Student Modelling: Modelling Affect

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1. Modelling Affect

Affect and Cognition

Numerous studies which strongly indicate that affect and cognition are related in a way which impacts on the quality of learning and ultimately on its effectiveness

[e.g. Keller,1983; Malone and Lepper, 1987; Burleson and Picard, 2004]

Human tutors tend to know when intervention and provision of affective support might be necessary and/or conducive to learning

[Higgins, 2001, Burleson, 2006]

Currently available artificial tutors lack the ability to engage in affective interactions in ways that fit with particular learners' needs in specific tutoring sessions

Modelling motivation

Moving from focus on cognitive aspects of the student model to affective ones

Lepper et al. (1993) expert human tutors spend as much time on affective aspects as cognitive ones.

Cordova & Lepper (1996) what strategies motivate students, and impact learning?

We focus on the prior/fundamental task of detecting student's motivational state.

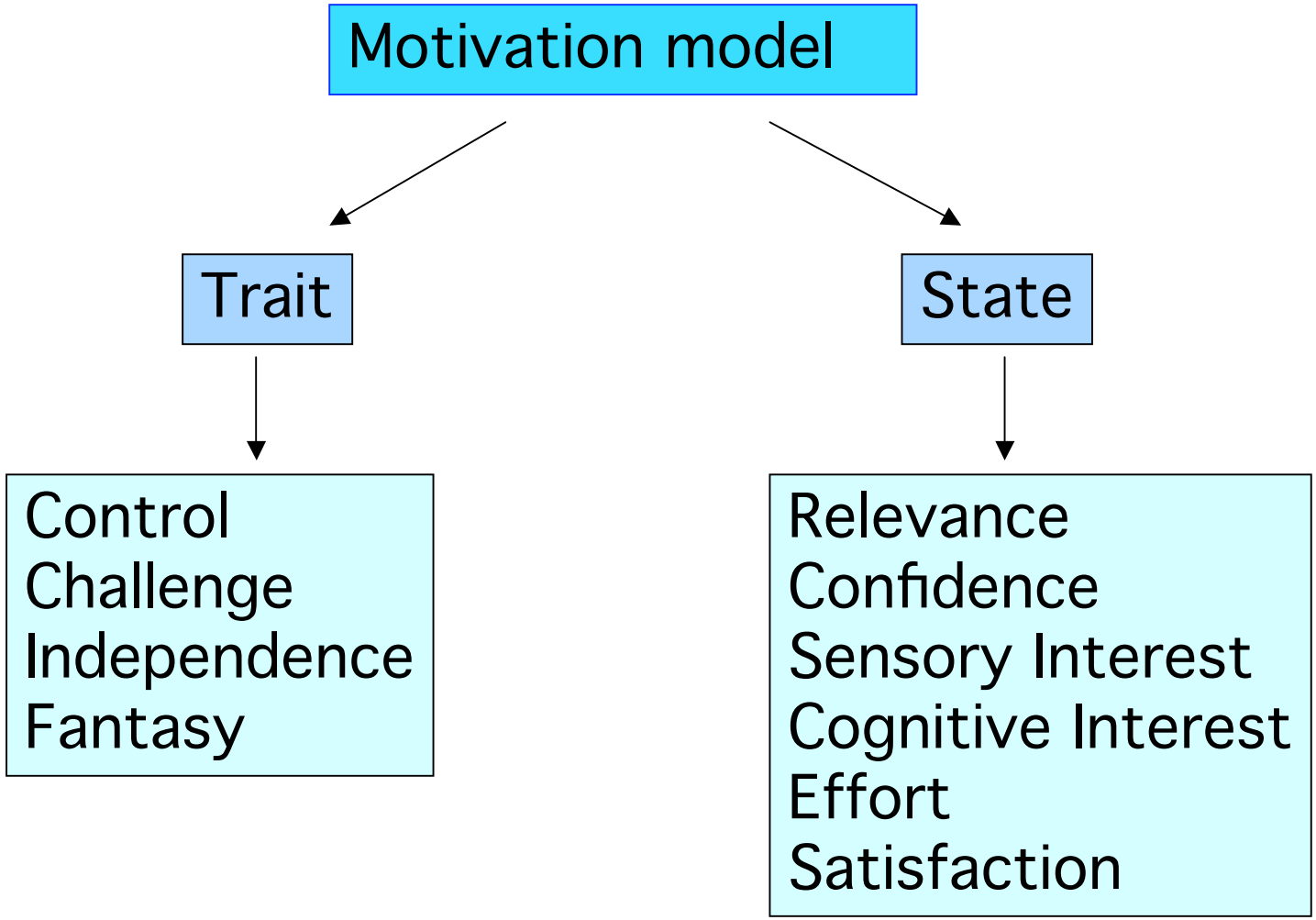
What aspects do we look at?

Factors that influence student motivation include:

- Challenge
- Curiosity (sensory/cognitive)
- Sense of control
- Fantasy

Lepper et al (1993)

Traits and States



Traits: definitions

Control: how much control the student likes to have over the learning situation

Challenge: how much the student enjoys challenging situations during the instruction

Independence: how much the student prefers to work independently, without asking for help

Fantasy: how much the student appreciates environments that evoke mental images of physical or social situations not actually present

States: definitions

Confidence: the student's belief in being able to perform the task at hand correctly.

Sensory interest: the amount of curiosity aroused through the interface presentation

Cognitive interest: curiosity aroused through the cognitive or epistemic characteristics of the task

Effort: the degree the student exerts himself in order to perform the learning activities.

Satisfaction: the overall feeling of goal accomplishment

Finding out about the student

- Look at the student's past history
- Observe and reason from the student's behaviour *(more later)*
- Compare to existing student models
- Build new models and test predictive power
- Ask the student
- Ask the teacher

2. Methods for Modelling Affect

Observational Methods

1. **Direct Observation**
   e.g. teacher-student interaction through a chat interface
2. **Video recording of behaviour**
   e.g. Recording keyboard use and mouse movement
3. **Transcript analysis**
   e.g. Use annotation tools to mark-up teacher-student dialogues
4. **Sentient Analysis**
   e.g. sensors to detect physiological states (GSR)

Knowledge Elicitation Methods

1. **Interviews** e.g. post-session, semi-structured to determine feelings and attitudes
2. **Questionnaires** e.g. as expert evaluation in design phase, or later model validation
3. **Self-report and verbal protocols** e.g. Student externalising feelings, or tutor making means of diagnosis explicit (issues of cognitive load)
4. **Wizard of Oz** e.g. formative testing of design, or gathering data to populate student models
5. **Comparison to external standards** e.g. personality tests

Diagnosing affect

Physiological sensors and haptic devices have become common tools used to detect emotional states and arousal levels of students
[Picard and her group: 'the galvanator']

Conati and Maclaren 2004 use skin conductance as basis for developing formal models of affect

Other attempts include real time multimodal affective sensors including posture chair, facial expression camera and linguistic cue analysis in order to enhance their agent' abilities to interact with students

Affective Learning Companion (Picard, MIT Media Lab)

Infers and responds to student's affective state

Posture movements give indications of interest and boredom via machine learning of affect states labeled by teachers

For discriminating interest level: 69-83% accuracy recognising is child is in state of

High Interest, Low Interest, Taking a break

Pressure sensitive mouse: may increase with frustration, distress

Learning companion that senses and responds to multiple affect channels: head tracker, eye tracker, pressure mouse, skin conductivity, seat posture

Also takes student's self-report

(Mota and Picard, CVPR HCI Wkshop 2003)

Lower bandwidth correlates

Physiological sensors and haptic devices cannot be provided in all classrooms, and their use may impact on the learners' affective states.

An alternative is to identify lower bandwidth behavioural correlates and substitute themore valid and reliable measures with quick and easy ones.

Lower bandwidth behavioural correlates include delays in student responses, which might indicate the level of student hesitation, use of smileys and punctuation such as question and exclamation marks.

3. Asking the Student

Asking the student

Goal: to obtain more accurate student models and promote learner reflection on their own affective states, e.g.

1. **de Vicente and Pain**, diagnosing motivational models
2. **Open or Participative Learner Modelling (Morales)**

- effects on learners of access to their models,
- using machine learning to construct learner models

3. **Collaborative Inspectable Student Models (Bull, Brna)**

- students state their confidence in input to an ILE
- discuss their beliefs about their knowledge
- defend their views when disagree with its assessment

Motivation detection

Cues such as *facial cues, posture, etc*. are perceived unconsciously

How human teachers detect their students' motivation has been little explored

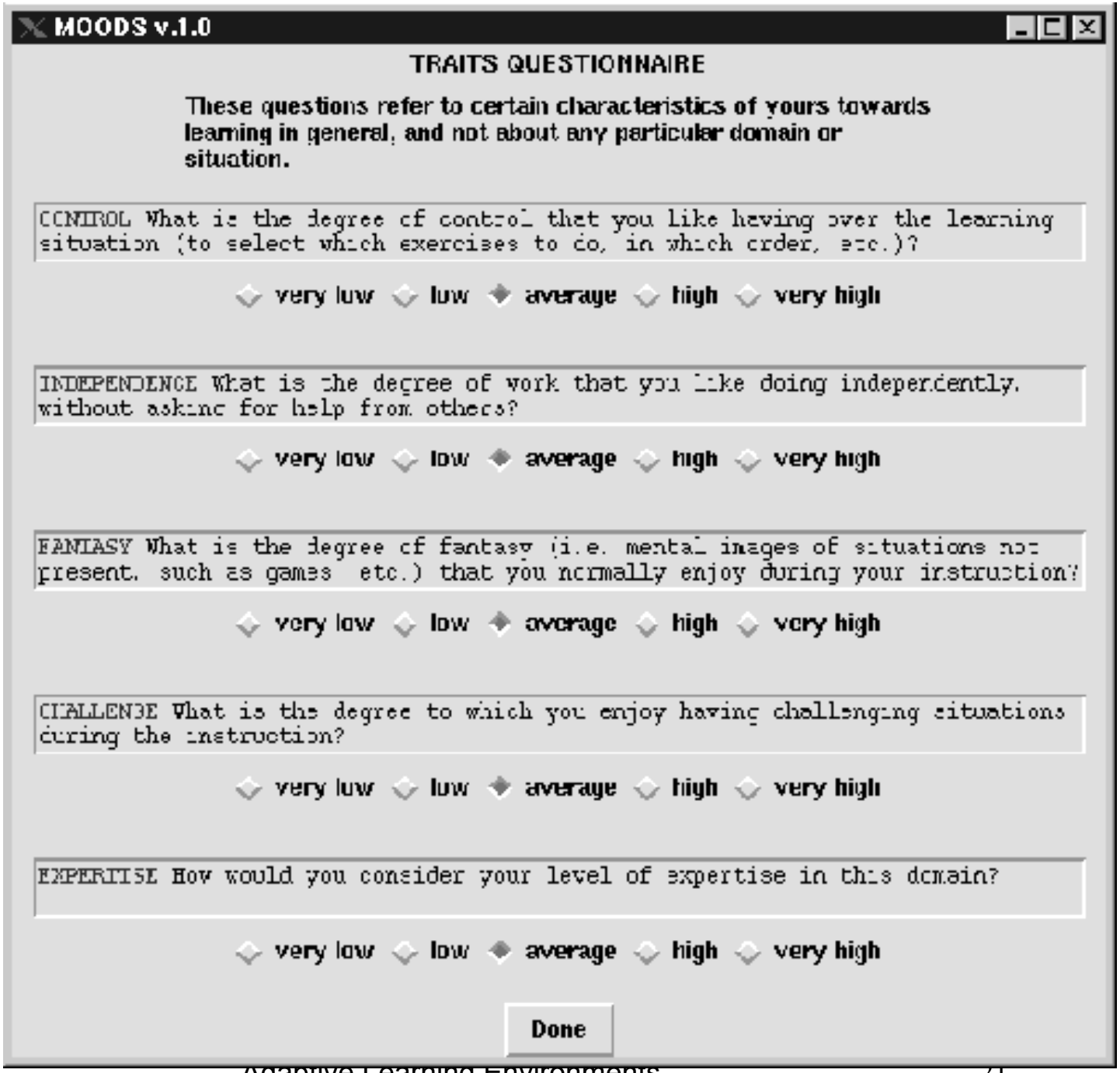
We can use empirical studies:

- to elicit formalised motivation diagnosis knowledge
- to inform the design of tools to detect the motivational state of a student.

Self-report study: questions

- Is self-report too intrusive?
- Is it acceptable to students?
- Do the study results inform the motivational model?
- Is the information obtained reliable?

Traits questionn-aire



Self-report study: method

Trait questionnaire then interact with the system...

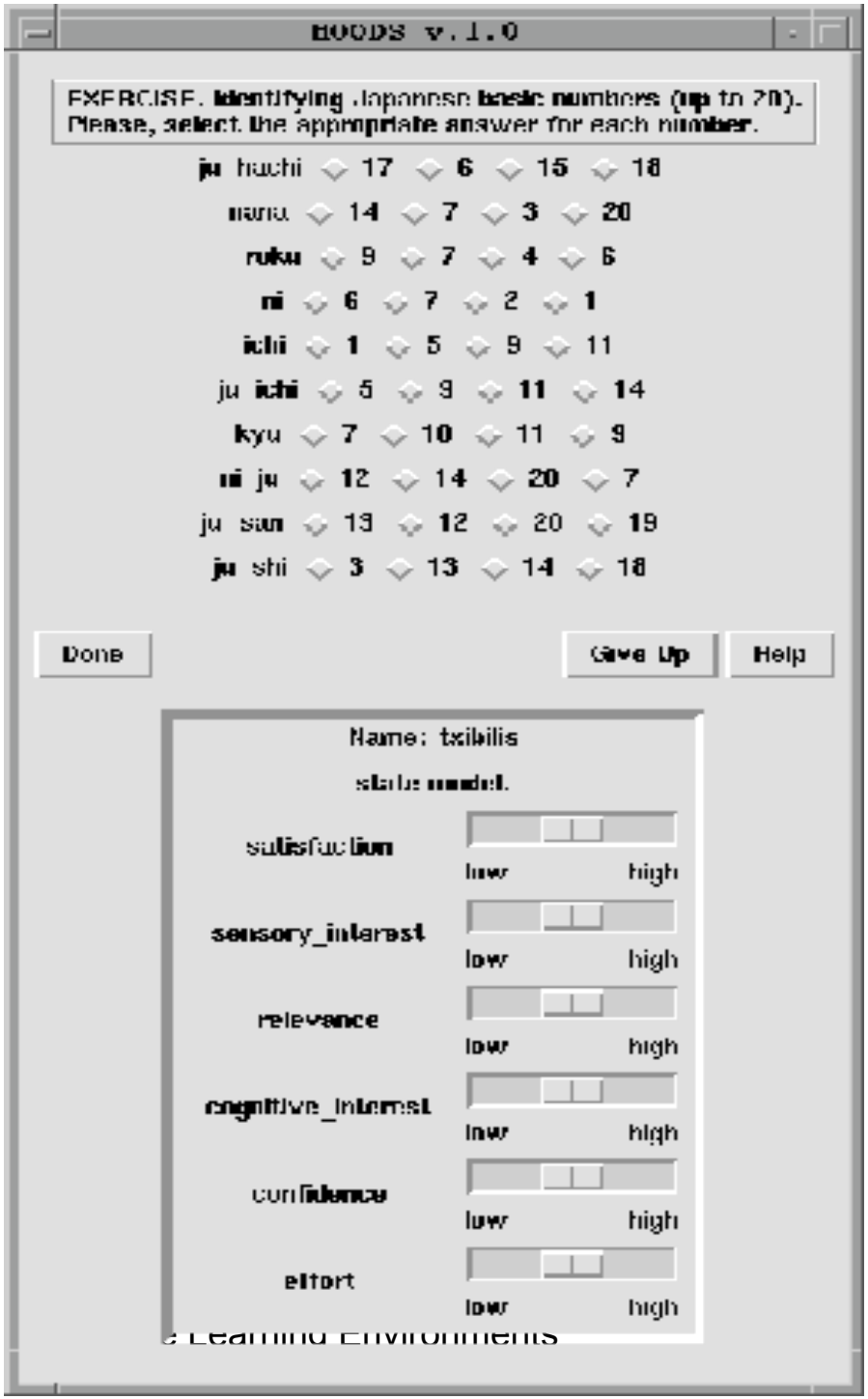
"use these sliders as often as possible whenever you think there is a change in any of these factors, since it is necessary for the computer to understand your current situation in order to modify the instruction accordingly"

Post-questionnaire:

13. I would prefer not to have to update the motivational state sliders, even if it makes the instruction more efficient and personalized

    strongly agree 1 2 3 4 5 strongly disagree

Moods Interface



Self-report study: results

High acceptance of self-report method

Confidence and **Effort** updated most,
Relevance least

Effort - mostly in last 20%
Satisfaction - middle and end
Confidence - some at start, more towards end

Sensory interest, cognitive interest, relevance
- fewer updates
- mostly beginning and end

=> *offer as options but not in main interface*

Self-report study: conclusions

Self-report motivation diagnosis satisfactory

+ accepted as good method, not intrusive
- but less interest over a longer period?

Satisfaction: slider available at all times

Confidence: ask at start and end of lesson

Effort: question at end of lesson

Sensory interest and **cognitive interest**: make available when needed

Relevance: superfluous

4. Asking the teacher

How do teachers detect motivation?

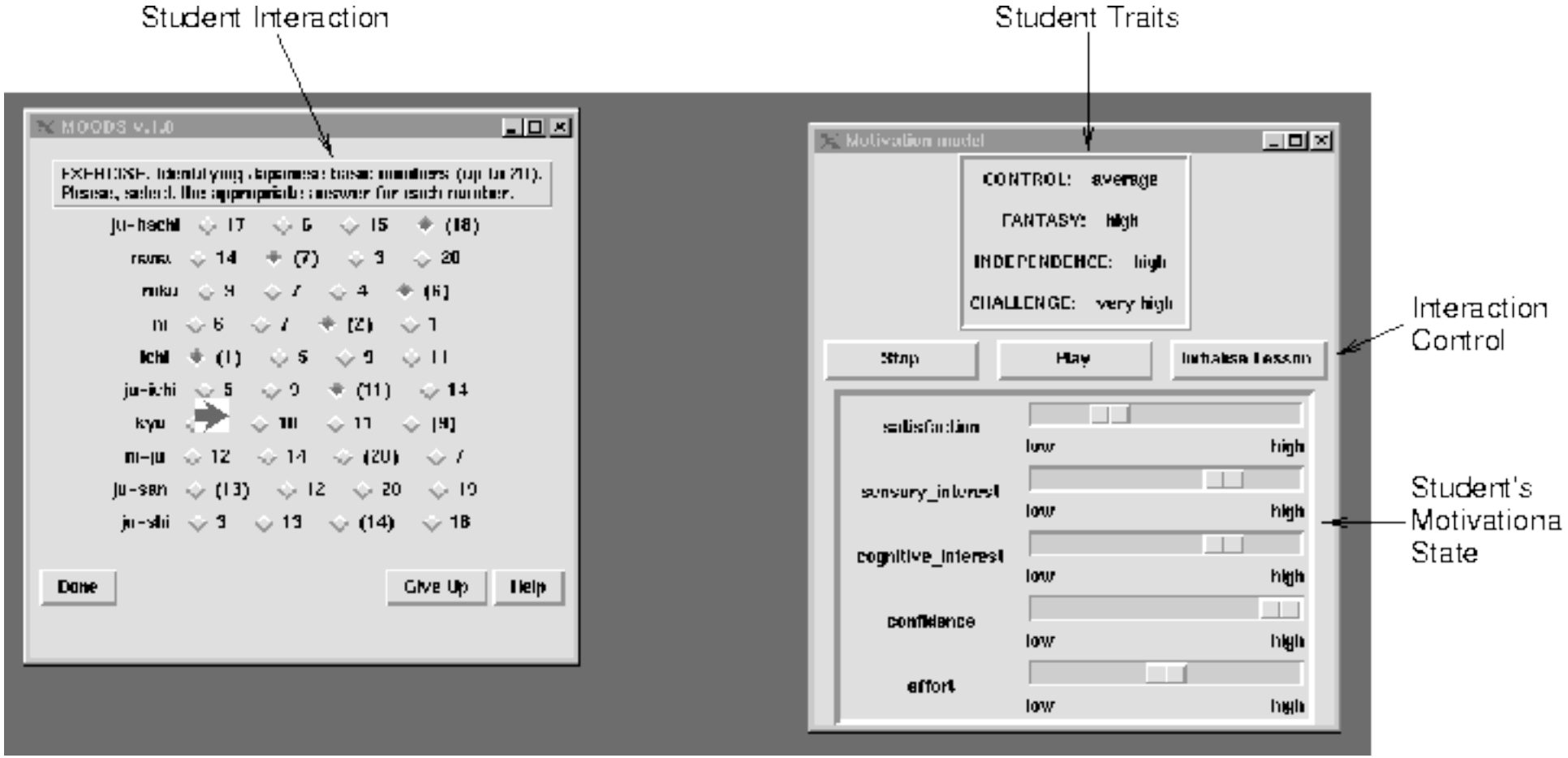
Teachers were asked to rationalise their motivational diagnosis knowledge:

- **viewing a replay** of the interaction between student and system, via interface

Throughout interaction, and at stop points,

- **update motivational state variables**
- **comment on student's motivational state** and **possible factors** affecting it

A_MOODS Interface



Motivation diagnosis study: excerpt

Interviewer: *And [...] why do you think he is satisfied at this point?*

Participant: Well, [...] he is hovering the mouse over the answers each time, he wasn't randomly moving the mouse, he is looking for the answer, [...] and that he didn't take a long time to answer the questions.

To me that would suggest that the task is interesting enough to complete with some attention and to do it properly, if you like. [...]

So, I would increase the satisfaction here, just for the fact that he did it with confidence, [...]

Motivation diagnosis study: results

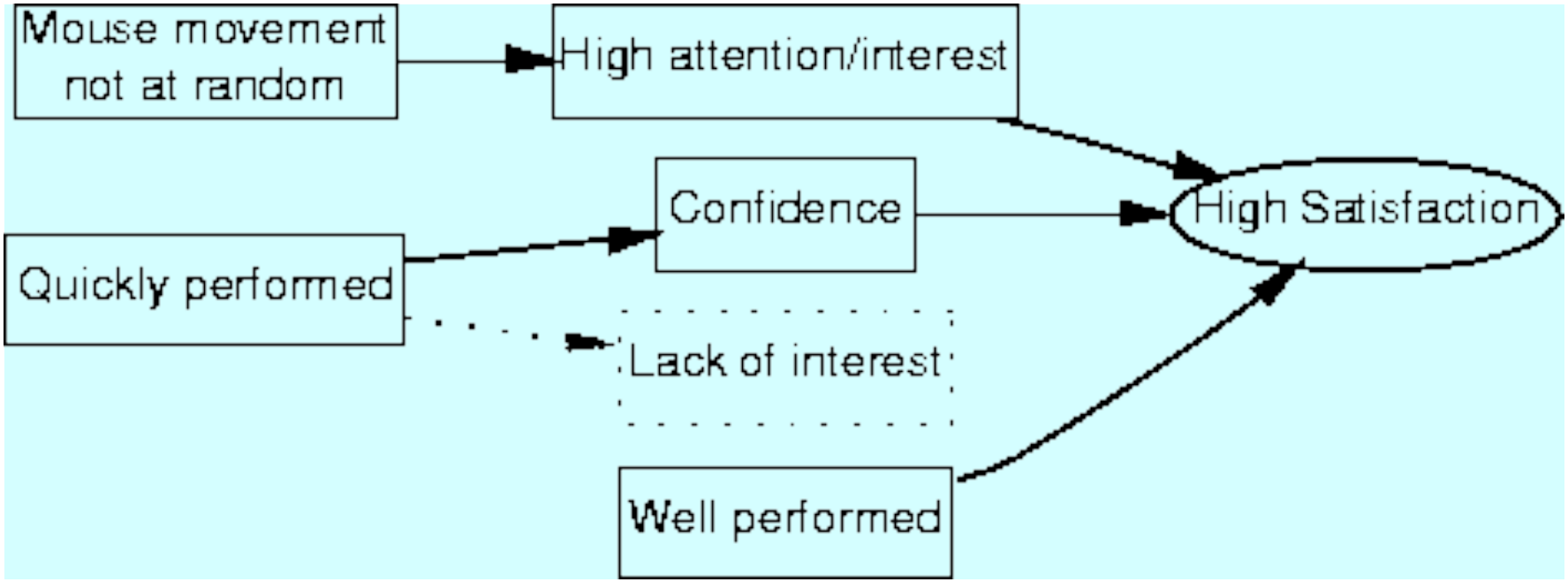
Participants thought the task would be impossible….

85 inferences made, **61 rules extracted**

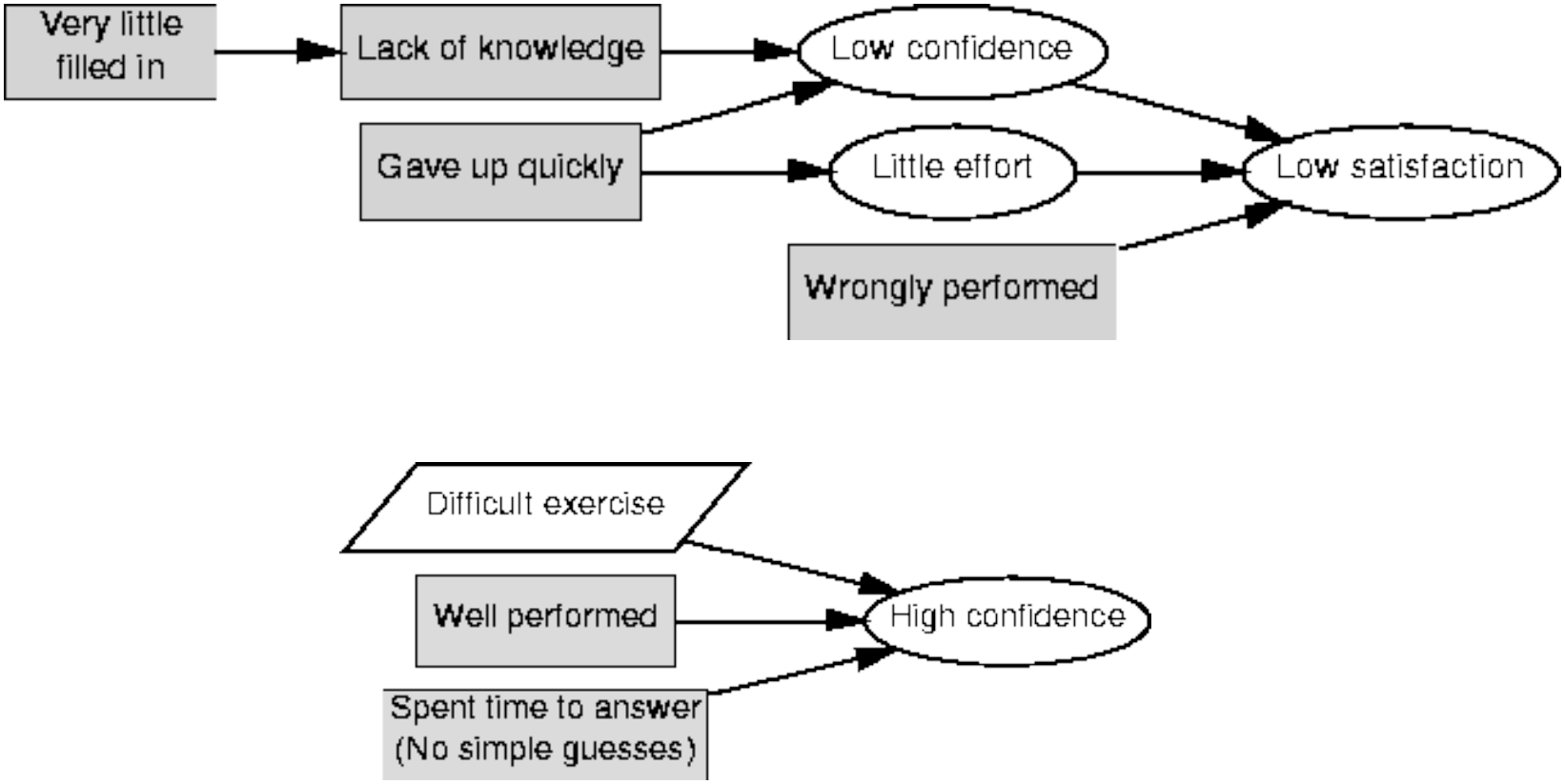
Input characteristics mentioned (ordered):
- performance
- teaching materials
- motivation states
- motivation traits

Output categories were:
- state variables
- others

Rule inferred from excerpt



Example knowledge-based rules



Validating diagnostic rules

Method:

33 participants (2+ years teaching)
Web-based (through mail lists)
various subjects (maths, spanish, education)
30 questions each, at random

Results:

973 answers (15+ for each rule) e.g.

Rule + prediction		Teacher rating		
DS1	(low)	High 0	Low 15	DK 0
DS4	(decrease)	Inc 3	Dec 2	DK 11
DE2	(average)	High 8	Avg 0	DK 9

Validating diagnostic rules

For each of the 61 rules identified, teachers were given an instructional setting, and a question regarding a motivational factor:

41 of the 61 rules were validated

*The student **completed a large part** of the exercise.*
*The student **completed the exercise in average time**.*
*The exercise was **difficult**.*

*What do you think his **Effort** level will be at this point?*
* *High*
* *Low*
* *Don't know*

Optional comment:

Validating diagnostic rules: Results

973 answers (15+ for each rule) e.g.

DS1	(low)	High 0	Low 15	DK 0
DS4	(decrease)	Inc 3	Dec 2	DK 11
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If same as in rule = *accept*
If not same or don't know = *reject*

Chi-squared: null hypothesis 'no preference'

For 41 rules the null hypothesis was rejected ($p<0.01$), with preference for accept

Validation Study - Comments

- Motivational factor depends on an extra variable
- Relation between rule inputs and outputs not clear
- Not enough information
- A choice is made, but under certain assumptions, or certain information is missing
- “Don’t know” selected, but a choice is actually made
- Elaborations

Motivation diagnosis study: conclusions

Viewing interaction through a tutoring interface is sufficient to make inferences about student motivation.

Combination of student self report and empirically defined rules provides a robust approach to motivation diagnosis.

Empirical information to be incorporated into an affective tutor - but first rules need validation.

5. Modelling the Situation
(Porayska-Pomsta)

Situation Model in Student Modelling

The **Situation Model** (SM) is a specialisation of the Learner Model (LM)

- Captures the ***immediate situational context*** at a specific time in a learning episode for a particular learner
- Contributes to the ***diagnosis of affective and motivational factors***
- Recommends the ***optimal presentation*** of tutor feedback for the learner in this situation
- Gives ***suggestions for the appropriate tutorial actions***

What is a Situation?

Situational Factors:

Motivation oriented factors:

e.g. student's confidence and interest

Lesson oriented factors:

e.g. difficulty and importance of an exercise; time pressure

Performance oriented factors:

e.g. student's overall aptitude; correctness of student's action

A combination of situational factors (and their values) constitutes a situation

Relative importance of each factor to tutor's feedback decisions varies **depending on a situation**

Situational Factors

Student's confidence	The level of **student's positive self-belief in their ability to tackle and solve a given problem**
Student's interest	The level of **student's positive attitude** towards the just completed task.
Student's effort	An estimate of the **amount of work done** by the student on the just completed task.
Student's aptitude	An estimate of the **student's ability** to solve a given problem correctly.
Difficulty of material	**Difficulty of task** obtained from the metadata associated with the task
Importance of material	**Importance of task** obtained from the metadata associated with the task
Correctness of student's answer	The **degree of correctness** for the just completed task
Knowledge	An **estimate of a student's having mathematical content pre-requisites** for the current task

Sources of Evidence

1. Hesitation level – variables are:

(a) **elapsed time** between tutor question or instruction and commencement of student response;

(b) **time expected** for the commencement of student response, initially average response time determined through current studies.

2. Linguistic cues – specific instances are:

use of interrogative forms in providing answers **("?", "…")**

use of hedges **("maybe")**

3. Achievement level – variables are:

number of recent student tasks under consideration (default 4)

degree of correctness (mark) for each task

adjacency of the same marks within the set

4. Difficulty – **the rating of difficulty** obtained from the metadata associated with the current task (default) and previous task

Sources of Evidence contd.

5. **Spontaneous admissions** – variables are:
   enjoyment, confusion, boredom, enthusiasm
   e.g. "This is great", "I am confused", from a look up table

6. **Granularity of solution steps** – variables are:
   number of steps taken by the student to present the solution
   number of steps represented in correct path in domain reasoner

7. **Student's initiative** –specific instances are:
   Student **asks a clarification question**
   Student **volunteers to complete next possible step**
   Student **volunteers to complete a further task**

Frequency of evidence: used in all cases to determine strength
(a) **number of occurrences** of a source of evidence
(b) **recency** of occurrence

Importance of evidence 1: low, 5: high

Confidence:	Student Hesitation	5	Student initiative	4
	Linguistic cues	5	Granularity of solution steps	3
	Spontaneous admissions	5		
Interest:	Student initiative	5	Spontaneous admissions	5
	Granularity of solution steps	5	Achievement	3
Effort:	Student initiative	5	Difficulty	4
	Granularity of solution steps	5	Achievement	3
Aptitude:	Achievement	5	Difficulty	5

SM Recommendations

For each tutor feedback it calculates levels of

Autonomy: a level of a student's ***need to be allowed the freedom of initiative*** (i.e. more or less Guidance)

Approval: a level of a student's ***need to be liked and approved of by the tutor***

Rules for combining values of situational factors and individual importance ratings based on a study with teachers (Porayska-Pomsta, 2003)

Example of use

1. SM determines current situation based on evidence from LM and LH
   e.g. **student's confidence**: ***confident***
   student's interest: ***bored***
   difficulty of the exercise: ***low***
   correctness of student's answer: ***partially correct***

2. SM calculates autonomy and approval for the determined situation
   e.g. **autonomy:** medium **approval:** medium-low

3. Passes values to *Tutorial Component* and *Dialogue Manager*

4. TC and DM use the values in making appropriate tutoring and linguistic feedback decisions, e.g.
   - **TC instructs** (as opposed to *suggests* to) the student they look up a term in the dictionary
   - **DM** uses indirect language ***"Are you sure about this?"***
     (rather than explicit instructions "Try again!")

6. Current Trends

Student Modelling - Current Trends

- Continued Emphasis on Diagnosis and Error Modelling
- Modelling Affective and Motivational Aspects of Learner
- Open and Participative Models
- Use of Statistical and Machine Learning Techniques
- Adaptive to Wider Range of Users (Including Disabled)

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