Journal of Expertise
2021. Vol. 4(4)

ISSN 2573-2773

Profiles of Experts' Cognitive and Metacognitive Processing during Performance of a Novel Problem-Solving Task

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Abstract

Although much is known about the instructional outcomes related to science simulations, less is known about the cognitive and metacognitive processes individuals employ during these simulations, and how this processing relates to important science learning outcomes, such as scientific explanations of phenomena. In this study, we sought to develop profiles of experts' problem solving during a physical simulation task that was outside their scientific discipline. The simulation involved working with a box with an unknown internal mechanism that varied water output in relation to water input. Eleven experts in four scientific disciplines (i.e., psychology, biology, chemistry, and physics) from a large public university in the southeastern United States engaged in a novel simulation of a scientific phenomenon. They worked with the simulation for 30 minutes, thinking aloud while they did so, and, following the experience with the simulation, developed a scientific explanation for the phenomenon they observed. The think- alouds and explanations were coded to reveal both the processing profiles and the scientific explanations associated with those profiles. These data indicated that many aspects of the experts' processing profiles were similar (e.g., their use of observation as a high-frequency strategy). However, important differences in processing were identified that appeared to influence the precision and openness of the resulting explanations. Suggestions for future research, such as comparing these profiles to non-experts, and suggestions for classroom practice, such as modeling multiple patterns of strategy use during science tasks are discussed.

Keywords

Cognitive processing, metacognitive processing, strategies, expertise, think-aloud protocol, scientific modeling

Introduction

Over the past thirty years, seminal reports on science education reform have increasingly focused on effective problem solving as critical for improved student learning in science (e.g., AAAS, 1989, 1993; National Research Council, 1996). One outcome of this heightened attention to problem solving in science has been the shift away from having students learn strictly *about* science to having them learn how to *do* science to understand disciplinary content better (National Research Council, 2012). Further, this shift toward doing science has embraced novel and cognitively challenging problem-solving activities that require students to engage in the evidence-based thinking and reasoning aligned with actual scientific practice (National Research Council, 2005). These procedural approximations provide a conceptual framework for students to make meaning of the factual components of science. One category of challenging problem-solving activities entails the use of science simulations. These science simulations are intended to capture a scientific procedure in a novel way so as to motivate students and provoke the perceptive, analytic, strategic, and evaluative processes that are the hallmark of a scientific mind (NGSS Lead States, 2013).

At their most basic, science simulations are physical or computer renderings of phenomena that cannot be easily experienced directly, perhaps because of their magnitude, infrequency, inaccessibility, expense, or the dangers they pose (de Jong & Van Joolingen, 1998; Quellmalz et al., 2012). Although less common than computer simulations, physical simulations, like that employed in this study, provide learners the chance to be immersed in a challenging physical or social problem (e.g., hospital simulations) and educators or educational researchers the opportunity for close examination of learners' approaches to problem solving (Hollinshead & Yorke, 1981). This examination includes learners' analyses of the problem or system and the cognitive and metacognitive processes they manifest in response to their analyses. In this way, what is revealed about problem solvers during the simulation can then be used to enhance student performance in the future, to modify the instructional environment, or to ascertain the particular effects of the experience on science learning and performance (Lee et al., 2006; Scalise et al., 2011).

Despite the extensive literature on the instructional value of simulations (Scalise et al., 2011), less is known about the cognitive and metacognitive processing exhibited during these important science experiences or how those processes are reflected in the quality of the scientific solutions produced (Dinsmore & Zoellner, 2018). There is certainly ample evidence that effective problem solving in science—as well as other domains— requires the orchestration of cognitive and metacognitive processes (e.g., analysis, regulation, and evaluation), particularly when the problem encountered is both novel and complex (Hofer, 2004; Kitchner, 1983). Yet what constitutes novelty and complexity does not solely reside in the features of the problem but depends as well on the expertise of the problem solver (Paletz et al., 2013). For those who are new to a field (i.e., in acclimation), many domain-specific problems that appear novel and complex would be viewed as more commonplace and relatively simple by more competent learners and certainly by those regarded as experts (Weisberg, 2006). Moreover, domain experts have repeatedly been found to display a breadth and depth of cognitive and metacognitive knowledge and strategies that those in acclimation or even competence do not display (e.g., Dinsmore et al., 2015; Sternberg, 1998; Veenman & Elshout, 1999).

Despite these advances in knowledge, what remains less understood about scientific simulations is how experts utilize their cognitive and metacognitive knowledge and strategies when engaged in a simulation activity that is outside their realm of expertise (Schraagen, 1993). Are these "intelligent novices"—to borrow Brown and Campione's description (1990)—able to draw on their extensive conceptual and procedural knowledge to facilitate performance? Or do they, as Voss (1987) contended, lose their performance edge when they are called upon to solve novel, out-of-domain problems? These are precisely the questions we explored in this investigation.

A more complete understanding of how experts in a variety of scientific fields engage in adaptive and flexible problem solving outside their disciplinary home can prove invaluable to educators and educational researchers. The insights gained could be used to construct problem-solving profiles that would not emerge under other circumstances and build theory related to how experts in scientific disciplines use these cognitive and metacognitive process as current theoretical guidance in these areas is lacking. Likewise, these profiles could serve as the basis for larger intervention studies or as guides for instructional programs intended to enhance the reasoning and problem solving of students in acclimation and competence after additional evidence is collected.

The Theoretical Framework

In order to construct meaningful profiles from experts' efforts to solve a novel science problem delivered by means of a physical simulation, our overall design and approach to data analysis was informed by the Model of Domain Learning or MDL (Alexander, 1997, 2004). Within this framework, expertise development is seen to unfold in three stages—acclimation, competence, and proficiency or expertise—each characterized by particular interrelations among subject-matter knowledge (domain and topic), strategic processing (surface-level and deep-processing), and domain interest (individual and situational). In this study, the profiling of experts' approaches to solving a novel simulation task centered primarily on their display of surface-level and deep-processing cognitive and metacognitive strategies. According to Dinsmore & Alexander (2016), *surface-level strategies* can be defined as "those that pertain to initially encoding the problem at hand," whereas *deep-processing strategies* "entail probing or transforming a given problem" (p. 214).

Within the MDL, problem solvers' reliance on surface and deep strategies is dependent on their stage of development. Those in acclimation, for example, have limited subject-matter knowledge and the interests they show are rather fleeting and tied to features of the task or context. Consequently, in their efforts to work through a science simulation activity, we would expect these novices to rely heavily on surface-level strategies as they struggle to make sense of the task and attempt rather inelegantly to reach some solution. Learners who are competent within a domain, in contrast, would come to the simulation task with greater understanding of the scientific phenomenon being represented than those new to the domain. Therefore, their problem-solving efforts would be aided by their ability not only to analyze the surface features of the simulation task, which they still do, but also to analyze the problem more deeply and engage in self-monitoring and self-evaluation of their performance.

By comparison, if those in the proficiency stage of the MDL were to undertake a science simulation activity in their field of expertise, we would expect these experts to move quickly toward solution. The reason for this expectation is that experts would come to the task with a well-honed mental model of the problem to guide their thinking and a depth of knowledge about the phenomenon being modeled. This problem-solving and content knowledge would then allow these experts to engage almost exclusively in deep analysis of how the simulation is capturing some underlying, albeit abstracted, scientific phenomenon. These experts would also be more perceptive and more practiced in data gathering and interpretation, more aware of how their work was progressing, more likely to reach a solution efficiently and effectively, and more capable of evaluating the viability of their proposed solution. They may even choose to consider alternative solutions as a way to test solution viability.

While the MDL is the central framework of this investigation, we do want to point out the MDL is congruent with other influential frameworks of expertise (Dinsmore & Dumas, in press). For instance, the framework by Feltovich and colleagues (e.g., Feltovich et al., 2006) posited that expertise is a long-term process gained through experience and practice. Thus, while we examine here what current practice looks like in this novel task, we should bear in mind that similarities and differences in problem solving as experts is part and parcel of their experiences through a wide variety of scientific practices— both inside and outside individuals' respective disciplines (e.g., biology versus psychology). The MDL can be further illustrative here, as we return to in the future directions section—along with frameworks such Feltovich and colleagues'—to point to further longitudinal investigations of the questions under study here.

So, what would be expected when experts in a scientific domain are asked to tackle a simulation problem that is *outside* their realm of expertise? Would these experts look more like competent learners, using both surface-level and deep-processing strategies, or would they be able to bootstrap their existing knowledge and problem-solving abilities to work effectively and efficiently at this novel task? These are the intriguing questions that framed the current investigation.

The Current Study

In order to investigate experts' cognitive and metacognitive processing when working outside their specific area of expertise, we invited scientists from different fields (i.e., biology, chemistry, physics, and psychology) to participate in an *in-vitro* (i.e., laboratory) problem solving study (Dunbar & Blanchette, 2001; Klahr & Simon, 1999). Although the simulated problem used in this research represented a scientific phenomenon, it was one that was not central to these experts' fields, and it was represented in a novel way. This decision to conduct a laboratory study was made to allow us to observe these experts closely and to gather think-aloud data during task performance.
The novel task expressly chosen for this study has been referred to as a "Black Box" simulation (Cartier et al., 2005) that poses a rather ill-structured problem in a manner meant to provoke scientific thinking and reasoning. The task is considered ill-structured because there is not a singular correct solution to the problem being represented and no one strategic path to solution (Simon, 1973). To make their internal processes available for scrutiny, the experts were asked to think aloud during task performance, and their verbalization was recorded and transcribed. In addition to those think-aloud data, we measured their science knowledge and science interest before the task and evaluated the quality of the explanations of the scientific phenomena they generated to fit the data they recorded during the simulation. We used these data to address the following questions:

1. What problem-solving profiles, based on the frequency and form of strategy use, emerge for experts solving a novel simulation task that is outside their area of expertise?
2. To what extent are the resulting profiles related to the quality of the explanations experts generated as explanations for the simulation data they recorded and the underlying scientific phenemona?

Method

Participants

Eleven university faculty members regarded as experts in several physical, natural, and social science domains were recruited from a mid-sized public university in the southeastern United States. All participants had received doctoral degrees in their respective disciplines—Biology (n = 3), Chemistry (n = 3), Physics (n = 1), and Psychology (n = 3)—and they ranged in age from 36 to 56 years of age (M = 44.09, SD = 6.59). This sample was relatively gender balanced (55% male; 45% female), although predominantly Caucasian (82%). This gender and racial breakdown was reflective of the faculty demographics in these disciplines for this particular university.

These experts were chosen to represent disciplines which would have expertise in explaining scientific phenomena (e.g., interpreting data, building hypotheses). While the physical system in the Black Box—described below— may be more familiar to those in the physical sciences than the social and life sciences, this task was assumed to be novel as none of these participants' research areas incorporated the movement of water through a system. This expertise would be more typical of faculty in the College of Engineering at this university. They were not included as this would likely not be a novel task for them.

Apparatus and Research Task

The problem-solving task selected for this study consisted of manipulating an unfamiliar simulator of a physical phenomenon. Specifically, the simulation consisted of a Black Box activity co-developed by researchers at the University of Wisconsin-Madison and teachers at Monona Grove High School in Wisconsin (Cartier et al., 2005). The Black Box (Figure 1) consists of a funnel at the top of a box and an output tube at the bottom of the box, both of which are visible. Covered by the outer shell of the Black Box, and therefore not visible to the problem solver, are mechanical components that regulate how the water moves through the box. Importantly, there are water repositories and mechanisms within the box that do not allow the water input and output to occur in a 1:1 ratio. These mechanisms are arranged in a vertical series from top to bottom in the box with tubes for water flow connecting these mechanisms. For example, when 100mL are poured into the funnel, 200mL may come out of the tube. On another trial that same 100mL input may result in no water coming out of the tube. To allow participants to experiment with input-output ratios, graduated cylinders for measuring water input and output were provided. Specifically, these vessels consisted of the following: two 1000mL beakers graduated every 50mL, a 1000mL cylinder graduated every 20mL, a 500mL cylinder graduated every 10mL, and a 50mL cylinder graduated every 1mL.

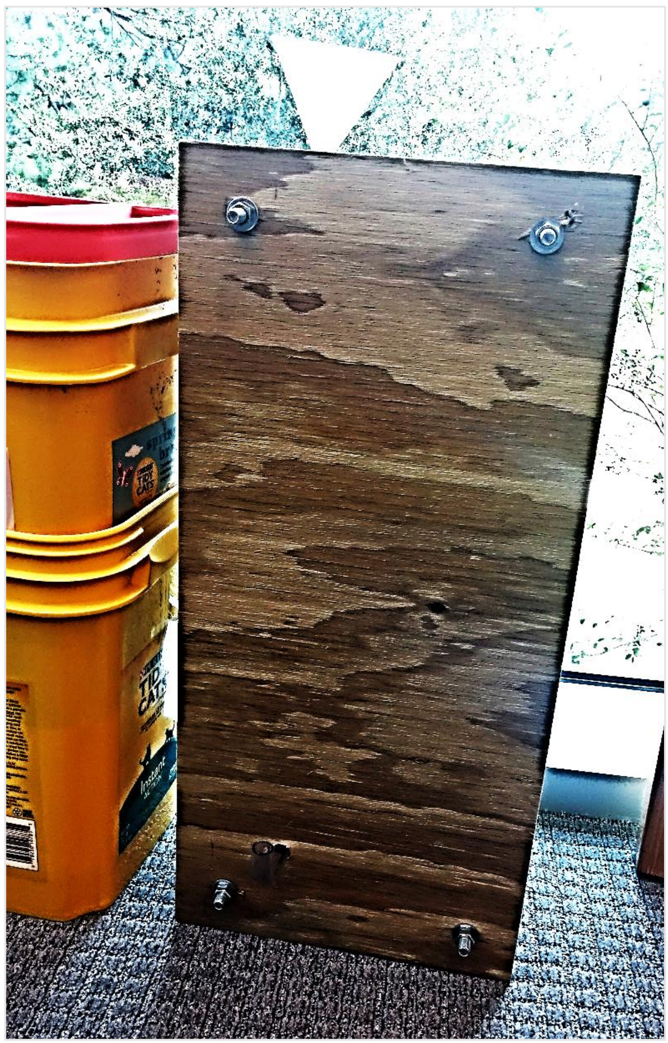

Figure 1. The Black Box apparatus

A Priori Measures

In this study, participants' science knowledge and interest were measured *a priori*.

Knowledge About Scientific Model Building

For this investigation, we used a measure of knowledge about developing scientific explanations and model building (e.g., generating hypotheses, interpreting data) as confirming evidence for our designation of participants as experts in various science domains. This measure was developed from previous descriptions of scientific model building and explanations of scientific phenemona (Lederman et al., 2002), a document that captures the scientific processes closely aligned with the simulation task described below.

These items were constructed and scored using a graduated response model (Alexander et al., 1998). The graduated response model consisted of four levels: an in-domain correct response (4 points), an in-domain incorrect response (2 points), and out-of-domain incorrect response (1 point), and a "folk" answer in which someone without domain expertise could be easily fooled (0 points). A sample item from this measure was as follows:

> Natural phenomena can be understood through the following:
> a. observable stimuli
> b. two-page research articles
> c. common language
> d. data patterns

For this sample item, *d* was the correct in-domain (scientific reasoning and explanation) option, and *a* the incorrect in-domain (scientific reasoning and explanation) option. Option *b* represented the out-of-domain (i.e., not scientific reasoning and explanation) distractor, while *c* was the pedestrian or everyday distractor. Thus, total scores on the prior knowledge test could range from 0 to 44. However, rather than report total scores, we calculated the average score per item for each participant. This average is more interpretable as it gives us a value which represents their typical response, whether the average is closer to 4, which would represent someone typically choosing the correct in-domain responses, or an average score closer to 1, which would indicate someone typically choosing the incorrect out-of-domain response. These averages could range from 0 (i.e., choosing all everyday distractors) to 4 (choosing all correct in-domain responses).

As per our expectations, the performance of the 11 experts participating in this study was consistently high, approaching ceiling effect. Specifically, the average score for participants on these items was 3.27 (SD = .22). Additionally, scores for each of the disciplines were relatively consistent for biology (M = 3.25), chemistry (M = 3.12), physics (M = 3.45), and psychology (M = 3.39). The reliability of the science knowledge measure could not be ascertained by conventional means, due to the small and select sample. However, given that all item difficulties were near ceiling, it would appear to support the contention that these were experts in science.

Science Interest

As in prior investigations involving competent or more expert participants (Alexander et al., 2004; Fountain, 2017; Jetton, 2018), we chose to use a measure of *enacted* versus *professed* interest. By enacted interest, we are referring to participants' reports of their involvement in domain-related activities over a given timeframe. This approach to interest assessment stands in contrast to mere expressions of potential interest common in the literature. The rationale for such a procedure is that individuals personally invested in a specific field of study will naturally be engaged in activities aligned with that field.

For this study, participants' personal interest in science was measured by means of a 10-item measure documenting their engagement in scientific activities (e.g., "writing about scientific topics for scholarly journals"). Participants responded to these items on a 100-point visual analog scale from "never" to "very frequently." We averaged across the 10 items for a maximum science interest score of 100. The reliability of this interest measure was found to be good for experimental purposes (α = .81).

Again, in keeping with the designation of participants as experts in science domains, the mean for this measure was relatively high (*M* = 68.34; *SD* = 14.22), with scores ranging from 46.40 to 89.50. Interestingly, differences in reported interest were found for the four science domains represented in this study: Biology (*M* = 62.43), Chemistry (*M* = 75.66), Physics (*M* = 67.27), and Psychology (*M* = 67.27). However, the small and select sample precluded any statistical analysis of those differences.

Think-Aloud Protocols

As a means of gathering evidence of their cognitive and metacognitive processing, participants engaged in think-alouds during task performance that were audio and video recorded. Specifically, the experts were directed as follows:

> First, we have supplied pencil and paper for you to take any notes as you work on the simulator. Second, while you're engaged in the simulator, we would like you to say out loud anything you are thinking or doing as you engage in the simulation and develop your model. There are no right or wrong things to say here, just say whatever is going through your head as you work. If you are quiet for a period of time, I'll ask you to say what you're thinking. Do you have any questions?

The audio files were then transcribed by the third author. A subsample of the transcriptions was coded by the first author using an existing coding scheme of cognitive and metacognitive processes used during simulations (Dinsmore & Zoellner, 2018) with acceptable interrater reliability similar to previous studies (*k* = .48).

Since the simulation in the previous study was web-based and this study was the manipulation of a physical simulation, several modifications to the existing scheme were made. For one, the physical simulation had a temporal aspect to it, in that the water that was part of the procedure took time to enter and then leave the Black Box. Therefore, an *Observing* code was added to capture participants' attention to the time element. For another, the code for *Using a Text Feature* was dropped since the physical simulation did not contain any text-based information.

Descriptions of the cognitive and metacognitive codes, along with examples, are included in Table 1 (cognitive) and Table 2 (metacognitive). The cognitive processing variables are broken down further into those that are *surface level* versus those that are *deep level*. For example, observing (i.e., restating the conditions or findings about a particular trial) is a surface-level process since it pertains to encoding aspects of the problem. Interpretation/elaboration (i.e., deciphering or expanding on the results of a trial or trials) is a deep-level process since it pertains to transforming the problem using the participant's own prior knowledge or experiences to do so.

The metacognitive processes are broken down into three codes (metacognitive knowledge, metacognitive experiences, and goals) in line with Flavell's (1979) metacognition framework. These processes monitor and control the cognitive processes described previously. For instance, metacognitive experiences (i.e., cognitive or affective experience that pertains to a mental operation) are monitoring processes used to determine whether or not the participant's current cognitive processes are sufficient to solve the problem.

Table 1. Coding for Cognitive Strategies

Code	Code Description	Example
Surface Level Processes		
Control of Variables (CV)	Changing an input variable to see what happens to an output variable	*I'm pouring in 50mL and seeing what comes out.*
Rerunning/repeating (RR)	Running an identical trial in the simulation again	*Okay, well let's try that same thing again.*
Observing (OB)	Restating the conditions or findings about a particular trial	*Still nothing coming out of the box.*
Deep Level Processes		
Cued History (CH)	Attempting to change output variable(s) to some degree by manipulating input variables	*Okay, so my hypothesis is that there is a reservoir in there, so if I inundate it with water, I should be able to overflow the reservoir.*
Predicting (P)	Guessing the result of a particular trial	*200mL should come out this time.*
Questioning (Q)	Asking a question	*I wonder if there is deception involved with this simulation?*
Arguing (A)	Arguing with a particular parameter or result	*That shouldn't happen that way.*
Global Restatement (RG)	Summarizing the results of multiple trials	*I put 600 in and got 450 out, then I put 200 in and got 300 out. So that's 800 in and 750 out total.*
Interpreting or Elaborating (IE)	Deciphering or expanding on the results of a trial or trials	*The results of these trials seem odd so there is always a chance that the tube and the funnel are not connected.*

Table 2. Coding for Metacognitive Strategies

Code	Code Description	Example(s)
Metacognitive Knowledge (MK)	Knowledge or beliefs that affect the course of mental operations about a person, task, or strategy.	*I don't know anything about this.*
Metacognitive Experiences (ME)	Cognitive or affective experience that pertains to a mental operation.	*I'm currently trying to better understand what is going on in there.*
Goals (G)	Setting a cognitive goal.	*I want to figure out what is happening inside this box.*

Scientific Explanations of the Simulated Phenomena

The principal outcome measure in this study was the explanations the experts constructed that would accounted for the data gathered during the Black Box simulation task. To externalize these experts' mental models, they were supplied with paper and pencil and instructed as follows:

> Record your theoretical model that explains the data generated from the simulator using either drawings and/or prose. You may transfer any information from your notes from the simulation if you wish.

While the experts were given whatever time they required to complete their final model, they all finished within approximately 5 minutes.

The resulting explanations were coded along two dimensions, precision and openness. These dimensions were derived from the empirical, yet tentative components of Lederman et al.'s (2002) framework for the nature of science and Cartier et al.'s (2005) focus on observed data patterns helping form and evaluate a scientific explanation. *Precision* refers to the degree to which the explanation or prediction in the theoretical model either matched the mechanism inside the Black Box or would be a precise description based on the data they collected. For example, Participant 6 described their model with precision that drew on their data. In explaining their model, they stated the following: "There is capacity for approximately 600 milliliters of water to be added before it triggers the overflow mechanism." This contrasts with a less precise model described by Participant 4: "Water goes in the top and sometimes comes out the bottom." While correct in an overall sense, this participant did not connect the data they observed to their explanation in a specific way.

Openness refers to the degree to which these experts presented one or multiple explanations to describe the phenomenon or evidence as to whether they thought multiple models were possible. The data generated from the task would allow for multiple representations of the scientific phenomena to be explained. Given the possibility for multiple explanations to fit the data they recorded, we evaluated their willingness to consider alternative explanations of the scientific phenomena. For example, Participant 6 developed a precise model (as described previously) but was still open to the need for more detail: "I am still not sure if containers tip to overflow or how much water starts in the box." Participant 8 described their model with certainty through statements such as, "Any water above 800 milliliters triggers drainage of the whole system, including the holding tank." There was little discussion of a need to run more trials or the uncertainty of their findings when describing their model.

The first and second authors coded these explanations by creating scales for both precision and openness. Precision was coded on a number line continuum (using inches to represent the preciseness of each explanation) from *imprecise* to *precise* where total imprecision would represent an explanation of the phenomena that could not possibly accurately represent the data generated; total precision would represent the phenomena in the Black Box exactly. *Openness* was coded in the same manner, from *closed* to *open,* where totally closed would represent an explanation that considered only one possible explanation and no allowance for other interpretations while totally open would represent an explanation that provided multiple possible explanations and the allowance for additional interpretations.

Since these experts were expected to produce quality scientific explanations, scores on those explanations, with regard to precision as well as to openness, are relative to this expert sample with lower scores not meant to imply that they would be low relative to participants in acclimation or competence.

Procedures

Experts who participated in this study were recruited via email from the faculty of selected departments within the university. Those willing to participate were scheduled for a time to come to the lab where the apparatus was set up. After completing consent forms, the experts completed the demographics, science knowledge, and science interest measures online. They were then asked to engage with the simulator for up to 30 minutes and told that they could interact with the Black Box in any way they wanted as long as they did not reposition or open it. They were given scratch paper and a pencil with which to take notes. We gave the experts a five-minute and two-minute warning if needed. After the 30 minutes or when they signaled termination, the experts were asked to generate the explanatory scientific explanation for the physical occurrence they had observed in the simulation task.

Analyses

Because the purpose of this study was to describe expert processing patterns in a novel, simulated task, we relied on descriptive data (both quantitative and qualitative) to accomplish this goal. Specifically, we tracked the trend in both the quantity of processes used (i.e., *how often* they were used) as well as their conditional use (i.e., *when* they were used), since multiple aspects of strategy use have been shown to predict problem-solving outcomes more closely (Dinsmore, 2017). These data are represented in Gantt-type charts (all 11 participants' strategy profiles are presented in Appendix A). *Frequency* of use is indicated by the *darkness* of the bars for each process, with darker bars representing *more* frequent use of that process. The mean and standard deviations for each process are also indicated in these charts. Specifically, the mid-point of each line marks the mean, whereas the left and right endpoints represent one standard deviation below and above the mean, respectively.

To examine when experts employed these processes during the simulation we calculated when that particular process occurred relative to all other processes employed. We did this by assigning a number to each process in the order it was used (i.e., the first process was assigned a "1", the second process was assigned a "2", and so on). Then for each process that number was divided by the total number of processes used. Thus, the first process used was a number slightly above 0 and the last process used was 1. The median process would be assigned a number around 0.5. For each process both the average and standard deviation of these values were calculated. In the Gantt charts, *when* strategies were employed is represented by *the horizontal positioning* of the bars corresponding to each process. The farther to the left the bar is positioned, the earlier the process was used. Conversely, the farther to the right the bar is positioned, the later the process was used.

Results and Discussion

Expertise Confirmation

Our goal in this investigation was to examine the problem-solving profiles of experts manifest from cognitive and metacognitive processing data gathered as they verbalized their thinking and behaviors during the performance of a novel simulation tasks that fell outside their particular domains of expertise. Although the focus of this investigation is squarely on the strategic component of the MDL, we want to acknowledge participants' performance on the other key dimensions of that model—subject-matter knowledge and personal interest. In this investigation, the eleven participants displayed a near-ceiling level of science knowledge and strong evidence of involvement in science activities (Table 3). Both these outcomes serve as corroboration that these individuals are rightfully situated in the proficiency/expertise stage of the MDL.

Table 3. Participants' Knowledge and Interest Scores

Participant #	Mean Knowledge Score	Mean Interest Score
1	3.64	58.50
2	3.45	89.50
3	3.36	46.40
4	3.18	61.67
5	3.18	51.40
6	3.00	-
7	3.36	81.90
8	2.91	84.30
9	3.45	67.00
10	3.09	69.89
11	3.36	72.80

Table 4. Frequencies of the Percentage of Cognitive and Metacognitive Processes Employed

	Average (%)	Standard Deviation (%)
Control of Variables	4.38	4.11
Repeating/Rerunning	9.52	3.78
Observation	23.36	5.51
Cued History	5.98	4.24
Predicting	3.30	3.01
Questioning	4.81	4.02
Arguing	0	0
Global Restatements	9.49	2.91
Interpreting/Elaborating	22.06	6.12
Metacognitive Knowledge	2.84	2.37
Metacognitive Experience	8.01	2.93
Goals	5.73	3.90

Frequency of Scientific Strategy Use

The time that these experts interacted with the simulator task was between 9 to 30 minutes. While only one participant completed the task in 9 minutes, the ten other participants took between 27 and 30 minutes to finish. During the period they were engaged with the simulation task, the total number of cognitive and metacognitive processes identified in the think-aloud data for the experts ranged from 33 to 125. Since the total processes these experts reported differed so significantly, we report differences in the frequency of processing by percentage and use standards deviations to represent when these processes were employed. This was done by dividing the frequency by which the participant employed a particular process divided by the total number of processes they employed. For instance, Participant 10 employed a total of 125 processes and employed the *observing* process 30 times, meaning that they employed the *observing* process 24% of the time. For the sample then an average percent of frequency of employment was calculated by averaging these percentages across the sample and the sample standard deviation by calculating the square root of the average deviation from the mean.
Table 4 displays the percentages and standards deviations of the frequencies of each cognitive and metacognitive process described in Tables 1 and 2. These data are also presented graphically in Figure 2.

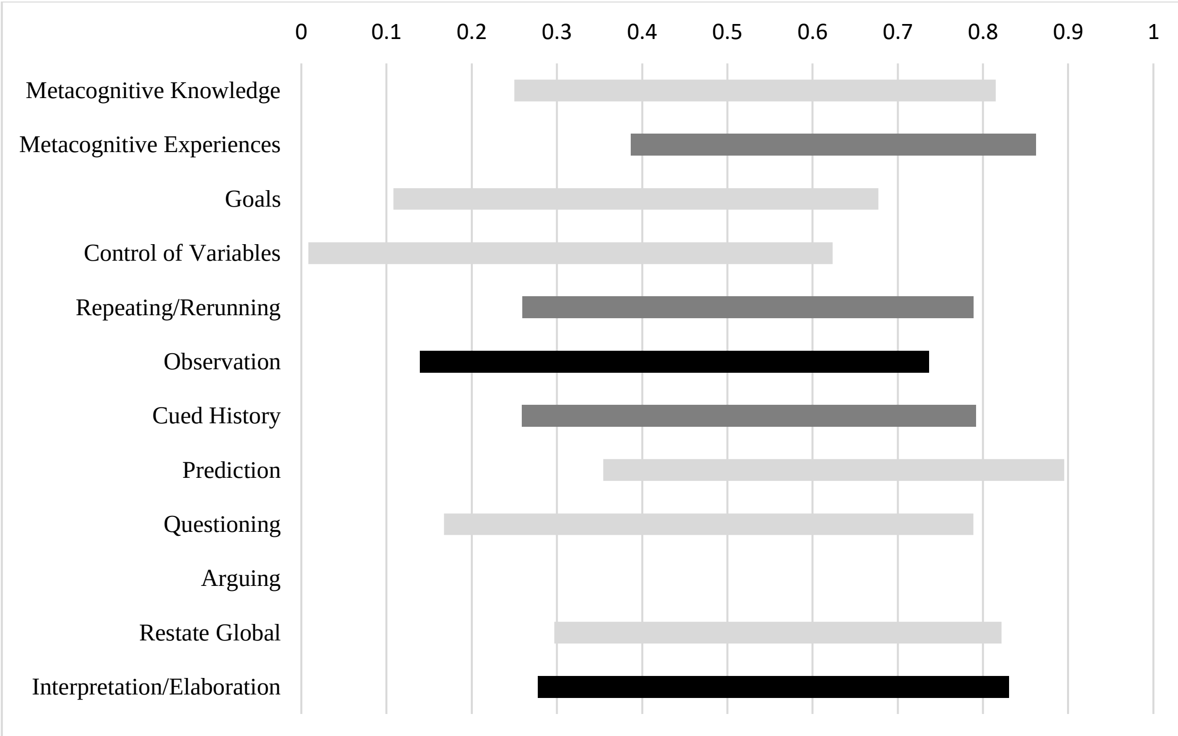

Figure 2. Typical employment of cognitive and metacognitive processes during the task.

Overall, these experts employed the *interpretative/elaborative* and *observation* processes most often (22% and 23% respectively). In contrast, *arguing* and *predicting* were rarely employed (0% and 3% respectively). For the most part, deviations in how often these experts employed these processes was quite low ranging from 2.37% for metacognitive knowledge to 6.12% for interpretation/elaboration. This suggests that the experts across this sample were relatively homogenous in how frequently they employed these particular strategies. However, there were individuals who demonstrated some divergent processing patterns. For example, Participant 3 employed no *control of variables* processes (i.e., changing an input variable to see what happens to an output variable), while Participant 4 employed that particular process more often (13 times or 12% their total processing).

With regard to levels of processing, these experts relied on deep-level processing more often (45.65%) than surface-level processing (37.27%), and they engaged in metacognitive processes 16.58% of the time. This deep-to-surface distribution is theoretically more aligned with high competence than expertise in the MDL, but it is likely attributable to the novel of simulation task and the fact that it was not specifically in these experts' fields. Further, while difference in the relative frequency of deep to surface processes was small for participants (*SD* for levels of processing between 6.24 and 8.68), there were atypical patterns e recorded. For example, Participant 1 employed surface-level processes more often than deep-level (52% versus 33% respectively). Additionally, some experts relied more heavily on metacognitive than cognitive processing, whereas Participant 5 metacognitive processes encompassed 24% of the total.

Conditional Use of Science Strategies

Conditional use (i.e., *when* the strategies were used) for the entire sample is represented in Figure 2 by the horizontal positioning of the bars. As these data suggest, the experts in this study typically employed one metacognitive process (i.e., goals) and two cognitive processes (i.e., control of variables and observation) earlier in the task. By comparison, metacognitive experiences and prediction were typically employed later in the task. Again, referring to the sample as a whole, these processes were typically utilized across a large proportion of the task from beginning to end. One standard deviation of the use of these processes stretched across 47.57% of the task for metacognitive experiences (the shortest duration) to 61.52% of the task for control of variables (the longest duration).

Given this rather broad use of processing across the tasks, we next examined whether this variance was the result of certain individuals using a particular process during one period of the task (e.g., earlier) and another participant using that same process during another period of the task (e.g., later), or were the participants more homogenous in their use of these processes throughout all periods of the task as the sample means and standards deviations would suggest. An examination of each individual's use of strategy revealed that the group averages, with regard to conditionality, held across most of the participants with a few exceptions. For example, Participant 1 was atypical because even though the participant did employ the control of variables process, the participant only did so for a very short duration. Participant 3 did not employ the control of variables process at all, instead this participant began employing the cued history process very early on in the simulation, which was atypical for these experts. The processing patterns of Participants 1 and 3 are represented in Figure 3.

Relation of Profiles to the Scientific Explanations

Our final research question concerned the relation between these experts' processing profiles and the quality of their explanations. Data from our assessment of the experts' explanations are graphically represented in Figure 4, with precision on the vertical axis (with more precise explanations higher on the axis than less precise explanations) and openness on the horizontal axis (with more open explanations on the right and less open explanations on the left). As expected, all experts produced explanations that were at least reasonably precise, meaning their explanations had a relatively good fit to the data they generated from the stimulation. In other words, all of these models were plausible explanations of the phenomena in the Black Box; however, some were certainly more precise than others as depicted in the graph. Thus, the designations of higher or lower precision indicated in Figure 4 must be understood as rather fine-grained distinctions among the explanations produced by experts. If those in acclimation were included, we would fully expect explanations from this group to include models that were more imprecise than these experts.

There were, however, larger differences among these experts with regard to openness. Approximately half of the explanations were positioned on the left-hand side of the graph, indicating that only one possible explanation was generated from the data. The other half of these experts developed multiple explanations to fit the data they recorded. One discipline-specific difference that stands out is that the psychology experts, who developed less precise explanations on average, were more likely to hold open the notion that multiple explanations were certainly possible.

To examine differences in the experts' explanations in relation to the cognitive and metacognitive processes recorded in their think-alouds, we first identified the experts who constructed the more theoretically viable explanation (more precise and more open) and those producing the less viable models (less precise and less open) as one would expect from higher quality scientific model building (Cartier, et al., 2005; Lederman et al., 2002). We then compared those experts' processing profiles to the indicators of explanation quality. The resulting comparisons profiles appear in Figure 5 with Participants 3 and 6 representing the more viable explanations and Participants 4 and 8 representing the less viable explanations. The noticeable similarities in the four profiles displayed in Figure 5 are another reminder that these are comparisons among science experts and are likely more constrained than might be the case for samples of non-experts.

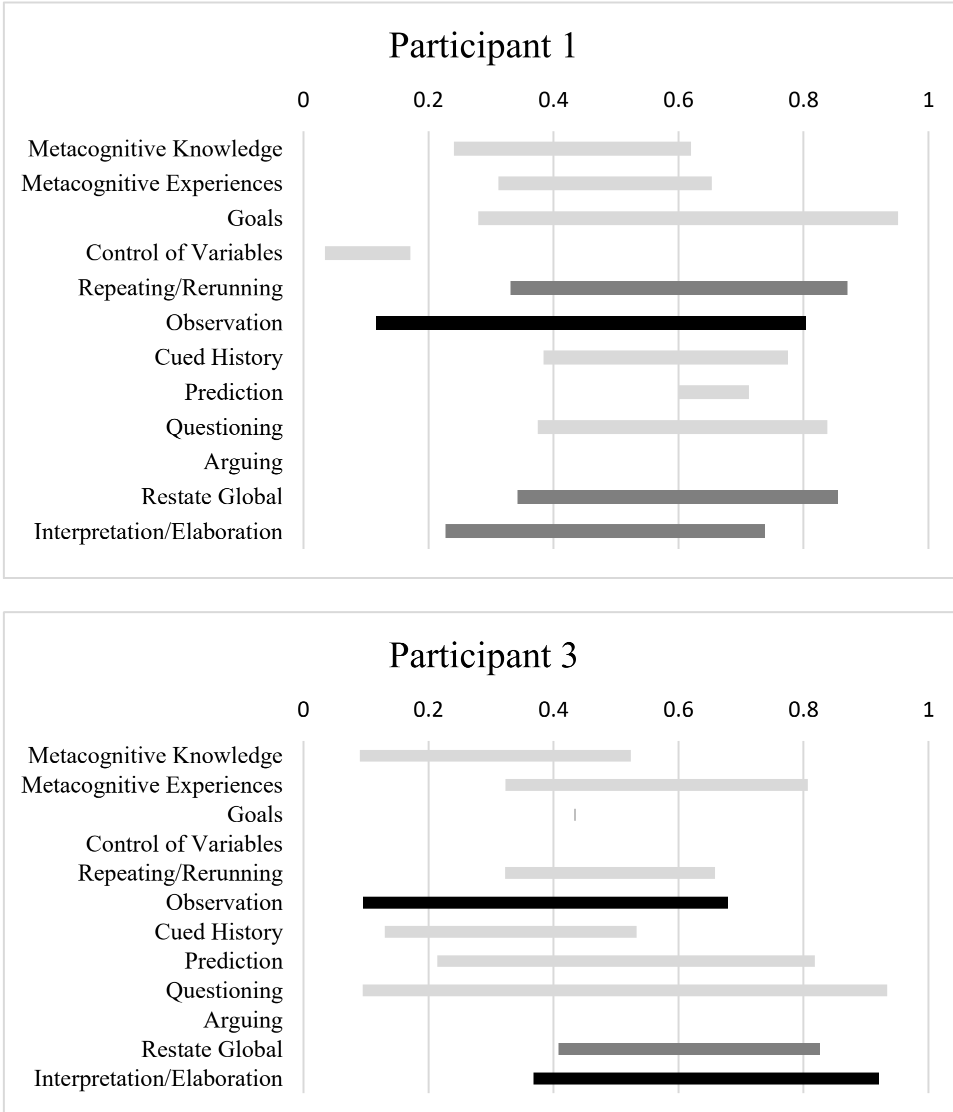

Figure 3. Processing profiles for Participants 1 and 3.

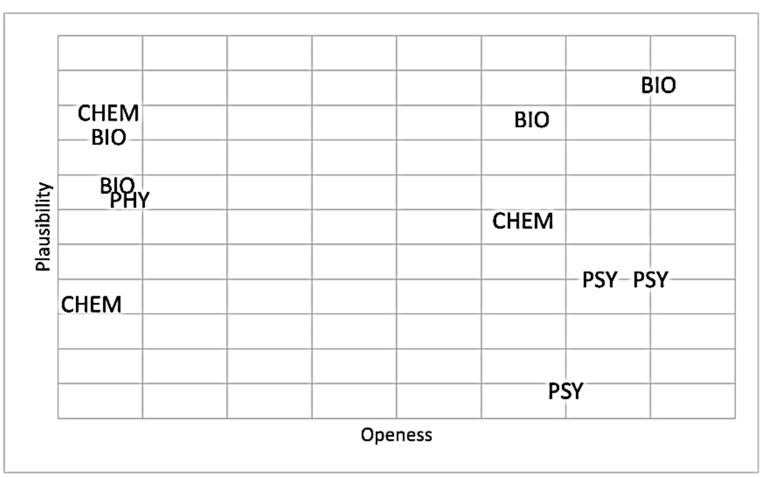

Figure 4. Plausibility and openness of the experts' theoretical models by discipline.
Note: CHEM = chemistry; BIO = biology; PHY = physics; PSY = psychology

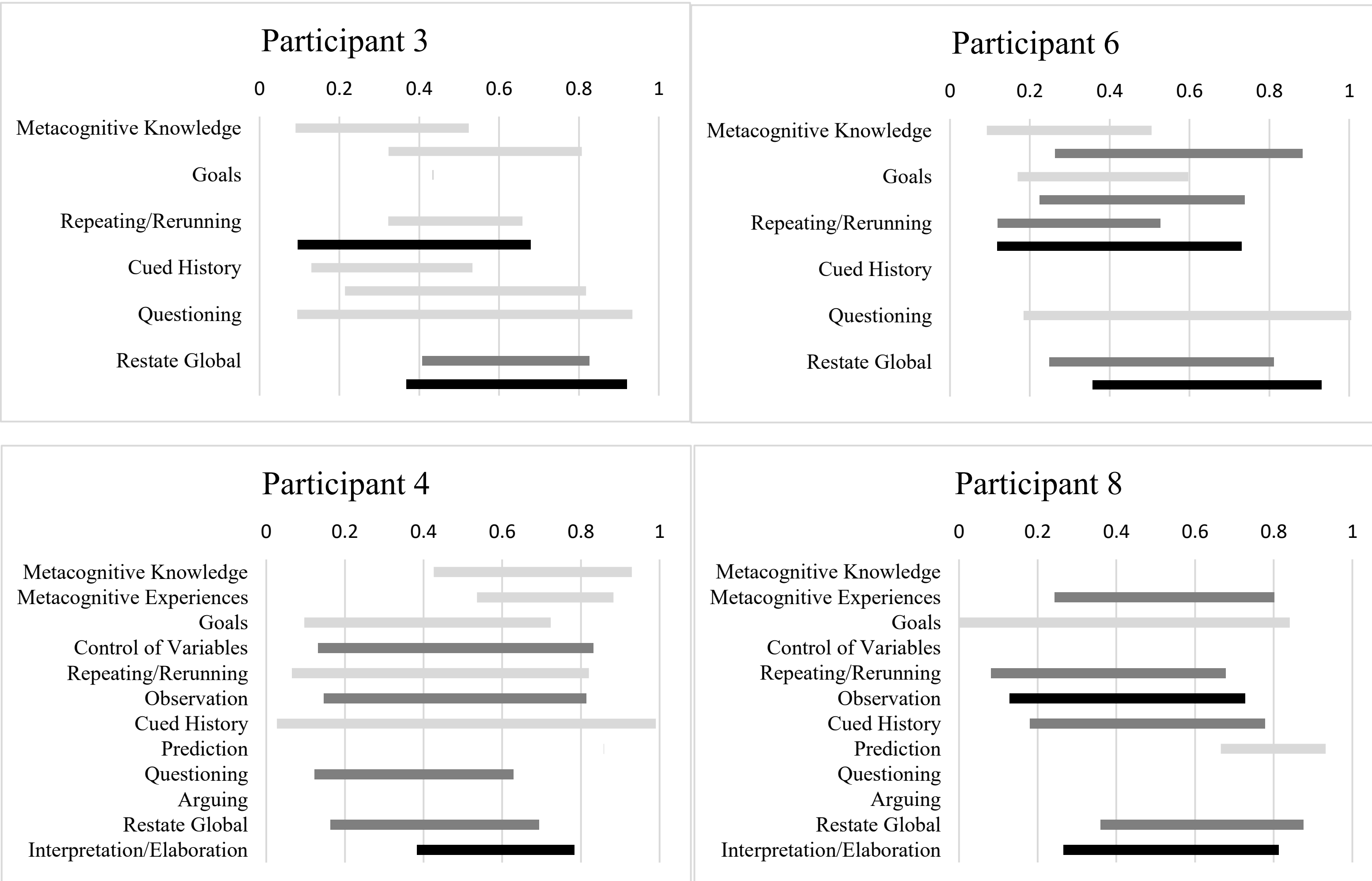

Figure 5. Processing profiles for more successful experts (Participants 3 & 6) and less successful experts (Participants 4 & 8).

Some differences, however, merit examination. First, Participants 3 and 6 reported a heavy reliance on the interpreting/evaluating and observing processes. Participant 4, on the other hand, did not rely as heavily on the observing process and used the interpretation/elaboration process for a shorter duration. This is contrasted with the profile of Participant 8, who did rely on the interpretation/elaboration and observation processes with about the same duration as Participants 3 and 6, yet this expert generally relied on fewer processes with greater frequency than either Participants 3 or 6. Additionally, for Participant 8, these differences in the processing profile may have been reflective of more limited science background. In fact, among this select group of experts, this individual received the lowest score on their science knowledge measure and their explanation.

Conclusions and Implications

Our goal in this investigation was to delve into the cognitive and metacognitive processing profiles of 11 science experts engaged in solving a complex, novel simulation task outside their discipline of scientific expertise. Because the group we observed in this study was very select, we had to find creative methods to gather, analyze, and report the profiles that emerged. We are also well aware of the limits on generalizability for this study because of the size and uniqueness of our sample. That being said, we were able to uncover patterns in these experts' problem-solving performance that were both revealing and informative.

Foremost, we found that with certain modifications and exceptions, these 11 science experts retained many of the attributes indicative of expertise. For one, the overall frequency of surface-level strategies documented was more consistent with those in the higher levels of competence rather than in expertise. For another, there were explanations produced that, while certainly adequate, were not as precise or open as might be expected for experts. Yet, it must be remembered that our willing participants were asked to undertake a novel and complex simulation task that was not in their discipline of expertise.

What we also determined from our analysis was how much more alike than different these 11 science experts were, despite the diversity of their disciplinary roots. Yet there were still relevant distinctions that merited consideration. For instance, the frequency and conditional use of cognitive and metacognitive processes uncovered in the think-aloud data and graphically displayed in the results demonstrated dynamic processing, a finding consistent with the literature of strategic processing (Dinsmore, 2017; Bonner, 2013; Carr & Alexeev, 2011). Thus, consistent with the MDL, these experts were both adaptive and flexible in their use of cognitive and metacognitive processes. Indeed, we observed many patterns of processing that represented cyclical sequences of strategy use and adjustment when that cycle began to break down.

Moreover, by means of fine-grained analysis, we could identify individual experts who were more or less successful at producing an explanation that was a good fit with the data they collected. There were also certain experts who were content with a single, adequate explanation, while others continued to probe for alternative and better models to explain the phenomenon the Black Box represented. Of course, there is no way to ascertain from this study whether such variability in strategy profiles or explanations was reflective of characteristics of the individual experts or of the disciplines from which they come. This is a question that warrants further exploration—and a topic to which we turn next.

Implications for Research

In pondering potential next steps in this program of research, we want to acknowledge certain methodological challenges that researchers should be prepared to confront. One especially daunting challenge relates to the time and labor demands involved in collecting, transcribing, and interpreting the think-aloud data, which served as our principal information source. It is understandable why researchers often rely on self-report measures in lieu of think- alouds, particularly when they wish to gather information from large numbers of participants or those less willing to expose their thinking than experts. However, self-reports of cognitive and metacognitive processing have long been viewed as questionable data sources (Dinsmore et al., 2008; Veenman et al., 2006; Winne & Perry, 2000). Thus, it seems that researchers must continue to explore methodological alternatives, unless they are willing to commit the time and energy required to tackle think-alouds protocols.

In addition to collecting more data on experts, there is also a need to compare these expert profiles to profiles of those in acclimation and competence. One particular strength of the MDL as a theoretical framework is the ability to use that lens to describe how these profiles are expected to change over the course of learners' academic development. For example, would we find that those in acclimation exhibit a strong dependency on surface-level strategies, as the MDL predicts, while those in competence demonstrated more variable use of both surface and deep strategies during task performance? Further, what might we expect for the conditional use of these strategies for acclimating and competent learners?

Finally, we return to a discussion of the developmental nature of the MDL as well as other framework of expertise (e.g., Feltovich et al., 2006). While the MDL encompasses the more formally schooled development of constructs such as knowledge, interest, and strategies, and other frameworks that delve deeply into the "rich instrumental experiences in the world and extensive practice," (Feltovich et al., 2006, p. 46) should also be explored. In other words, what experiences in the disciplines under study here (e.g., biology versus psychology) may result in better or worse problem-solving outcomes in experts in that field?

Whatever methods and measures researchers elect to employ, and whether they choose to focus on experts in domains or those at other points in their academic development, it is our hope that the literature into the strategic profiles evidenced during problem solving will continue to expand. There is so much more to learn about the strategic patterns that learners exhibit when solving both novel and familiar problems, as well as problems that vary in complexity and structuredness. Similarly, there is still much more we do not understand about the variability or consistency of students' strategic profiles as they move from one problem to another or from one academic domain to another.

Implications for Educational Practice

Because of the very exploratory nature of this investigation and the select group of participants involved, we are somewhat hesitant to forward implications for educational practice. Nonetheless, there are recommendations that we feel justified in proposing based not solely on the evidence in this study but made in conjunction with related research. Those recommendations pertain to the utility of physical simulations, like the Black Box activity, to provoke students' scientific habits of mind and behavior. Specifically, because of their novelty and ill-structuredness, simulations like the Black Box can be motivational tools (Chang et al., 2010; Garris et al., 2002; Koh et al., 2010). They can also encourage students to observe and gather data, to speculate about unseen mechanisms more freely, to attempt building explanatory models that make sense of their observations and their data. Moreover, students in these contexts are free to engage in these valued activities without the expectation of knowing the "correct" answer offhand, or without undue stress of already possessing the "right" background knowledge.

In other words, the Black Box is a task that has the potential to be an activity not only for documenting expert performance, but also for analyzing those in acclimation or competence. What can be learned about acclimating and competent learners' problem solving and strategy use when engaged in the task and the scientific explanations that they generate as a result can serve as the basis for learning experiences that enhance or reinforce the performance patterns that are identified. In addition, while physical and computer simulations are most often used in STEM domains (Scalise et al., 2011), the ability to engage in effective problem solving when tasks are novel, complex, and ill-structured is prized in all academic domains (e.g., Shin et al., 2003; Simon, 1973). Thus, the more that can be garnered about students' problem-solving approaches and strategic profiles, the more educators can devise meaningful and appropriate learning environments the allow students to progress in their academic development (e.g., NRC, 1996).

In sum, we humbly offer this initial study as a sacrificial first step into building rich and diverse learner profiles that encompass not only patterns in strategy use but also incorporate information on learners' knowledge, interests, and the quality of outcomes they ultimately produce. It is our hope that these initial conclusions pave the path toward better understanding, and ultimately, improved scientific practice in both formal and informal educational contexts.

Authors' Declaration

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the Journal of Expertise.

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

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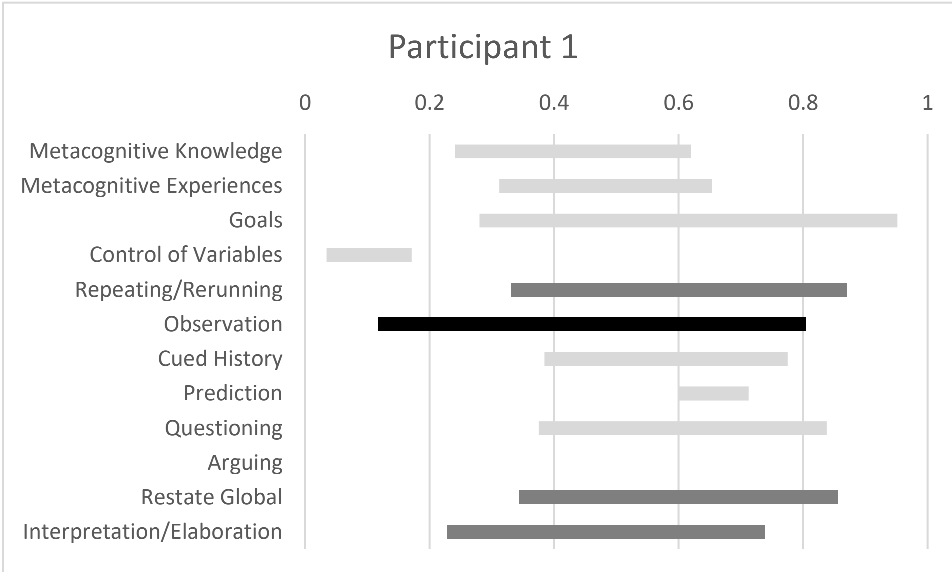
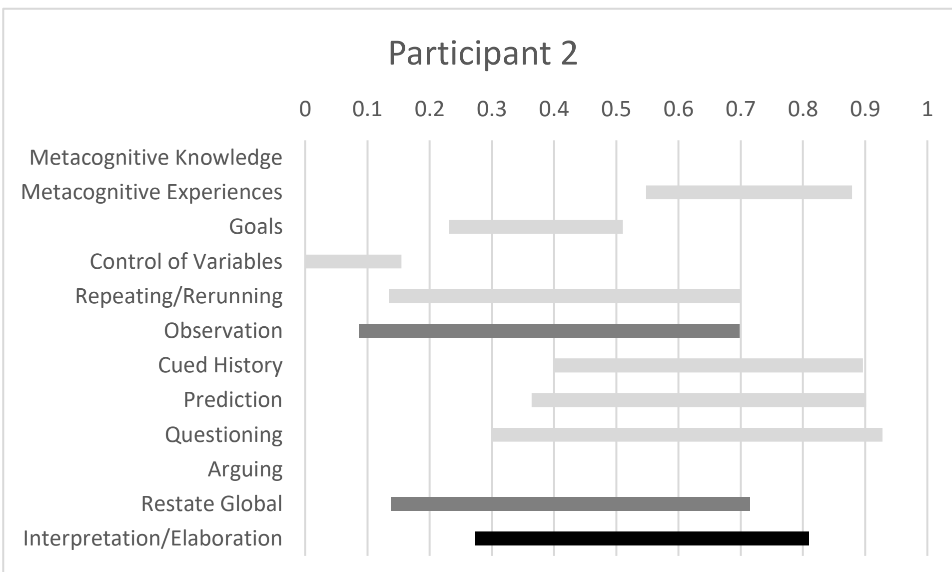
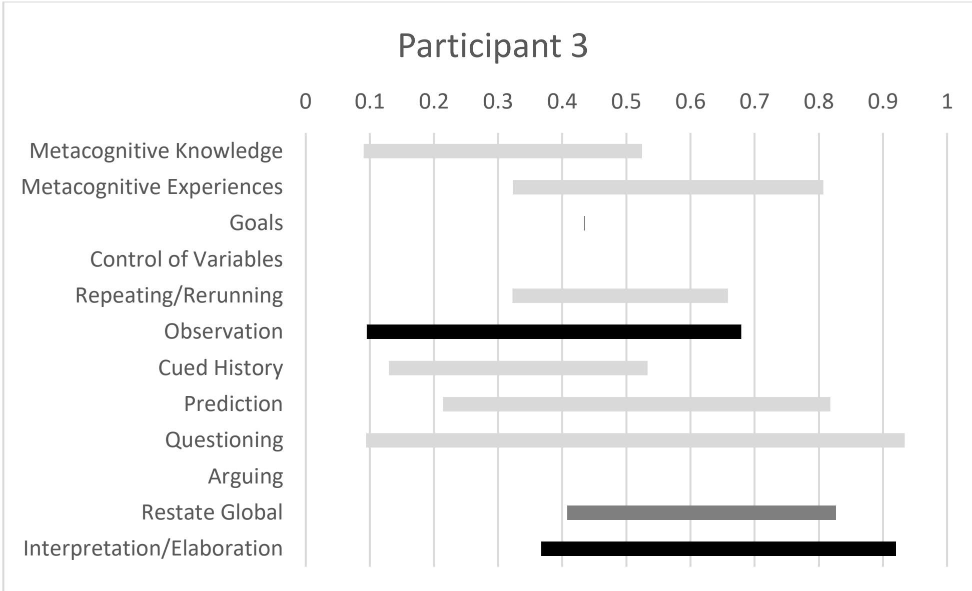
Submitted: 17 May 2021
Revision submitted: 8 January 2022
Accepted: 10 January 2022

Appendix A: Processing Profiles of All 11 Participants



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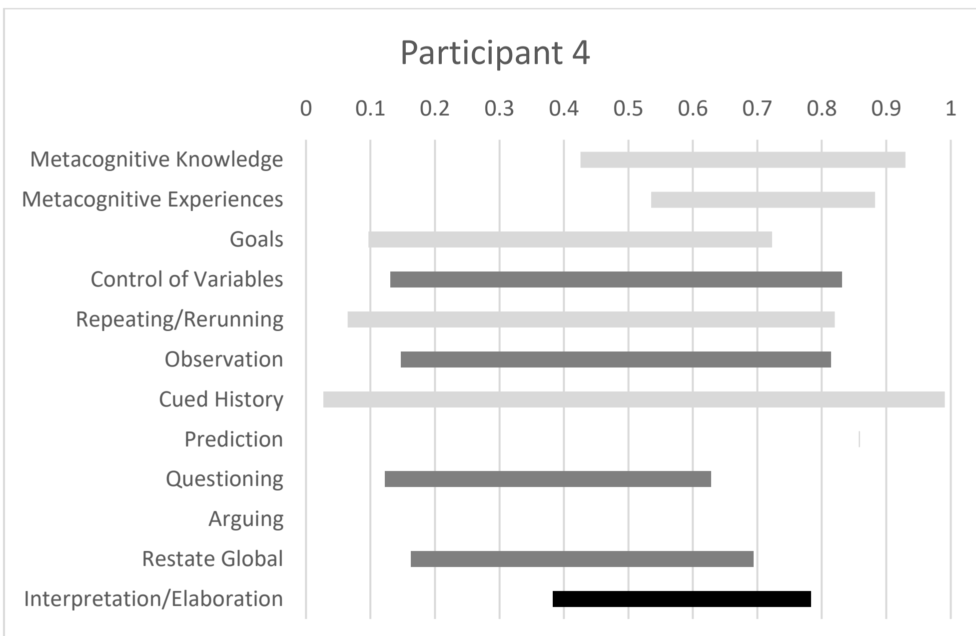
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Metacognitive Knowledge
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration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0.1
0.2
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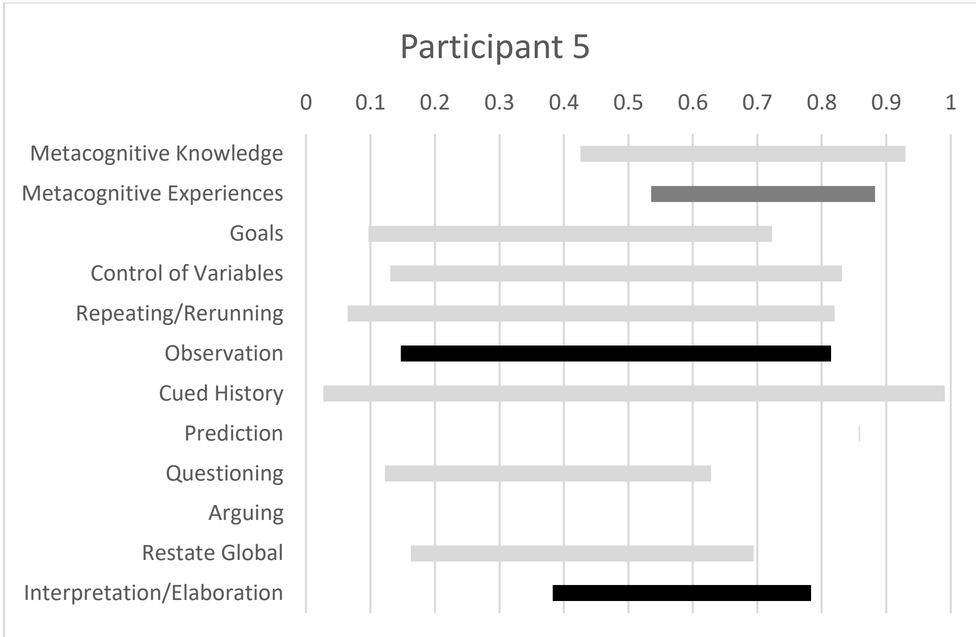
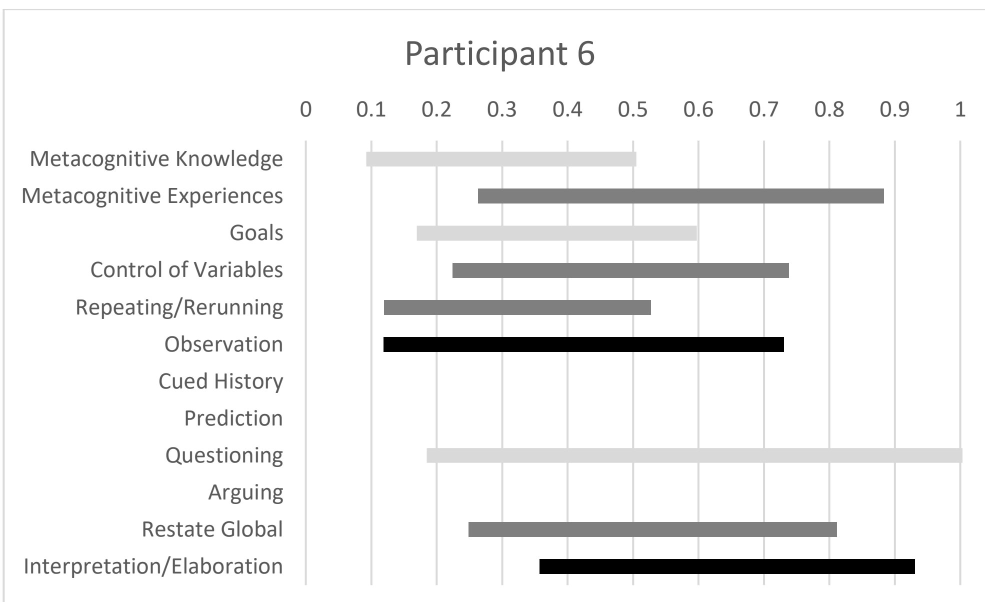
0.4
0.5
0.6
0.7
0.8
0.9
1
Metacognitive Knowledge
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration



Participant 5
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Metacognitive Knowledge
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration



Participant 6
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0.9
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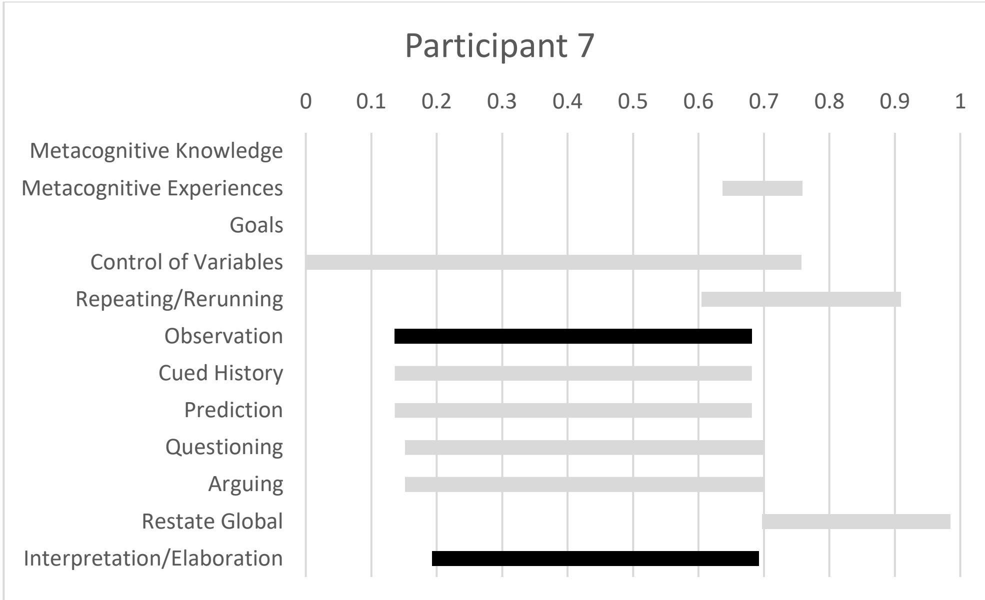
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration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0.9
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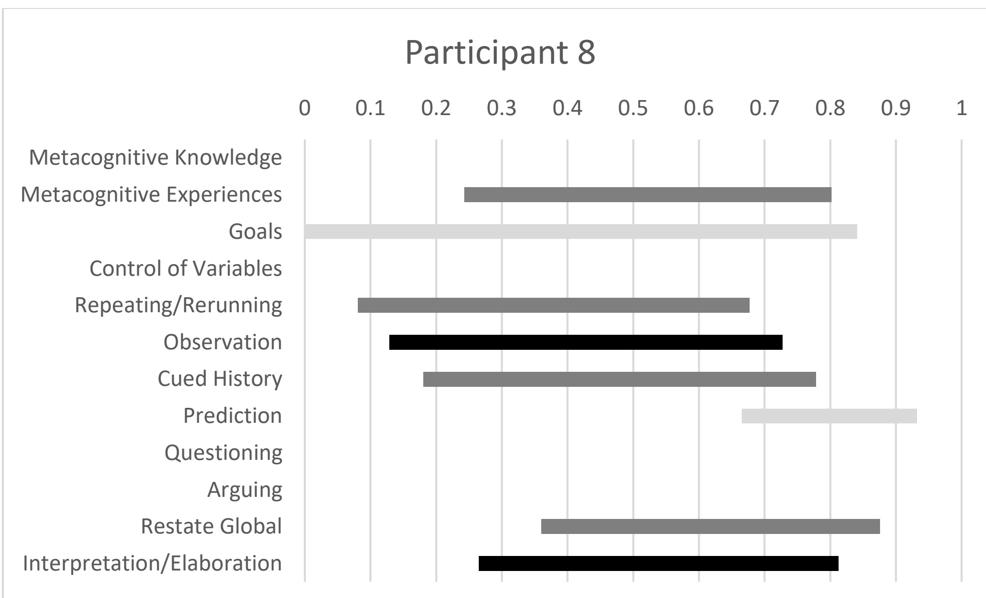
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration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0.9
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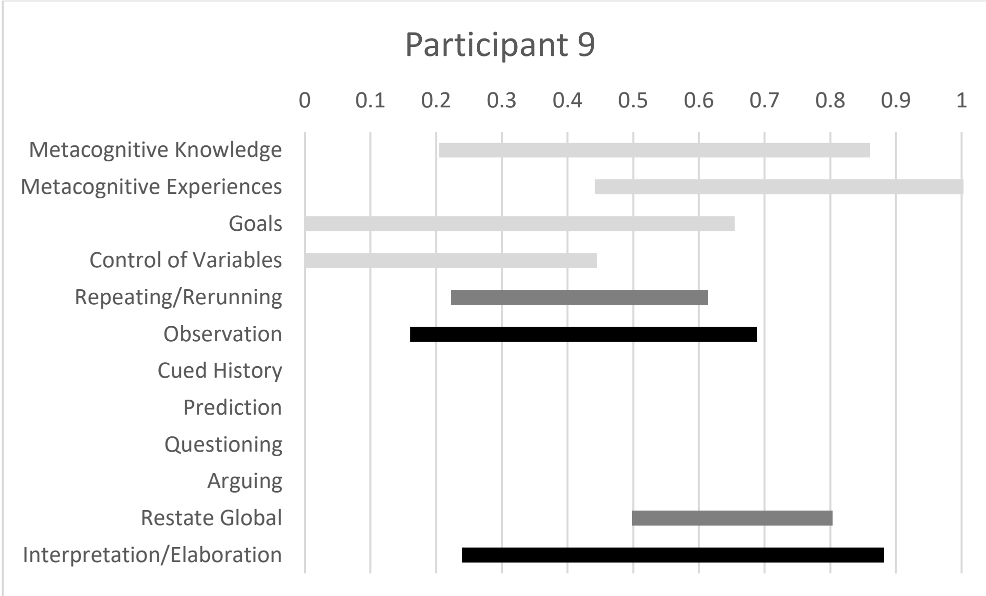
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration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0.8
0.9
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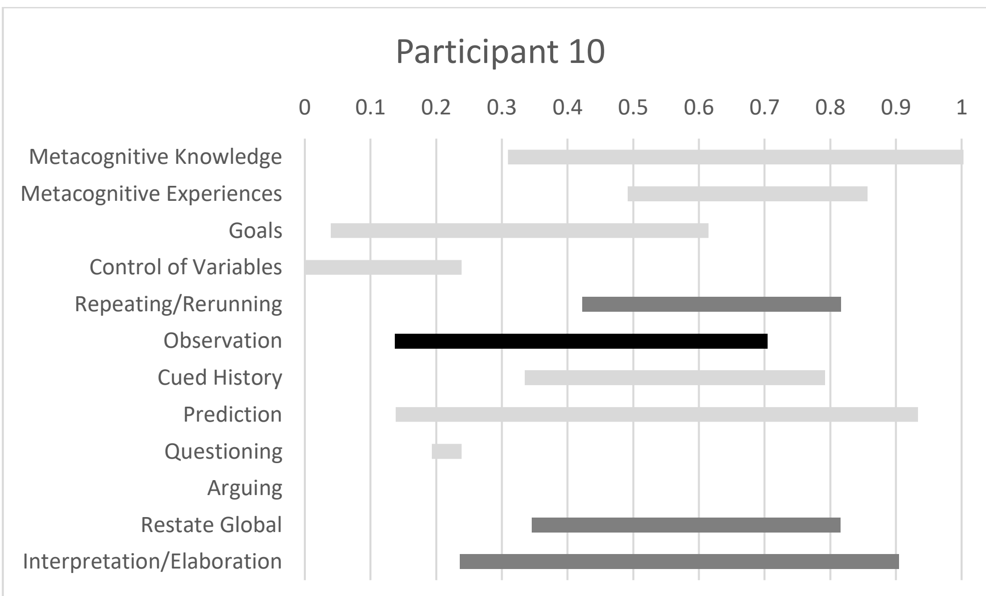
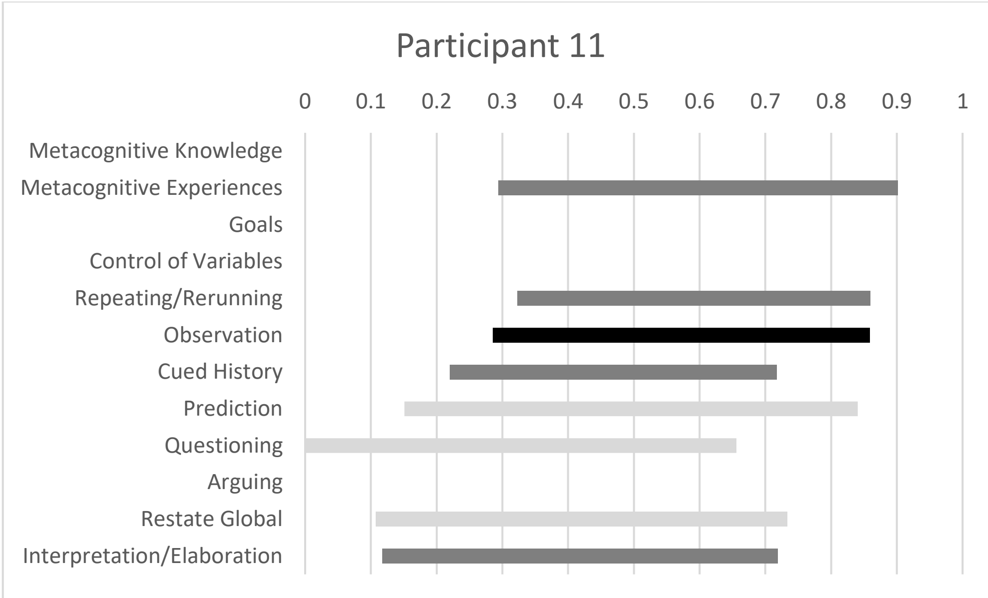
Metacognitive Knowledge
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration


Participant 10
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Metacognitive Knowledge
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration


Participant 11
0
0.1
0.2
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1
Metacognitive Knowledge
Metacognitive Experiences
Goals
Control of Variables
Repeating/Rerunning
Observation
Cued History
Prediction
Questioning
Arguing
Restate Global
Interpretation/Elaboration