fig. 3, the distribution of cognitive codes peaked at evaluating and synthesizing (code #6, 12.84 %), and was the third most activated process for this cluster. Their predominant strategy was to build hypotheses of two or three potentially habitable homes, rank them according to their degree of habitability, send probes back to back, and compare results to determine the best fit for the species. Choosing between two or more habitable homes increased the problem's complexity and compelled them to access multiple representation tools to perceive all factors impacting the situation and manage cognitive demands. Kyle, for example, accessed mission status center, the notebook tool, spectral database, periodic table, and other tools to support synthesis and evaluation processes:

> This is really hard…I see similarities in both places about what they need, but I need to figure-out which ones are most important because I do not want them to die…Part of it is that I don't know how much they need of certain materials. The spectrometer showed that there is sulfur and nitrogen on Venus but it looks like very small amounts, but also the probe was destroyed. So I don't know if it was just higher up in the atmosphere that it didn't have those things or if there was more of it closer to the surface. But then there is plenty of sulfur in Io, but does not have enough…well, it doesn't have any nitrogen. I am balancing that with the gravity on Venus. It is much stronger than what they are used to and the last thing I want to do is crush them.

Kyle's use of multiple tools for evaluating the results initiated comparing (code #2), evaluating and synthesizing (code #6), planning and strategizing (code #8), and state of mind (feeling uncertain) (code #11). The final solutions evidenced deep understanding of scientific concepts and argued how the aliens could use innate abilities and physical characteristics to overcome the limitations of an imperfect environment.

The success of Cluster 3 was not predicated on the amount of prior knowledge they had when beginning the problem, but on consistent procedural operations for building structural knowledge that gave way to forward reasoning processes. The analysis showed Cluster 3 provided an exemplar case of how learners with minimal background knowledge in a domain could use cognitive tools strategically to solve an ill-structured problem more expertly.

Cluster 4: high prior knowledge, highly successful

Cluster 4 learners quickly inferred the problem's underlying concepts, had high solution scores, and solved for two problems in the time it took other participants to finish one problem. They had high frequency of prior knowledge activation, and this ranked as the cluster's fifth most applied cognitive processes. Quinn and Brooke, doctoral students in astronomy, relied on their structural knowledge of the solar system, which minimized their use of tools. Jodie and Ian, graduate students in education, had less conceptual knowledge of the domain, but applied cognitive strategies and had prolific tool use at all stages of problem solving to derive quick solutions.

Highly developed structural knowledge of the domain Most novices struggle with recognizing the problem, setting it up, forming a solution path, and applying relevant knowledge to the task (Bransford et al. 2000; Patel and Groen 1991; Savelsbergh et al. 1998). However, Quinn and Brook exemplified these aspects of developing expertise from the first cycle. They processed information about the aliens against their prior knowledge of the solar system without relying on tools for comparing data. For example, when reading about the Jakla-Tay, Shay said: "I am trying to think in what ways it compares to our solar system and also get a feeling for the different types of planets that were inhabited versus the ones that weren't inhabited." She compared the data she processed about the aliens against her internalized knowledge of the Earth's solar system without referring to the solar database. In fact, many of the cognitive processes the tools were designed to support, particularly those for hypothesis generation, testing, and evaluation, were already internalized for these learners. In only one cycle, she hypothesized Io as a good match for the species: "After reading the type of atmosphere that their planet had, I had immediately thought of Io. I am trying to remember what it was composed of. Their planet sounded a lot like Io, so I am just reading it [in the solar system database].” Brooke exhibited similar behaviors, having targeted a habitable home in just two cycles. “I almost just want to skip to the end [laughs]!”

Brook and Quinn used prior knowledge to its maximum benefit. They used tools for confirming the accuracy of their hunches or whenever they grew curious of a tool’s functionality. Their progression through the program was mostly a matter of forward sequence and their use of tools was a necessary means to a pre-determined outcome. After analyzing her probe results, Quinn stated: “I was hoping that I would find something more detailed than I already knew about Io, but I didn’t really feel that I found anything that was more beneficial or useful. I just wasted money.” Like Cluster 3 learners, both were conscientious of project costs and associated excessive expenses with inadequate planning.

Active cognitive processing approach Jodie’s and Ian’s knowledge of the solar system was less thoroughly internalized, but both solved the problem within only three cycles. Jodie was a doctoral candidate in Learning and Cognition and Ian a master’s candidate in IT. They leveraged what prior knowledge they had of the solar system with the cognitive strategies and use of multiple tools to think across and make connections between data representations, which facilitated quick and well-substantiated hypotheses. They applied high frequencies of synthesis and evaluation tools from the first cycle of problem solving. They had an active cognitive processing approach characterized by “activating prior knowledge, questioning, interpreting, analyzing, and processing new information and concepts in light of past experiences; monitoring, developing, and altering prior understanding, and integrating current experiences with past experiences” (Gillespie 2002, p. 1). While all of the participants enacted these processes, Jodie and Ian, combined these processes at all stages, which distinguished them from the other participants who relied upon Category 4 tools (see Table 2) for activating these processes. Their cognitive processing infused seeking information, comparing, and applying prior knowledge regardless of what tools they were using. Beginning with the first cycle, they applied knowledge of the aliens’ needs and preferences to evaluate information they processed about the Earth’s solar system. Ian, for instance, said: “I am looking for other rocky worlds; that kind of limits what I am looking at. I just know that this particular species came closer from their original sun. So for now I am limited myself from Mercury to Mars and then Mars’ moons.”

Activated argumentation operations at all stages They showed advanced cognitive skills in that they formed arguments for how aliens could adapt to the constraints of a potential home long before they decided to send probes and evaluate results. For example, after researching a planet with a high gravitational pull, Jodie said: “This species are strong, they are short. They do hard labor, so I don’t think a higher gravity would necessarily affect them.” After reading about the high temperature on Venus, Ian said: “I didn’t see anything about [the alien’s] bodies that said they couldn’t survive in extremely hot temperature, but you never know.” He combined his knowledge of the aliens’ physical characteristics with the knowledge he possessed about the planet to infer that the species could withstand its high gravity. Instead of automatically eliminating a home on the basis of its deficiencies, as learners in Cluster 2 had done, they evaluated how the aliens could mitigate the constraint it posed by comparing and synthesizing data they had gathered regarding the species. The ease with which they made inferences, synthesized information, and developed hypotheses during the research stage suggested that they relied on their advanced cognitive processing skills in conjunction with the prior knowledge they had.

Cluster 4 was characterized by advanced domain knowledge and strategies for processing information. The pattern of reading, making inferences, developing and testing hypotheses dominated each of their cycles, allowing them to solve for two problems within the time frame others only solved one. Consequently, Cluster 4 demonstrated the most expert-like performance of all participants.

Summary of clusters

The performance trends that characterized each cluster indicated that the frequency of high-level cognitive processes was an unreliable indicator of successful performance. Far more important was how skilled learners were at keeping their cognitive processes focused on discerning relevant factors, identifying unknowns, and developing knowledge for generating a solution. Successful problem solving operations among learners with low prior knowledge activation (Cluster 3) was associated with self-regulation of knowledge development, formative response to failure, and bringing multiple representations together to compare, synthesize, and evaluate. Unsuccessful performance among low prior knowledge activation learners (Cluster 1) was associated with ineffective procedures for developing an integrated knowledge base, performance oriented behaviors, and inconsistent self-regulation. However, even learners with high activation of prior knowledge and familiarity of the problem domain (Cluster 2) encountered difficulty with general problem solving skills that impaired performance. They had a tendency to misrepresent the problem and act on a solution path without recognizing all factors. These setbacks kept argumentation operations inert when evaluating results. The most successful learners (Cluster 4) had developed a highly integrated knowledge that increased cognitive power at all stages of problem solving, allowing them to work with great efficiency, accuracy, and solve for two problems. Our descriptive analysis suggests that individual differences in learning orientation, prior knowledge, and skill in self-regulating knowledge development impact how cognitive processes are applied toward successful solution operations.

Thresholds of knowledge development: a cross cluster analysis

To further explore the association between cognitive processes and performance differences among the four clusters, we examined how learners' cognitive processes corresponded with facets of mental model development, which include (1) Building a procedural model, (2) building a structural model, (3) building an executive model, and (4) building arguments (Jonassen and Strobel 2006). As shown in Fig. 5, the outer arrows represent the steps associated with the problem solving cycle (Bransford and Stein 1984). The outer circle represents self-regulation in the application of cognitive processes across each of the four thresholds. The middle circle identifies the tasks, or essential operations for each threshold. Finally, the inner circle represents the cognitive processes that learners applied toward carrying out those tasks. For some clusters, it took multiple cycles to master the operations within a threshold, and mastering them was necessary for successful operations in later thresholds. In the preceding discussion, we present the dominant cognitive processes and operations associated within each threshold as well as areas where novices may require scaffolding within each threshold.

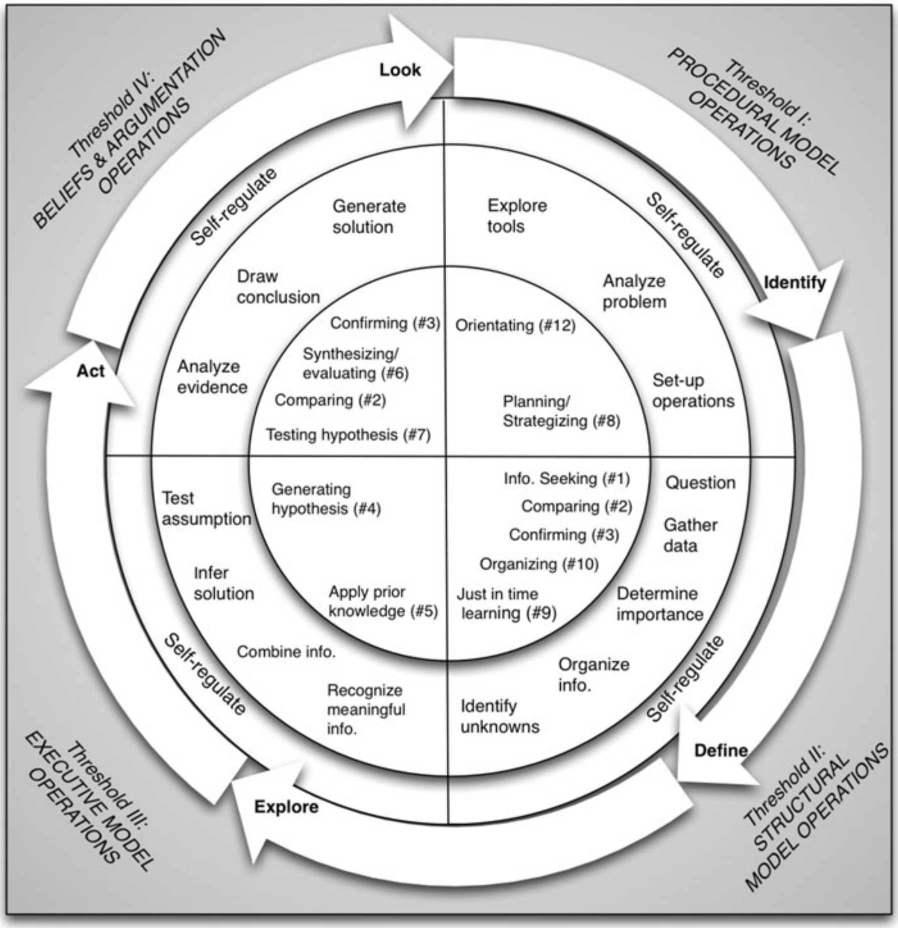

Fig. 5 Thresholds of knowledge development

Threshold I: developing a procedural model

Developing a procedural model involved generating procedures for operating in the problem environment, and developing plans for solving the problem. It required analyzing the problem and discerning the function and purpose of tools for executing a solution path. The dominant cognitive processes for developing a procedural model were planning/strategizing (code 8) and orienting (code 12), both of which were associated with self-regulation (Azevedo and Hadwin 2005; Lajoie 2008). The most successful learners developed procedures for how they would use tools at different stages of problem solving, and implemented a methodological approach for use of building and integrating domain knowledge (Cluster 3, 10.82 %; Cluster 4, 11.87 %). Doing so was critical for learners who had low activation of prior knowledge and had little else but the tools from which to set up the problem. Cluster 3, for example, strategized using the tools to build hypotheses of two or more homes, send probes, and compare the results. Cluster 1 had the highest proportion of planning-strategizing (17.03 %) of all the clusters, but had a tendency to mismatch tools with the cognitive processes, and use tools that were ineffective for developing structural knowledge. They had to keep returning to this threshold until they developed sufficient procedural operations. Disproportionately high frequencies of planning-strategizing as compared to other clusters indicated struggle, numerous cycles of problem solving, and cognitive overload more than efficient problem solving.

All clusters had similar rankings for orienting, which involved qualitative analysis of the problem through exploring the problem space and the function of tools. Orienting was lowest among the clusters with advanced domain knowledge (Cluster 2, 0 %; Cluster 4, 1.53 %). Most notably, Cluster 2 was the only group who had no application of orienting, which compromised the qualitative analysis of the problem. In summary, orienting, planning, and strategizing featured prominently in problem analysis and developing solution procedures. However, knowing which tools can best support different cognitive processes is a meta-awareness that is not automatic for some learners, especially novices (Puntambekar and Hübscher 2005; Simons and Klein 2007). Novices need support for building associations between tools, cognitive processes, and stages of problem solving to form students' initial representation of the problem and help them use the right tool for the tasks at hand.

Threshold II: developing a structural model

This threshold involved developing a structure of concepts underlying the problem that were relevant to its solution. Learners used their procedural model of tools to build domain knowledge and discern missing elements that related to the solution. The dominant processes included information seeking (code 1) and comparing (code 2). The most successful learners applied these processes for gathering data, questioning, determining the importance of information, and identifying unknowns.

Information seeking (code 1) was the top ranked process for each cluster. However, it is noteworthy that the lowest scoring cluster had the least application of information seeking (Cluster 1, 18.49 %), and the highest scoring cluster had the highest levels of this process (C3, 22.10 %). The development of structural knowledge increased cognitive demands for both these clusters, requiring them to keep track of unknown information, research questions, and relevant data. Cluster 3 relied on methodological use of tools to manage these operations, while Cluster 1 was inconsistent with keeping cognitive processes focused on these tasks. Self-regulatory tools (Azevedo and Hadwin 2005) are necessary at this threshold so that learners can stay focused on building structural knowledge of the domain.

Comparing (code 2) was a critical process in the development of structural knowledge. By thinking across two or more representations, learners were apt to make connections between data, infer probabilities, and discern relationships. Comparing was the second most activated process for Clusters 3 and 4 (Cluster 3 14.09 %; Cluster 4 12.61 %), which had the highest solution scores. It was the third most applied process for Cluster 2 (Cluster 2; 13.03 %). However, Cluster 1, which averaged the lowest scores, had fewer instances of comparing (Cluster 1, 8.49 %), and was the cluster's sixth most activated cognitive process. Considering that these learners also had the lowest average frequency of prior domain knowledge (Cluster 1, 2.51 %), they were in the most need of building a structural representation. Failure to use tools methodologically made it difficult for them to transcend backward reasoning processes. Given that comparing was a distinguishing factor in learners' success, tools that intentionally scaffold comparing processes for building structural knowledge can be of considerable benefit to novices.

Other cognitive processes frequently activated in this threshold were confirming (code 3), organizing (code 10), and just in time learning (code 9). Confirming was most often applied by the least successful clusters 1 and 2. They took more cycles to solve the problem and had not integrated relevant information (Cluster 1, 7.19 %; Cluster 2 8.93 %). The more successful clusters (Cluster 3, 4.04 %; Cluster 4, 5.13 %) activated this process to check the accuracy of their inferences before determining a course of action or drawing conclusions. Organizing shared a similar ranking across clusters, but was highest for Cluster 4 (Cluster 1, 4.95 %; Cluster 2, 4.03 %; Cluster 3, 3.49 %; Cluster 4, 6.68 %). *Just in time learning* was among the lowest of all processes activated for each cluster, but occurred more often within Clusters 3 and 4 (Cluster 1, 1.25 %; Cluster 2, 0.51 %; Cluster 3, 1.97 %; Cluster 4, 2.79 %). The higher occurrences for Cluster 4 can be attributed to those learners having solved a second problem. Both Clusters 3 and 4 had consistent operations for seeking information and comparing with Category 1 tools (see Table 2), and gradually integrated other cognitive processes as their domain knowledge grew more advanced.

Given the critical role of developing structural knowledge, novices can benefit from representation tools that adjust to their mental model. Tools that provide learners flexibility organizing content into meaningful and related chunks as they process new information are recommended. Concept maps and diagrams along with a notebook tool can provide a visual medium for helping learners to notice what they know from what they need to find out (Henning 2004; Kozma 2003). Flexible representation tools can also offer insight into how a student is thinking about the problem and where critical concepts remain unformed (Kim 2012). When these representations cultivate such awareness, they can also scaffold the formulation of research questions, plans, and strategies for seeking information and comparing (Puntambekar and Hübscher 2005; Simons and Klein 2007).

Threshold III: developing an executive model

Executive operations involved having perceptual awareness of relevant information in the problem space that triggered solution generation procedures. It involved knowing when and why to activate prior knowledge (code 5) to generate hypotheses (code 4). Executive operations infused procedural and structural models, which increased learners' perception of critical concepts underlying the problem and awareness of the factors impacting the problem. Operations within this threshold included combining relevant information, inferring possible solutions, and testing assumptions. Learners who functioned successfully at this threshold had a developed structural knowledge of the domain, an adequate representation of the problem type, and strategic use of tools. Such effective operations produced executive operations that were accurate, forward reasoning processes.

Activation of prior knowledge (code 5) was critical to triggering executive operations. This code represented knowledge that participants had acquired outside of the technology environment that they used to solve the problem. Clusters 1 and 3 had low levels of prior knowledge activation (Cluster 1, 2.51 %; Cluster 3, 2.98 %). It was the 11th most activated process for both clusters. Cluster 3 entered this threshold only after mastering the developmental tasks in the prior thresholds. As their structural knowledge grew in tandem with procedural operations, the power of their cognitive operations increased and they enacted forward reasoning operations. Few learners in Cluster 1, however, functioned successfully at this level. Inadequate formation of procedural and structural operations resulted in misdirected cognitive operations and superficial hypotheses. Activation of prior knowledge was higher for Clusters 2 and 4 (Cluster 2, 6.44 %; Cluster 4, 8.40 %). It was the fifth most applied process for Cluster 4 and the seventh for Cluster 2. They ascended to the executive threshold in just one cycle. Infusing procedural and structural knowledge allowed them to discern underlying concepts, and form hypotheses as they sought information in the research databases. They compared, synthesized, and evaluated data when processing new information without having to rely extensively on the tools for initiating these processes.

Generating hypotheses (code 4) was the other cognitive process associated with the executive operations. Clusters 1 and 4 had high frequencies of generating hypotheses (Cluster 1, 9.12 %; Cluster 4, 10.3 %), and it was the fourth most applied process for both groups. However, Cluster 4 solved for two problems, which is why they had high occurrences of this code. Cluster 1 had disproportional levels of generating hypotheses compared to the more successful Clusters 2 and 3 (Cluster 2, 6.29 %; Cluster 3, 7.9). They had attempted operating in this threshold without having developed adequate structural knowledge of the domain, and therefore formed hypotheses based on limited or superficial information. Clusters 2 and 3, having developed a stronger structural representation, recognized meaningful information and applied more robust combinations of cognitive processes toward developing well-substantiated hypotheses organized around scientific concepts. In this threshold, novices need assistance when making connections among data representations and drawing inferences for potential solutions. Interactive visual prompts can be useful for scaffolding executive operations by asking learners what they need to find out, how the information they are gathering connects with what they already know, and what they can infer by combining this knowledge (Bixler and Land 2010; Xun and Land 2004).

Threshold IV: developing beliefs and argumentation

The final threshold involved refining beliefs about the problem and developing an argument. Beliefs are the "reflected and unreflected assumptions underlying parts of the model" (Jonassen and Strobel 2006, p. 5) from which individuals base their representation of the problem. It involved composing an argument for a feasible solution from evidences collected. The dominant processes for this threshold included testing hypotheses (code 7) and synthesizing-evaluating (code 6). Supplementary cognitive processes for this threshold included comparing (code 2) and confirming (code 3). The essential operations included gathering the relevant findings from test results, drawing conclusions from the data collected, and generating an evidence-based solution. Learners most often used Category 3 and 4 tools (see Table 2) to support their cognitive operations at this threshold.

Hypothesis testing revealed much about the efficacy of participant's operations at this level. Cluster 2 had the highest occurrence of this process (Cluster 2, 9.22 %), and it was the cluster's fifth most applied code, indicating inconsistent self-regulation. They had integrated procedural and structural knowledge, but their mental model of the problem as being well-structured restricted operations in this threshold to comparing and confirming. They had gathered all the data they needed for generating a solution, but argumentation process remained inert until they had developed a representation of the problem that allowed them to function successfully at this threshold. Cluster 1 had the lowest activation of hypothesis testing of all the clusters (Cluster 1, 4 %), and it ranked as its tenth most applied code. They often used Category 4 tools for operations in Threshold II. For example, they designed and launched probes, a hypothesis testing procedure, to seek information without having an actual hypothesis to test. When they did test an actual hypothesis, they failed to synthesize or evaluate relevant data from multiple sources. They generated arguments that were based on foredawn conclusions from a limited set of data.

Success at this threshold required a well-developed structural knowledge, as well as procedural operations for bringing together multiple data representations alongside probe results to scaffold evaluation and syntheses (code 6) of relevant data. Highly successful learners used Category 4 tools to evaluate probe results against knowledge of planetary science, physical science, and anthropological considerations related to the aliens' ability to adapt to a new environment. Cluster 3 brought together the right information and all categories of tools to build a coherent argument through high concentrations of synthesis and evaluation (Cluster 3, 12.94 %). They made connections between relevant data to combine and interpret data, test assumptions, make decisions, infer solutions, and build arguments. Their partnership with tools to support their thinking (Jonassen 1996) and to build arguments at this level allowed them to produce the highest average solutions scores even though they began with little domain knowledge. Cluster 4 often applied argumentation operations without assistance from tools. They solved two problems and still had low levels of syntheses and evaluation (Cluster 4, 8.37 %).

Clusters 1 and 2 had similar levels of synthesis and evaluation, (Cluster 1, 11.02 %; Cluster 2, 15.88 %), and they often applied these processes to irrelevant data. Operations at this threshold for analyzing relevant information and building credible arguments were not possible until they had formed an integrated mental model of all the factors impacting the problem. When evaluating results, learners needed scaffolds for perceiving gaps in their knowledge development and determining next steps. Novices can also benefit from tools that trigger self-regulatory processes, which could come from cues in the form of questions or comments that redirect the learner toward next steps (Xun and Land 2004).

The role of self-regulation

Solving a complex problem successfully depends a great deal upon enacting self-regulation skills to keep cognitive processes focused on operations within each threshold. Self-regulation was evidenced in how effectively learners used tools strategically to monitor progress and resources, prioritize tasks, and keep track of sub goals. Self-regulation also involved evaluating outcomes and adjusting plans and strategies in response to setbacks. The cognitive processes we associated with skill in self-regulation were planning-strategizing (code #8), state of mind (code #11) and metacognition (code #13). The clusters had similar levels of metacognition (Cluster 1, 4.81 %; Cluster 2 3.73 %; Cluster 3, 3.79 %; Cluster 4, 3.36 %). However, being metacognitive, which involved awareness of why one was executing procedural operations, did not necessarily produce self-regulatory behaviors. Clusters 1 and 2 seldom revised their representation of the problem and delayed adjusting plans and strategies when encountering setbacks. Setbacks reoccurred until they discerned the underlying causes of these failures, adjusted their representation of the problem, and developed new plans and strategies for mastering the threshold that corresponded with their level of knowledge development. Highly self-regulative learners, such as those in Clusters 3, often readjusted their plans and strategies based on their developing representation of the problem, which required evaluating outcomes and responding productively to setbacks to both identify knowledge constraints and build a more dynamic mental model of the problem. Tools are needed to help novices re-strategize after evaluating outcomes.

Solving a complex problem is a messy, non-linear, and non-routine endeavor that requires trial and error, but setbacks during an activity can increase frustration and cause learners to lose focus from the problem (Pekrun 2006). Learning orientation behaviors (Pintrich 2000) appeared to have influenced how learners with low prior knowledge activation perceived setbacks as occasions for refining their model of the problem. The mastery orientation behaviors as exhibited among Cluster 3 learners capitalized on setbacks for re-strategizing and monitoring resources. The performance orientation behaviors as shown by Cluster 1 learners perceived setbacks as indicators of incompetence, and this disposition inhibited progress. Feelings of anxiety, frustration, and exhaustion surrounded operations for this cluster. As they encountered successive setbacks, their actions became perfunctory and they formed premature conclusions. Managing emotions was an aspect of self-regulation for which these learners had little support other than their own volition. State of mind (code 11), which included emotions the learners reported experiencing, was the fifth most applied cognitive process for clusters with low prior knowledge activation (Cluster 1, 8.84 %; Cluster 3, 8.51 %). Professing state of mind occurred much less for the advanced knowledge clusters (Cluster 2, 3.88 %; Cluster 4, 2.96 %). Only in the case of Cluster 4, which included the most expert-like learners, did metacognition trump state of mind. They regulated actions in response to outcomes without commenting much on the emotions outcomes elicited. Consideration should be given to what tools or affordances in technology learning environments can help learners adopt a mastery learning orientation and manage emotions constructively when coping with multiple setbacks under pressure.

Considerations for further research

In this study, we analyzed verbal reports and problem solving behaviors to infer how cognitive processes contributed to differences in performance outcomes and the development of a mental model. Development of mental models is typically made known through examining external knowledge representations (Spector 2010), but research is needed to examine how learners' interactions with tools in the task environment and the cognitive processes they activate provide insight into how mental models develop. In other words, how reliably do configurations of tool use patterns, solution operations, and cognitive processes serve as an index for how mental models are developing? Along these lines, additional research is needed to examine the effect mental models may have on increasing or decreasing cognitive power when problem solving. Based on our analysis, we hypothesize that when learners ascend to a higher threshold, they build a more integrated mental model of the problem, and cognitive power increases. They become more accurate in perceiving conditions in the task environment that warrant the application of cognitive processes and apply robust combinations of cognitive processes toward executing solution operations.

The findings also indicated that self-regulation was important for keeping cognitive processes focused on setting up and carrying out operations within each threshold. However, frequency in applying cognitive processes mattered far less than one's intention for activating them. Additional research should consider when, why, and how learners apply cognitive processes associated with self-regulation. One's intent, we hypothesize, is a function of the learner's mental model—particularly the beliefs the learner has formed about the problem—as well as the individual characteristics of the learner such as learning orientation, domain familiarity, and tool use. Additional research should consider how these individual differences interact to determine the efficacy of learner's self-regulation skills.

We also recommend further consideration into how a technology environment can cultivate dispositions in which self-regulation becomes a habit of thought and action. For example, designing the self-regulation tools that are constitutive of the identities learners perform in a problem simulation are important considerations for designers, and we see value in research that examines the effects this has on regulating cognitive processes in development of mental models.

Finally, as the field continues to investigate the nature of complex problem solving, there is a need for a shared language for describing solution processes. We see value in a synthesis of research that can assist researchers and instructional designers in distinguishing between cognitive processes, strategies, and skills commonly associated with solving complex problems, and mapping them with different categories of technology tools for supporting knowledge development.

Limitations

The multiple case study approach allowed for drawing inferences about problem solving from multiple data to construct a rich and holistic account of how advanced learners solved a complex problem. Since the researcher is the primary instrument of data collection and analysis, the possibility of researcher bias increases when conducting case studies (Stake 2006; Yin 2003). We attempted to minimize this by involving five researchers in the coding processes until there was 100 % inner-rater reliability. As with all case studies, the small sample size and context-specific situation from which the data were collected and analyzed reduces claims of generalizability. However, case study research does not derive its power from generalizability, but from thick descriptions that may illuminate or increase understanding of multiple variables that underlie a phenomenon (Stake 2006; Yin 2003).

Conclusion

Assessing learners' knowledge development when solving a complex problem has typically involved evaluating learners' external knowledge representations as an index of how mental models formed; such evaluations usually occur after the learning event and with minimal consideration of the cognitive processes that are involved (Kim 2012; Jonassen 2006; Jonassen and Strobel 2006; Spector 2010). In this study, we focused on the cognitive processes and behaviors that influenced learners' knowledge development during problem solving by analyzing stimulated recall, think-aloud, solution scores, and direct observation of problem solving processes. We provided a descriptive analysis of how advanced learners' application and frequency of cognitive processes and behaviors corresponded with performance outcomes and facets of mental model development. The findings showed how cognitive processes and learners' behaviors interacted in the development of mental models, or thresholds of knowledge development to form a robust representation of the problem. The frequency of cognitive processes, no matter how high-level, did not produce successful operations until leaners applied them toward operations within each threshold to develop a richer mental model. Successful problem solvers, with consistent self-regulation, focused cognitive processes on carrying out operations in each threshold to advance their representation of the problem. As they progressed through each threshold, their mental model of the program grew more integrated and their cognitive power increased; that is, their solution operations focused on the most relevant aspects of the problem and the combinations cognitive processes they applied grew more diversified and sophisticated. As such, the analysis posits the development of mental models as a multifaceted, ongoing, and dynamic process that is necessary for increasing one's awareness of where to apply cognitive processes and the executive power of procedural operations.

Viewing complex problem solving as the progression of developmental thresholds provides a framework for predicting where novices will require support for applying their cognitive energies in concert with their developing representation of the problem. Given the interdependent nature of these interactions, we believe instructional taxonomies and information processing models of knowledge development that posit an isolated and linear pathway in the application of cognitive skills and processes are less helpful. Instead, designers of complex problem solving environments should consider how successful problem solvers apply cognitive processes toward mastering tasks within thresholds to anticipate where novices may require support at each threshold of problem solving. Toward those ends, this analysis has provided an integrated model of complex problem solving that we hope is beneficial for instructional designers, educators, and students.

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Appendix

See Table 5.

Table 5 List of cognitive codes and definitions

Cognitive code[a]	Definition and example
1. Seeking information	Looking for, finding, figuring out, looking up, searching, and skimming through
	This is a process whereby the learner searches for and acquires information to be used in the problem solving process. The process of seeking information may be used to acquire background knowledge necessary for problem solving or to address potential self-identified gaps in knowledge in which missing information is needed in order to solve the problem
2. Comparing	Finding similarities and differences, evaluating, differentiating, and discriminating
	Comparing occurs when the learner compares two or more pieces of information (e.g., comparing the characteristics of two potential planets) to identify potential similarities and differences. This process often occurs as the learner works to discriminate between possible problem solutions within the environment or when evaluating the extent to which a potential solution addresses the problem (e.g., how well a planet meets the needs of a particular alien). The learner may quite often use the words "compare" or "comparing" in describing this process
3. Confirming	Checking, going back and seeing, making sure, and looking back (over notes)
	This is a problem solving process where the person wants to ensure that s/he has the correct data—typically recorded in the notebook but sometimes mentally stored
4. Generating hypothesis: general and specific	This is problem-solving process where the person develops the idea of an appropriate world for an alien species. Rarely does the person actually use the word "hypothesis." Rather, this process can be inferred by the actions and words of the person. For instance, if a person is sending a probe to a world and states the s/he is doing it to gather specific information rather than for general data gathering purposes, then the person has developed a hypothesis that that world may be appropriate for an alien species and wants to see if the new information will agree with his or her hypothesis. Generating the hypothesis is often linked with "testing hypothesis." So, in the abovementioned example not only did the person generate the hypothesis but has already started testing it by sending a probe
5. Activating prior knowledge	An indication that the user already knows something and he/she uses that knowledge as a base to solve problem. Some verbs/phrases used include "recalling", "thinking of", "I have the knowledge", and "I knew." For example, "after reading the type of atmosphere that their planet had, I had immediately thought of Io" (Quinn). "I think a lot of it is just simply because I kind of have some prior knowledge of the different planets and moons, but I don't remember all of them" (Quinn)
6. Evaluating and synthesizing	Putting together and making a comparison of pieces of info gathered; and making a judgment

Table 5 continued

Cognitive code[a]	Definition and example
7. Testing hypothesis	Testing hypothesis occurs after they target a potential home(s) they think may be a good fit. For example: "Well I think of all the planets and all of the moons of the planets it is my number one priority target for these aliens just because it seems to fit most of the criteria" (Quinn) In many cases, when testing a hypothesis, they have specific questions they want answered about home(s) they have targeted, and they cannot locate the answers in the databases. They attempt to answer these questions by sending a probe. For example: Parker says, "I want to know more about its atmosphere. Like 'Does it have nitrogen?'" Kyle says: "The only thing they didn't say in the solar system database was the materials on the surface. It talked about how they need metal in their tunnels and what not. And it didn't say anything about that so maybe this will" Sending a probe does not always mean that the person has a hypothesis. Some people might send probes to generate a hypothesis. There's a difference between hypothesis testing and hypothesis generating. Hypothesis generating is when they collect information about a home they have think may be a potential candidate. Their search tends to be honed in on the home they are interested in. Usually, they want more information to determine if it is worthwhile to send a probe. For example: Quinn says, "Well, I basically narrowed down in my mind what planets or moons I thought would be most interesting. Now I am specifically looking at missions that were sent to those planets and seeing what information I can get out of it"
8. Planning and strategizing	Planning involves thinking about how they can get information they need. This is very common in the probe design room when they consider affordances and constraints of available instruments. Quinn says: "Well I am thinking I want my orbiter to go past Jupiter to its moon Io, so I want to think about things like how long my power supply is going to last and what is ideal for being reasonably far away from the sun and the types of conditions it will run into once it gets close to Io as well" Sometimes planning involves thinking about how they can get and apply information for leveraging their search: Kyle says "So I have to back and read this because honestly I didn't remember much about Kelvin so I need to look at that again" Planning may also involve how they decode to deploy probes. Some people plan to send probes to multiple prospects at the same time so they compare the results. For example, "I was going to send one to Venus and I still might. I want to compare the two." In this case, Kyle plans to send two probes—one to Io and one to Venus—so he can compare results. This may also be considered a strategy for selecting the best home Since the researcher often asked the questions after they performed an action, we may not see a lot of instances of planning. The most instances of planning may involve statements such as "I need to do X" or "I should do X" or "I want to do X". Planning seems to happen the most in the probe design room This is the plan of attack for how the user breaks down the problem. Since 'strategizing' is synonymous with 'planning', this will pertain only to actions in which users are trying to make the problem easier to solve. In this definition, 'strategizing' is one aspect of 'planning'. For example, "I can definitely rule-out some", "I basically narrowed down in my mind what planets or moons I thought would be most interesting", and "I am trying to figure-out what is the most important thing to take into account when making a decision"

Table 5 continued

Cognitive code[a]	Definition and example
9. Just-in time learning	Using cognitive tools to learn information that they need immediately, e.g., "I was looking to make sure that I was reading the mass spectrometer report correctly. I thought I remembered the chemical symbols, but I wanted to make sure. So I looked at the Periodic Table to make sure I had the symbols correct" (Jodie)
10. Organizing (specifically In relation to notebook)	This is the organization of information for the purposes of scaffolding conceptual thinking. This could be done physically or mentally, but the end goal is that the user has a better idea of the situation. For example, "I just kept a mental checklist", "But then when I got over here I felt like I needed that information on the left. I am not saying that you should change it, but I thought that it caused me to think about reading things left to right", "making notes about what characteristics of this planet might match the needs of the Aliens", "I am trying to balance. I see similarities in both places about what they need, but I need to figure-out which ones are most important because I do not want them to die"
Secondary coding	
11. State of mind	This code was given when participants described their state of mind, e.g., curiosity, confusion, and so on…. For example, "the ones they used to farm with, which is problematic because Ganymede does not have nitrogen on it, so I am disappointed" (Noah)
12. Orienting	This code was given when participants' actions are related to using cognitive tools to browse or scope. For example, Noah says, "As it turns out I clicked on the first one which was Magellan…"
13. Metacognition	This code was given when participants' talked about their thought processes, showing a deliberate process of what they were doing. For example, "I am going to write down the reasons why I am eliminating these planets. My memory is not that great, obviously, and I need to write them down so I can keep them off my mind" (Noah)

[a] Codes for describing actions—what cognitive process does this person say he/she is doing (not what outcome this process may lead to)

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