Chapter 3

Problem solving: Understanding complexity as uncertainty

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Understanding complexity has dominated the domain of problem solving. There needs to be a cohesive idea about what makes problem solving hard in contexts broadly described as complex, and what are the sources of errors in problem solving in situations thought to be complex. This chapter argues that our understanding of complexity requires an overhaul, and perhaps a more encouraging and fruitful way forward in research on complex problem solving, is to reconceptualise "finding solutions to complex problems" as instead "findings ways of reducing uncertainty". This entails redefining the domain of "complex dynamic problem solving" into "decision making under uncertainty". This enables a Bayesian approach to understanding what makes a situation controllable, or appear to be controllable to a problem solver, and hence what cognitive and psychological factors they bring to bear on the situation.

Introduction

The Programme for International Student Assessment (PISA) project published a report in 2005, *Problem Solving for Tomorrow's World*, which identified problem solving as a key component for future assessment. Why? The report's argument, which applies equally to its studies in the domain of cognitive science, is that the value and importance of assessing problem-solving ability, is because it is a practical skill (OECD, 2005).

Typically the cognitive operation of problem solving refers to any type of goal-directed set of actions or cognitive activities (Anderson, 1982) designed to move the problem solver from a state in which the problem is identified and represented, to an end state in which manipulations of components of the problem are carried out in order to find a solution. Of course, it is also important to accurately represent the situation to facilitate the process of finding a solution, as well as to find the most appropriate strategy to move from the current to the end state (Jonasson, 2000).

The ability to identify and represent a problem accurately, as well to plan the sequence of steps to reach a solution is necessary in virtually all our personal and professional lives (Simon et al., 1987; Jonasson, 2000; Osman, 2010a). To investigate how we typically go about solving problems, and finding ways of training people to improve their skills, the cognitive science domain has developed at least six classes of problem-solving task: insight, information-search, analogical, mathematical, scientific thinking and complex dynamic. Each generally captures abstract aspects of everyday situations that involve combining actions in the most efficient (and often creative) way possible to reach an end state (for example getting three missionaries across a river without them being eaten by cannibals). One of these six branches that has garnered much attention in the PISA project and has been incorporated into the broad assessment criteria is complex dynamic problem solving.

The first aim of this chapter is to set out precisely what complex dynamic problem solving is, with illustrations from some everyday situations, as well as empirically notable examples. Through this it should become apparent: 1) why complex dynamic problem solving has had an established research tradition; 2) why the PISA project has identified it as an important component in its assessment criteria; and 3) why there is growing demand for researchers to communicate their findings more widely (Levy and Murnane, 2006). The second aim of this chapter is a little more challenging. Complex problem solving has a long tradition in psychology, and what is more, its reach extends to other disciplines, such as computer science, engineering, human factors, management, economics and other social sciences. The term "complex" is in and of itself complex. It has also been used to refer to problems that typically invoke a form of thinking in the problem solver that requires a complex sequence of actions. The main problem has been that, while researchers in the field of problem solving tend to notionally understand what it is that makes a problem complex, there is no agreed definition of what it is for a task to be complex, and no formal basis on which to distinguish complex from non-complex problems.

Thus, the second part of this chapter presents the case for approaching this type of problem from the viewpoint that the tasks developed to study complex dynamic problem solving actually invoke a form of decision making under uncertainty. To establish the argument, this section comments briefly on the differences between decisions made under risk, uncertainty and ambiguity. It presents a Bayesian framework that can be used to conceptualise the way people judge a situation, and uses a decision theory approach to establish the basis on which people then choose to act.

One might ask: why bother replacing the term "complex" with "uncertain"? The chapter responds in more detail later but, in short, there is a limit to how much we can understand and improve on the skills needed to tackle everyday situations if we don't have an agreed way of defining the situations in the first place. In general, the view taken here is that uncertainty can come from having to juggle multiple aspects of situation that need to be considered all at once – for example offsetting the side effects of drug treatment with the benefits of stemming the spread of a disease (i.e. a vast hypothesis space) – or from simply not knowing all of the aspects that need to be considered in the situation that one faces – for example buying an apartment in an economic downturn. There can be many more sources of uncertainty than just these two, but they all reduce to a subjective judgment that an individual makes as to the controllability of a situation, from which they then decide what action to take.

In this light, the assessments of complex problem solving in the student cohorts studied in the PISA project, and more generally in the cognitive science domain, might best be thought of instead as assessing people's ability to successfully and reliably reduce uncertainty.

Complex problem solving: Everyday examples

As part of a morning ritual, the doctor has advised us to take an aspirin every day. So, dutifully we take our aspirin from the medicine cabinet every morning, and replace it in its rightful spot routinely every day. On one occasion the box of aspirin is missing from the usual spot in the cupboard. We check the locations we visited in the house after we took the aspirin, and find that we'd put the box in our work bag, as a reminder to replace it because it is running empty. Aside from being mundane, and rather dull, this example represents a problem (locating the box) with a single goal (taking the aspirin regularly), and a simple solution: search the last known locations until the box is found (there are of course other simple alternative solutions). What also makes this example seem trivially simple is that it is a stationary problem: we couldn't find the box because we hadn't put it in its usual place; it is extremely unlikely that there are external factors that will alter the location of the box other than our own actions.

As soon as we enter into the realm of non-stationary problems things become increasingly difficult, and far less trivial. Climate change is one of the most critical issues that we currently face. Consequently, there have been various government initiatives in many countries encouraging people to moderate their fuel consumption. So, now imagine that we have decided to take action and become more energy conscious. As a result, we have installed an energy monitoring device (smart meter) to help reduce us track our energy consumption. This example represents a problem (work out the best course of action that will help economise home fuel consumption). There are now two competing goals (reliably reducing energy consumption while at the same time maintaining a standard of living that doesn't compromise all members of the household). The solution is also non-trivial (for example, working out the energy consumption of the appliances in the home and adapting our behaviour accordingly to reach an optimal balance). Our initial strategy is to start small by asking all members of the household to switch all appliances off at the mains after usage, recharge phones in the evening only and to shower five minutes less each day. Our smart meter shows that since installing it, for the period of time that we have been deliberately economising, we have successfully lowered our energy consumption, and moreover our fuel bill has marginally reduced. But, since this is a non-stationary problem, the strategy has to be flexible, because we know that things will change from one day to the next, such as individual demands, price structures and seasonal changes.

For instance, we would need to take into account the number of appliances used at any one time, the actually time the appliances are used and the frequency with which they are used. In addition, there will be other factors that change, such as the daily and seasonal differences in the demand for using appliances from different members of the household. More to the point, we need to evaluate our success relative to a target, otherwise we won't know how effective our strategies are over time, and relative to others. Therefore, we need to face a further issue of what target to choose. If we settle that issue, we face a further concern which is how to interpret the information we are getting back from the smart meter, which will be changing over time and only providing a gross indication of energy usage but, crucially, not how much energy each specific appliance uses over a specific amount of time. It is clear from just this case, which is a general everyday problem that households face, just how detailed and difficult a non-stationary problem can be.

Complex problem solving: Empirical examples

While not the earliest example (Toda, 1962), or the most empirically valid version (for example Dörner, 1975; Funke, 1992), one of the most often cited, and most famous examples of a complex dynamic problem-solving task was developed by Berry and Broadbent (1984, 1987, 1988). In their task, participants were presented with a story in which they are told that they are managers in a sugar factory. Their main goal is to figure out precisely how many workers should be employed at any one time to keep sugar production at a specified level. Participants need to track: 1) the amount of sugar actually produced (i.e. achieved outcome); 2) the amount of sugar that needs to be produced (i.e. target outcome); and 3) the number of workers they have chosen to employ at any one time (i.e. action). What makes this task non-static is reflected in the underlying rule that connects up these three variables. The task operates based on the following rule: $(P = (2 * W - P_{1t-1}) + R)$ in which the relevant variables are the workforce (W), current sugar output (P), previous sugar output (P1) and a random variable (R). The decisions of the participants in one trial will influence the outcome of the next. This means that the outcome will actually change, although in this case, it is still anchored to a choice that the participant must make. The addition of a random variable also obscures the relationship between decision and outcome, which makes the relations uncertain and of course harder to learn.

Compared with the everyday smart meter example, even though there are so few elements that need to be attended to or recalled, and even though only one element needs to be manipulated at any one time, Berry and Broadbent's task is still hard for essentially two reasons. In part, the difficulty comes from the ambiguity associated with uncovering the precise relationships between one's actions and their effects. The other reason is that participants are faced with two tasks at once: 1) learning about the relationship between actions and their effects; and 2) exploiting that relationship in order to reach and maintain a specific goal. Both these reasons are essentially the same critical issues that make everyday problem solving hard (Osman, 2010a).

A more recent complex dynamic problem-solving task which, like Berry and Broadbent's, also includes a random variable as a method of making it non-static, was developed by Osman and Speekenbrink (2011, 2012). In this task, participants are told that they are part of a medical research team conducting drug trials, and that their goal was to learn to reach and maintain a specified level of neurotransmitter ("N") release. They could achieve this by manipulating the amount of hormone from a choice of three (Hormone "A", "B" and "C") injected into a patient suffering from severe stress. By manipulating different levels of different hormones at different times they could learn the relationship between their actions and the effects on the outcome. More formally, the task environment can be described as in the following equation: $y(t) = y(t\text{-}1) + .65\ _{x1}(t) - .65\ _{x2}(t) + e(t)$, in which $y(t)$ is the outcome on trial t, $x1$ is the positive variable (Hormone A), $x2$ is the negative variable (Hormone B) and e a random noise component, normally distributed with a zero mean and standard deviation of 4 (low noise) or 16 (high noise). The $x3$ null variable (Hormone C) is not included in the equation as it had no effect on the outcome. Here the variables that participants need to track are: 1) the amount of neurotransmitter actually released (i.e. achieved outcome); 2) the amount of neurotransmitter that needs to be released (i.e. target outcome); 3) the number of hormones injected at any one time (i.e. action); and 4) the level of each hormone injected at any one time (i.e. action).

As with Berry and Broadbent's task, the outcome changes as a result of the participant's actions. However, even if the participant chooses to do nothing on a trial, the outcome will change anyway as a result of the way in which the random variable is included in the rule. Another difference between the two tasks is that in Osman and Speekenbrink's (2011) task, participants need to attend to, recall and directly manipulate more components at any one time. One might argue that because of these factors this task more closely approximates the everyday smart meter example discussed previously. But, how can one know?

It seems intuitive that one task (Berry and Broadbent, 1984) is less complex than the other (Osman and Speekenbrink, 2011). But what does that mean? In what way is one more complex than the other? Is it in terms of the task itself and its structure, or is it psychologically more complex? Clearly these issues resonate with any assessment exercise which needs to compare people's ability in a variety of increasingly difficult problem-solving tasks. One needs to know how they increase in difficultly, and if this occurs on the same identifiable dimensions. These issues also matter hugely in applied contexts. Imagine now that your smart meter not only gives you up-to-the-minute readings of your home energy usage, but also forecasts the likely usage of energy for the rest of the day with a detailed breakdown by appliance that could be used. By adding more layers of information onto existing devices such as smart meters or the systems people interact with from day to day, what new problem-solving situations will people face? Without knowing how to describe the contexts in which people have to perform complex dynamic problem solving, we won't know what the effects on problem solving will be when the contexts change.

Complexity by any other name: Uncertainty

As highlighted in the previous section, there is a need to characterise problems that seem to intuitively vary according to some form of complexity. In fact, uncovering the objective characteristics of a complex problem that make it complex has been a preoccupation in the study of complex problem solving, but to no avail (Campbell, 1988). Knowing the features that could be used to define a problem as complex has not helped to advance our understanding of why it is that people generally tend to falter in some problems and not others, or for that matter, why it is that some people are able to learn to control situations reliably better than other situations (Quesada et al., 2005). Psychological studies suggest that objective characteristics of complexity (the number of variables in the problem and the type of relationships between variables – i.e. non-linearities, and delays between a manipulated variable and an outcome) do not reliably predict our ability to surmount complex dynamic problems. They also cannot be used to accurately gauge the accuracy of people's representation and understanding of the problem (Osman, 2010a, 2010b).

In recent years, this has prompted a shift in research focus onto problem-solving behaviour (e.g. strategies, learning styles, control behaviours and transferability of skills) and examining the effects of psychological factors (e.g. self-doubt, anxiety, fear, misperception/misrepresentation of the problem) on problem solving (Bandura, 2001; Campbell, 1988; Gonzales et al., 2005; Sterman, 1994). This has been an alternative route to understanding complexity, by defining it in relation to the psychological factors that can lead to deterioration in problem-solving behaviour. I will argue here that in order to advance our understanding of the differences in the contexts in which dynamic problem solving is examined, and the effects produced on problem-solving behaviour, problem-solving researchers need to reconceive complexity in terms of uncertainty. In previous work in complex dynamic problem-solving tasks, I and others have shown that people form judgments of uncertainty while problem solving and the judgments correspond with, and can accurately track, changes in rates of learning and performance while solving a problem (Brown and Steyvers, 2005; Osman, 2008; Vancover et al., 2008; Yeo and Neal, 2006; Yu, 2007). One of the cues that people use when judging the uncertainty of a problem is the rate at which a non-stationary problem is likely to change over time (Osman, 2010a). They integrate this estimate with estimates of how confident they are that they can predict the changes occurring, and how confident they are that they can control the changes occurring. The following discussion focuses on demonstrating the role of uncertainty in the context of complex dynamic problem solving.

The connection between uncertainty and problem solving is by no means new. Take the following comment by Jonasson:

> "Just what is a problem? There are only two critical attributes of a problem. First, a problem is an unknown entity in some situation (the difference between a goal state and a current

state). Those situations vary from algorithmic math problems to vexing and complex social problems, such as violence in the schools. Second, finding or solving for the unknown must have some social, cultural, or intellectual value. That is, someone believes that it is worth finding the unknown. If no one perceives an unknown or a need to determine an unknown, there is no perceived problem (whether the problem exists independent of any perception is an ontological issue that is beyond the scope of this paper). Finding the unknown is the process of problem solving." (Jonasson, 2000:65)

As Jonasson claims, at the heart of what makes a problem an actual problem is the concept of the "unknown", and what needs to be surmounted in order to solve the problem is the process by which people transform the unknown to the known (i.e. problem solving). While the tasks that have been developed to examine complex dynamic problem solving are not uniform (in other words they cannot be made equivalent in terms of structure, or content), they reduce to one thing, which is that they present people with a context in which they are uncertain about what generates an outcome (i.e. the unknown), and they are tested on reaching a goal which reflects their ability to generate a particular outcome on successive occasions (surmounting the unknown).

In the study of decision making, a distinction is often made between decision making under risk, and decision making under uncertainty. I would argue that complex dynamic problem solving is an example of decision making under uncertainty. Although Knight's (1921) classic distinction was originally presented within the context of economics, the distinction between risk and uncertainty which concerns an agent's source of knowledge regarding outcomes and probabilities extends well beyond economics into psychology and neuroscience, in which it is often used. Knight distinguished between 1) *a priori* probabilities, which can be logically deduced, as in games of chance; 2) statistical probabilities, derived from data; and 3) estimates, arising from situations in which "there is no valid basis of any kind for classifying instances" (Knight, 1921/2006:225). Decision making under risk refers to situations in which people are engaged in planning actions against knowledge of the probabilities of the outcomes following their actions (i.e. *a priori* probabilities come to bear in these contexts). Decision making under uncertainty concerns situations in which people plan their actions from limited available knowledge of the possible outcomes, and in which the probabilities of the outcomes following actions is not known, or cannot be known, i.e. statistical probabilities and estimates come to bear in these contexts (Osman, 2011).

If we return to the examples discussed in the previous section, the objective that the problem solver is trying to achieve throughout is to find ways in which the cues can be manipulated by whichever means necessary in order to reach and maintain a certain outcome; in non-stationary environments the aim is to achieve this reliably over time. However, in all but one of the examples (i.e. the aspirin example) problem solvers have to find a way of acting in a situation with either incomplete or unreliable information. This can be compounded because the problem solver can be faced with ill-defined problems (Simon, 1973), for which there are no optimal or well-defined solutions, or in which the potential solutions to the problem can generate conflicts between choices of actions that serve competing goals. Regardless of the source of uncertainty (the number of variables that need to be manipulated, the underlying relationship between variables etc…), the uncertain will pervade because in complex dynamic problems the outcomes are non-deterministic, and the problem itself is non-stationary (for example the sugar factory task or the medical decision-making problem). Therefore, the problem solver cannot ever be sure how much the changes that are generated are based on their own actions and how much are based on the inherent workings of the problem situation itself (i.e. the underling endogenous properties of the system), or a combination of both (Osman, 2010a, 2010b).

Clearly then, from this characterisation, the everyday and empirical examples of complex dynamic problem solving fit within the definition of decision making under uncertainty (Knight, 1921; Osman, 2011). While researchers into complex problem solving might not be able to provide a comprehensive and systematic way of identifying complexity along a single dimension, or for that matter mapping complexity onto problem-solving performance, I would argue that it is possible to treat all complex dynamic control tasks as equivalent on the basis of their subjective degree of controllability, by reconceptualising complexity in terms of uncertainty. Thus, complex dynamic control tasks now lend themselves to a Bayesian approach in which researchers can examine what makes a situation more or less controllable, given the various sources of uncertainty (e.g. problem solving context, problem solver) that contribute to making an outcome dynamic.

The Bayesian approach proposed by Harris and Osman (2012) suggests that problem solvers evaluate situations from which they make assessments of controllability in two steps: first, they make a judgment about the controllability (or lack of controllability) of a situation, and second, they make a decision to act according to this judgment. The judgments are informed by the available evidence from the situation combined with a prior degree of belief in the controllability of the situation. This decision theory framework suggests that decisions are made following probabilistic judgments about the controllability of a situation. Harris and Osman (2012) proposed that the decision will be influenced by the utility (subjective goodness or badness) associated with misclassifications of controllable events as uncontrollable (misses/the illusion of chaos) and uncontrollable events as controllable (false positives/the illusion of control; see Table 3.1). Asymmetries in people's utilities enhance the likelihood for an objectively uncontrollable situation to be rationally, although wrongly (from an objective perspective), classified as controllable (the illusion of control), and explain why people act in objectively controllable situation as if they are uncontrollable (the illusion of chaos).

Table 3.1 **The four possible outcomes of decisions based upon the controllability of a situation**

		State of the world	
		Controllable	Uncontrollable
Act as though the world is…	Controllable	Hit	False positive (illusion of control)
	Uncontrollable	Miss (illusion of chaos)	Correct rejection

Source: Harris and Osman (2012), "Illusion of control: A reflection of biased perceptions of random outcomes or prior expectations of good and bad outcomes".

Cues to controllability

Both prescriptive frameworks set out precisely how to judge the controllability of a situation and how to act from that. To begin, the Bayesian framework represents degrees of belief as single event probabilities (or distributions over these probabilities), and people have a degree of belief in the truth of the hypothesis that "Outcome X is controllable". Bayes' theorem sets out the way in which people should update their degree of belief in a hypothesis (e.g. that an outcome is under their control) from evidence they receive:

$$P(\text{h}\backslash\text{e}) = \frac{P(\text{h})\ P(\text{h}\backslash\text{e})}{P(\text{e})}$$

Here, a problem solver's posterior degree of belief in the hypothesis, given a piece of evidence (from the problem solving situation itself), $P(h|e)$, is a function of their degree of belief in the hypothesis before receiving evidence (the prior), $P(h)$, the likelihood of the evidence given the truth of the hypothesis, $P(e|h)$, and the base rate of the evidence, regardless of the truth status of the hypothesis, $P(e)$. Prior beliefs will be informed by the extent to which they have found themselves in situations that are unfamiliar from which they were then able to control the outcome. For instance, to return to the home energy monitoring device (the smart meter). The father in the family may never have encountered a smart meter before, but he may have been used to using other self-monitoring devices for many years (blood sugar monitor, blood pressure monitor, pedometer). His experience with other monitoring devices may lead to his judgement of a high likelihood of controllability. Moreover, the problem-solving context will provide evidence. That is, the situation itself will also contain cues as to the controllability of the device, for example the simplicity of the interface, the number of buttons on the device, the comprehensibility of the instructions manual and the amount of information presented on screen.

Now imagine presenting the same individual with a smart fitness monitoring device which tracks intake (calories) and calories spent minute by minute through daily activities (e.g. walking, running, sleeping). How much more or less complex is this problem-solving situation as compared to managing one's energy consumption? While it might be hard to align both problems in the context of what might be deemed "objective task characteristics", by looking at the subjective judgments people make as to the controllability of both the smart meter and the fitness meter examples, we can place the two on the same dimension, which makes them comparable to each other. The advantage of empirical contexts is that we can manipulate complex dynamic problem-solving tasks in such a way as to understand more precisely the kind of evidence (i.e. cues to control) that people use to inform their judgments in combination with their prior experience of controllable situations. In two recent reviews Osman (2010a, 2010b) examined the findings from a literature that has been steadily amassing since the 1960s across diverse disciplines (economics, management, psychology, engineering, computer science, human factors and neuroscience). The list of criteria below is condensed from over 300 research articles on complex dynamic problem solving. Moreover, these aren't only the cues that people use to identify the controllability of a situation; these are also the criteria that people use to ensure that a highly uncertain non-stationary situation is made controllable.

1) **A consistent goal, and faith in the control system:** The person must have a clear and stable objective and hold a reasonable belief that their actions (through the control system) can affect the thing being controlled.

2) **A system fit for purpose:** The control system itself has a single, stable, overarching function, which coheres with the aims of the individual using it.

3) **A predictable system:** The control system must be (to some extent) predictable. For this, it must change at a manageable rate (not too rapidly or "violently").

4) **Time and space for control:** A series of sequential steps (that follow a linear order) are required, and these must happen in a particular time and place.

5) **A coherent system:** There is sequencing and synchronisation of the core operations in the system (i.e. the various components will work effectively together to further the core function of the control system). No part of a control system can function in a way that conflicts with the main objective of the control system.

6) **Feedback and controlled adjustment:** The information in the system feeds back on itself, and allows for adaptive adjustment to feedback (but with a threshold – so that adjustments do not threaten the overall objective of the control system).

The second component of the assessment of the problem-solving context is whether or not to act, which is simply a binary choice. Converting a ratio scale (i.e. a probabilistic belief in the controllability of a situation) to a simple binary choice needs a threshold value to be set. Harris and Osman (2012)'s application of decision theory to the context of control sets out that the output reflects both degrees of belief (probabilities) and the utility (subjective goodness or badness) of different possible outcomes. In any situation, there are two possible states of the world: the situation is controllable or the situation is not controllable. Similarly, one can act as though the world is controllable or uncontrollable. Thus, there are four potential outcomes as presented in Table 3.1.

In decision theoretic terms, there are two classifications, those which correctly correspond to the world as controllable or uncontrollable (hits and correct rejections) and those which are incorrect with respect to the world (false positives and misses). Positive utility is associated with correct classifications and negative utility is associated with incorrect classifications. Harris and Osman (2012) argue that if the positive utility associated with a hit equals the positive utility associated with a correct rejection, and the negative utilities associated with false positives and misses match, then the threshold for deciding that a situation is controllable or uncontrollable is: $P(\textit{controllable}) = .5$. As soon as there is an asymmetry in the utilities, however, then the threshold moves from .5. Thus, if one perceives higher costs with a miss than with a false positive, the threshold will be less than .5, increasing the likelihood of acting as though a situation is controllable.

Importantly, judgments of controllability will change, as will decisions to act, because the problem the solver is trying to resolve is a non-stationary one. Therefore, judgments of the controllability of the situation change as the problem solver continues to interact with the situation, and so will their decisions to act as if is the situation is controllable or not. Therefore, ongoing evaluations of performance in complex dynamic problem solving contexts should not only involve accuracy and reliability in control, but also ongoing judgments of control (Osman, 2008) and decisions of control.

Practical solutions to practical problems

At the heart of this article has been a pragmatic issue, and that is the need to understand the skills needed for effective problem solving, and the criteria that we use to define the problem, both in science and in the assessment exercise in PISA designed to enhance learning. In the domain of "complex dynamic problem solving", which I argue should be referred to as decision making under conditions of uncertainty, we are still very far off from tackling these issues. However, it is very bad form to end on a negative note. So, the parting message from this article is that there are ways of reconceptualising complex problems into uncertain situations. The advantage in doing so from an empirical perspective is that we can feasibly make a variety of different types of problems equivalent. This is an important first step because they can then be directly compared on the same dimension, and the dimension combines aspects of the objective characteristics of the problem and the psychological factors that problem solvers bring to bear. The simple solution to a very long and entrenched problem is to focus on the subjective judgments that people about the controllability of the problem-solving context. This may help to better understand an essential cognitive activity that has also been identified as key in a major worldwide assessment exercise.

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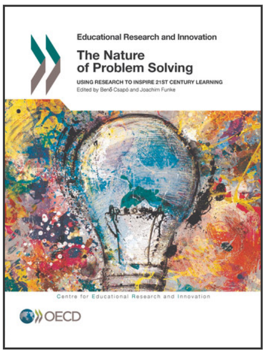

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