Using a Cognitive Theoretical Framework to Support Accident Analysis

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ABSTRACT

Current cognitive user models enable us to describe, analyze, and predict aspects of user cognition. However, none of the major cognitive models such as ICS, MHP, or CCT tackle the human error aspect of cognition explicitly. Operator performance is constrained to be error-free, expert performance. This paper argues that the analysis of human error in accidents will greatly benefit from representing a cognition-based error model within a cognitive architecture, such as ICS. A helicopter accident near Middlewich in 1996 acts as a case study. The resulting model is shown to aid reasoning about human error and its potential causes. Thus a more complete understanding of human error in accidents can be achieved.

Keywords

Human Error, Accident Analysis, Cognitive User Modeling, ICS

INTRODUCTION

The nature and causes of failures due to 'human error' remain relatively poorly understood (O'Hare et al, 1994). Reason et al (1990) maintain that 'one of the applied psychologist's more pressing task is to provide accident investigators with a better classification of the possible varieties of human failure' (op.cit.). O'Hare (1994) and his colleagues analyzed a database of aircraft accidents and incidents by applying two different error classification schemes. They stress that they only attempted to investigate *what* failed in each of these events, and not the 'mechanism of malfunction', meaning *how* it failed (op.cit.). This, however, needs to be determined 'to trace the information processing failures associated with each event'. This paper illustrates an approach which translates a catalogue of theory-based error classifications into the framework of a cognitive architecture. This can bridge the gap between mere categorization of error and 'probing [the available information] more deeply by means of theoretically based models of human information processing'.

The Case Study

On October 22 1996, five people were killed in an accident involving a helicopter AS 355F1 Twin Squirrel.

The accident occurred when the helicopter was returning to London from a private landing site in Lancashire with one pilot and four passengers on board. The aircraft was being flown at night in visual contact with the ground when the pilot decided to climb to a higher altitude. During the climb he was deprived of external visual references and the aircraft adopted a steep nose-up attitude during which the air speed reduced below a minimum recommended speed for instrumental flight. This unintentional manoeuvre then developed into a fast, spiral descent. The helicopter did not recover from the dive and it crashed into a field on the outskirts of Middlewich, broke up and caught fire (Air Accident Investigation Branch, 1997).

Integrating Error Models and Cognitive Architectures

Conceptual models of human error such as GEMS (Reason, 1990) present a taxonomy of error types that aids the prediction and detection of error classes, and can thus be exploited for their prevention and provision of recovery mechanisms (Taylor, 1988). However, stand-alone human error theories highlight at best possible sources of erroneous performance, but without providing a language in which to express these error tendencies when applied to human cognitive task performance.

Cognitive architectures can contribute to our understanding of the cognitive limitations of an operator performing a task. For example they can be used to analyse the detrimental effects that cognitive load can have on user performance (Barnard and May, 1993; Ashcraft, 1994). Human error can be described in terms of its underlying cognition. This analysis thus reaches beyond the surface categorization of failures.

Current cognitive user modeling strives to represent the cognitive processes underlying error-free performance, implicitly assuming expert performance in some perfect context (see for instance Simon, 1988; Grant and Mayes, 1991; Booth, 1991; Knowles, 1997). This idealizes real-life conditions of task performance and thus presents major deficiencies in applied user modeling.

Since user error presents a major source of accidents (Reason, 1990) we argue that the explicit analysis of human error within cognitive user modeling techniques constitutes a crucial source of understanding and thus a prerequisite of reducing erroneous task performance. This paper will use a cognitive architecture as a vehicle for expressing not only expert task performance but also the more realistic error-prone thought and action sequences processed by the human operator. By doing this, the error modeling capability implicit in the comprehensive ICS cognitive architecture is made the focus of inquiry into the underlying cognition of operator performance. Such explicit modeling of erroneous performance can thus help to communicate findings about operator cognition. It can also be used to ground design decisions in a cognitive theoretical framework. As a running example, error modeling will be applied to events leading up to the Middlewich accident.

We will use Interacting Cognitive Subsystems (ICS) (Barnard and May, 1993) to illustrate the modeling of human error within a cognitive architecture. ICS provides a comprehensive account of human cognition, which has been applied to real-life systems and tasks, such as cinematography (May and Barnard, 1995) and Air Traffic Control (Buckingham-Shum et al., 1994). It attempts to "satisfy the need for applicable theory" (Barnard, 1987). ICS, therefore, bridges the gap between theory-oriented cognitive architectures and task-oriented cognitive user models (Grant and Mayes, 1991; Simon, 1988). Alternative cognitive user models, such as Task Analysis for Knowledge based Descriptions (TAKD) (Johnson, P. et al., 1994), User Action Notation (UAN) (Hartson et al., 1990), or Soar (Newell, 1990) might have been used. However, they lack the level of detail in ICS’s representation of cognitive processes, or, as in the case of Soar, the inherent constraints that these have to satisfy (Wilson et al., 1988; Kjaer-Hansen, 1995).

Reason’s taxonomy of human error (Reason, 1990) represents a conceptual classification of error, as opposed to a contextual or a behavioural one. The latter, exemplified for instance by Hollnagel’s (1991) classification of error phenotypes, does not lend itself to the in-depth analysis of the underlying cognitive sources of error. For instance, a behavioural error category might include errors that exhibit the same surface characteristics without sharing the same cognitive basis.

Content and Structure of this Paper

The following section will take a closer look at the ICS architecture and Reason’s theory of human error. Reason’s error classification scheme will then be introduced. Readers familiar with ICS and GEMS can move straight to the third section, where the benefits of the suggested combined modeling approach are pointed out. ICS is used as a framework within which Reason’s classification of human error can be expressed.

A COGNITIVE ARCHITECTURE AND A HUMAN ERROR MODEL

This section describes Barnard’s ICS model and Reason’s human error taxonomy. This provides the framework in which the representation of erroneous operator interaction can be placed.

Interactive Cognitive Subsystems (ICS)

Cognition is represented in ICS as the flow of information between nine subsystems (see Figure 1), and the processing performed on this data. Each subsystem can receive several input streams and either achieves a blending of these, or else favours one input over the other. Each subsystem also has at its disposal a local image store. A copy of any input the subsystem receives will automatically be copied to this buffer, before being further processed.

Sensory subsystems:	
VIS	visual: hue, contour etc. from the eyes
AC	acoustic: pitch, rhythm etc. from the ears
BS	body-state: proprioceptive feedback
Effector subsystems:	
ART	articulatory: subvocal rehearsal & speech
LIM	limb: motion of limbs, eyes etc.
Structural subsystems:	
OBJ	object: mental imagery, shapes etc.
MPL	morphonolexical: words, lexical forms
Meaning subsystems:	
PROP	propositional: semantic relationships
IMPLIC	implicational: holistic meaning

Figure 1 The ICS Subsystems

The nine subsystems can be grouped into four categories. The visual, the acoustic, and the body-state subsystems are responsible for sensory processing. Articulatory and limb comprise the effector subsystems. The central subsystems comprise of the Structural (object and morphonological) and the Meaning (propositional and implicational) subsystems. They recover the structure of mental imagery and words, and give semantic and holistic meaning to those structures respectively.

Reason’s Classification of Human Error

Reason’s taxonomy of human error (Reason, 1990) represents a conceptual classification of error. It is predicated on assumptions about the cognitive mechanisms involved in error production. His categorization scheme is widely referred to in research into error modeling (Logan and Cowan, 1984; Green, 1985, Rasmussen, 1985, 1990; Rouse and Morris, 1987; Woods, 1988, De Keyser, 1989, Rouse and Cody, 1989).

Reason bases his error classification on the definitions of skill-based slips and lapses on the one hand, and rule- and knowledge- based mistakes on the other. He defines slips and lapses to result in actions or states that deviate from the current intention due to execution and/or storage failures. Mistakes, on the other hand, result in actions that may run according to plan, but where the plan is inadequate to achieve its desired outcome (see also Norman (1981) and Rasmussen (1983)).

The working definition for mistakes points out that these result in actions that may run according to plan, but where the plan is inadequate to achieve its desired outcome. Rules have been formed through interaction with the world, and are re-applied when appropriate. For any task, rules must be selected by the cognitive system. There might be several rules that compete for selection. The selection occurs according to which rule matches the given conditions best, supplies the highest degree of specificity, and can boast the greatest degree of strength. Rule strength is defined to be the number of times a rule has performed successfully in the past. Occasionally, rule strength might override the other factors, possibly resulting in the misapplication of 'good' rules. Reason calls this the application of 'strong-but-wrong' rules. For instance, it is highly likely that on the first occasion an individual encounters a significant exception to a general rule, the 'strong-but-now-wrong' rule will be applied. An example of such a 'First Exception' rule-based mistake will be examined in the case study below.

Thus, error taxonomies such as Reason's typically confine themselves to broad error categories such as slips and mistakes. A more detailed, lower level description of such classes might aid the further investigation of its instances. The accident analysis process might thus be tuned more finely to potential deficiencies pointed to by the operator error.

Cognitive modeling techniques, such as ICS, can provide a more precise vocabulary to augment the general descriptions of error taxonomies. We will illustrate this by modeling rule-based mistakes within ICS as the paper progresses.

Reason furthermore asserts that instances of his three basic error types are indirect results of what he calls the 'underspecification' of cognitive operations. In case of an ambiguity of the situational requirements, the cognitive system defaults to contextually appropriate, high frequency responses. This idea of default assignments features in most other cognitive theories, such as Bartlett's (1932) theory of schemata, and is well backed up by empirical evidence. ICS provides for this cognitive principle by referring to the depository role of image records attached to the individual subsystems. Thus ambiguous external input is complemented by internal input. In this way, ICS can be used to examine Reason's elementary concept of cognitive underspecification.

USING ICS TO EXPRESS REASON'S ERROR TYPES

Human error has been recognized as a predominant factor in aviation mishaps. O'Hare et al (1994) cites estimates of the proportion of mishaps due to human error as ranging between 60% and 80%.

Expressing human cognitive errors within the framework of a cognitive model will allow us to investigate and reason about their underlying psychological causes. A conceptual, systematic technique for categorization of errors is a prerequisite.

In the following section we show how errors leading up to the Middlewich accident can be categorized according to Reason's classification scheme and subsequently modeled in the ICS architecture. Thus, the relationship of these errors to the underlying cognitive mechanisms as propagated by Reason can be established.

Analysing the Underlying Cognition of Errors

At a crucial point in the run up to the Middlewich accident, the pilot became disoriented after he lost external visual attitude reference. In spite of several observed coping manoeuvres, he never recovered.

The investigation identified six causal factors, one of which concerned the commander's workload in marginal weather conditions. Another one suggested that the commander may have been distracted at a critical time by the opening of a cabin door. Underlying all of this is the pilot's disorientation, as recorded in the pilot's verbalisations, and his inability to recover from it.

Examining the pilot's behaviour in the light of these causal factors can give rise to several interpretations. Two of the possible viewpoints are discussed in detail as the section progresses. They refer to Reason's taxonomy of human error, and identify two rule-based failure modes underlying the pilot's inability to perform the appropriate recovery manoeuvres. On the one hand, as shown below, this could be put down to a rule-based mistake such as the 'First Exception' class of errors (described above). Alternatively, Reason identifies 'Information Overload' as a possible failure mode at rule-based level of performance. This could be seen as being a major contributing factor in the given accident sequence.

As can be seen, these two categorisations of pilot error are general in nature. We will show below how they can be complemented by an anlysis of the underlying cognition within the ICS framework. The more precise and detailed vocabulary offered by the ICS architecture can accommodate modeling to reach beyond surface characterisation of human error. We will illustrate this in the following section.

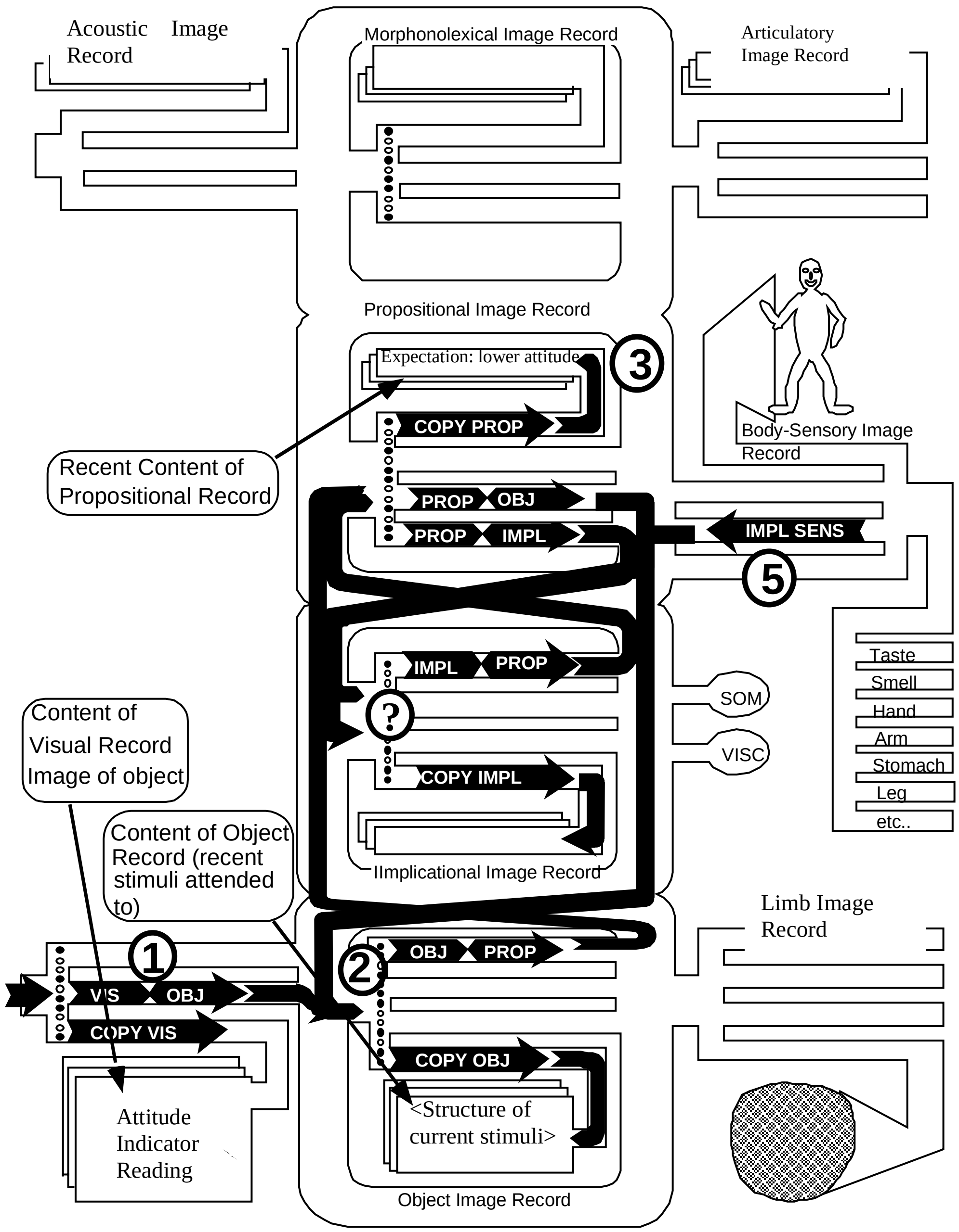

Figure 2 Rule-based Mistake: First Exception to General Rule

Reasoning about Alternative Analyses of Error Causes

Attitude information was available through the main attitude indicator, and should have been confirmed by the standby attitude indicator. The latter, however, had most probably not been switched on at the beginning of the flight, and therefore showed erroneous indications. Furthermore, the pitch rate was sufficiently slow and steady for the commander not to be aware of the attitude change. He was thus faced with a mismatch of his expectations and two diverging indications on the standby and main attitude indicators. If both instruments had been giving similar attitude information, the pilot may safely have assumed that he was experiencing from a perceptual illusion. Otherwise he had been hopelessly confused.

Referring to Reason’s taxonomy, the pilot’s cognition and resulting behaviour in the above-described chain of events might be classed as a misapplication of a good rule (see above). As pointed out earlier, Reason stresses the role of ‘first exceptions’ to a general rule which are most likely to be overridden by ‘strong-but wrong’ rules. The pilot's instrument flying skills had not been formally examined since April 1992, and he had not been required to rehearse recoveries from unusual positions. His loss of orientation caused by facing a mismatch of sensory perception and instrument indication can be seen as the ‘first exception’ to the general rule when not experiencing a mismatch.

The underlying cognition can be modeled in ICS as shown in Figure 2.

The visual data is received at the visual subsystem (1), sent to the object subsystem for the recovery of a structural description (2), and finally interpreted by the propositional subsystem (3). The information is fed forward into the implicational subsystem, which interprets the data in the light of the current context. In the meantime, the propositional subsystem receives contradictory information from the body-sensory subsystem (5), which claims to sense no change in attitude. If, as is the case here, the propositional subsystem receives ambiguous structural information, and it proves unable to blend the incoming data streams, a selection process will take place, based on the rules available to it and their respective strengths. The feedback information received from the implicational subsystem also plays a guiding role in input and thus rule selection.

The choice of input stream taken by the propositional subsystem might fit in with the implicational interpretation of what is perceived, and thus stabilize in the cognitive system. If the assumption underlying the choice of what data is used to eliminate the ambiguity is wrong, however, the representation of what is thought to be perceived will also be incorrect. The wrong data will be favoured. If this occurs then the pilot's recovery manoeuvres will be inappropriate to the helicopters attitude change and an accident might occur.

Modeling this scenario in ICS showed how an instance of Reason's class of rule-based mistakes could be investigated at a more detailed level. This complements the more general categorisation of human error by Reason's taxonomy alone.

The above interpretation of causal factors represents one possible underlying cause of the described error. However, the same manifestation of user behaviour might also point towards a second, different underlying cognitive mechanism. Employing Reason’s taxonomy, the commander not being aware of the attitude change can be classed as a rule-based mistake as modeled above. On the other hand, it could also be classed as a rule-based mistake as mediated by information overload.

Reason cites the abundance of information confronting the problem-solver in most real-life situations as one basis for rule-based mistakes. He states that this almost invariably exceeds the cognitive system’s ability to apprehend all the signs present in a situation. Applied to our case study, the interplay of contradictory attitude information on the one hand, and the opening of the cabin door on the other can be seen as leading to cognitive information overload.

This scenario particularly lends itself to being expressed in the ‘cognitive language’ provided by ICS. The limitations of human cognition in the face of information overload, or cognitive strain, is built into ICS as the architectural constraint of subsystems not being able to process simultaneous inputs which belong to distinct configurations. Using ICS can help to express the details of Reason's 'information overload' more precisely.

The problem-solving configuration described above remains, but now is supplemented by a second configuration, which describes the cognitive resources required when processing the opening of the cabin door (see Figure 3).

The second configuration (2) originates from the input at the acoustic subsystem by the noise of the opening cabin door. This information demands access to the meaning subsystems, currently utilized by the first configuration (1). Since Principle 1 in ICS does not allow access to subsystems by more than one configuration at a time, the two configurations compete for the available cognitive processing resources. Cognitive overload is established.

Using ICS to model the underlying cognition of the error provides a means of further investigating the behaviour trace leading to an accident. Expressing the rationale for different interpretations within a cognitive framework facilitates their more precise communication and more detailed analysis. In that way, not only *what* failed in accidents, but also *how* it failed is examined and thus included in the investigation of human error.

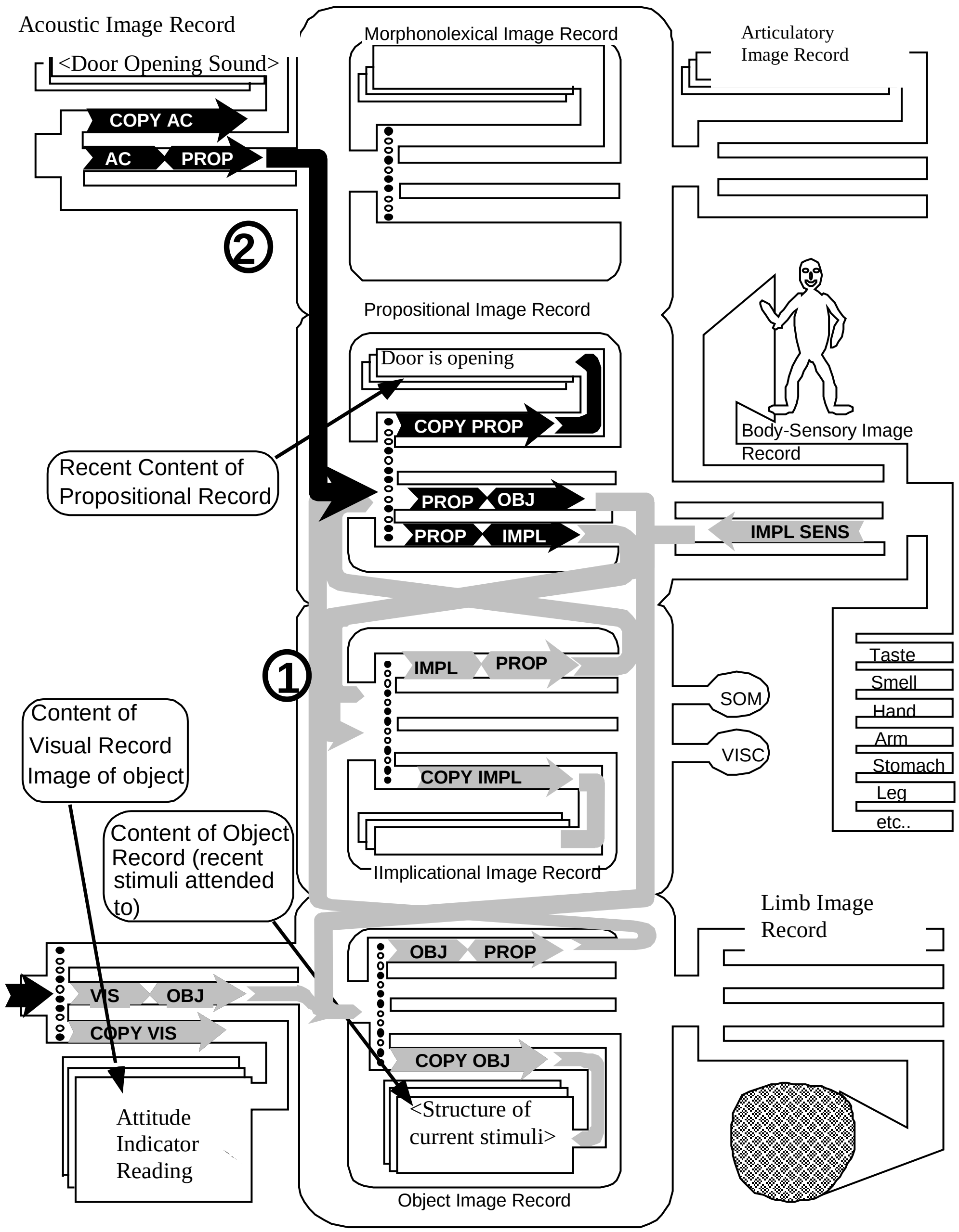

Figure 3 Information Overload - Competing Configurations

CONCLUSION

Cognitive user modeling enables usability engineers to gain a deeper understanding of the complexities of human task performance. Current techniques typically constrain this performance to be idealized, error-free and often at expert level. However, human error represents a major source of insights into the workings and limitations of operator cognition, and therefore into usability problems. By using cognitive models, the possibility of representing erroneous performance is inherent in these techniques. Few modeling techniques to date explicitly represent human error as we have done. This paper showed the adoption of Reason’s error taxonomy and Barnard’s ICS for the systematic representation of operator error within a theoretical cognitive framework. Operator error can be described more precisely by linking it to underlying cognition. Analysis can reach beyond surface categorizations, and it is possible to reason about the actual causes of error. As a consequence, this approach paves the way for accident analysis that takes full advantage of the insights expressed in cognitive theory. Recommendations for future error avoidance can be based on theoretical grounds. This might impact on future system design as well as for instance operator training procedures.

Embedding human error modeling into a cognitive theoretical framework helps to express accident investigators' understanding of the error sources. Communication of their reasoning, based on expertise and experience, is illustrated in this paper by using Reason's taxonomy and ICS. Further work might also take issues such as 'learnability' and level of complexity into account in the choice of the cognitive architecture employed.

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