How Tutors Characterize Students: A Study of Personal Constructs in Tutoring

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Theoretical Framework

Human tutoring provided on a one-to-one basis has been credited as *the* most effective form of instruction [Bloom, 1984]; [Cohen, Kulik, & Kulik, 1982]. It is not surprising, then, that efforts to isolate and describe the actions of expert tutors and the unique interactions that take place between tutor and tutee have intensified in recent years. Cognitive researchers, particularly those interested in developing intelligent computer learning environments, want to know how good tutors behave and think during interactions with students. Models of human tutoring provide a rich source of ideas for system designers and developers.

Through the use of verbal protocol and interaction analysis, techniques that focus on dialogue between tutor and tutee, current research is describing in great detail the nature of human tutorial interaction. Conversational analysis of tutoring sessions, focusing on such issues as how tutors frame tutoring sessions, ask questions, aid students in problem solving, and react to student errors, has been the dominant methodology [Fox, 1993]; [Lepper et al., 1993]; [McArthur, Stasz, & Zmuidzinas, 1990]; [Merrill, Reiser, Merrill, & Landes, 1995]; [Putnam, 1987]. Such studies have produced rich, detailed descriptions of tutoring in action. However, none of this work is directly addressing the question of what conceptual knowledge about students and tutoring is developed and used by expert tutors to help them in their task. If designers of machine-based tutoring systems want to model students from a tutor's perspective, they need to know what constructs tutors possess and use to describe and think about their tutees, what behavioral evidence they observe in order to profile tutees in terms of these constructs, and how their tutoring methods are selected or changed in response to perceived student profiles.

This study identified mental constructs used by five experienced tutors to help them characterize and tutor their students. To isolate these constructs, we adapted a research method, the repertory grid interview, originally inspired by George Kelly's Personal Construct Theory [Kelly, 1955]. This method has been used frequently in expert systems development [Boose, 1985] but, to our knowledge, not previously applied in tutoring research. Kelly proposed that individuals live and operate within specific worlds or domains (or communities of practice?) that can be broken down into the major components or elements that comprise them. An individual's perspective and understanding of that world can be described in terms of the constructs he or she uses to distinguish among and think about those elements. Thus, in an experienced tutor's world of tutoring, the ways in which students are modeled by that tutor are largely defined by the personal constructs used to describe, categorize and think about them during tutoring.

We combined Kelly's repertory grid interview methodology with statistical analysis to elicit a set of fundamental concepts that tutors used to describe and differentiate among tutees with whom they had recently worked and were very familiar. We also acquired information from each tutor regarding which constructs were most important and how they were used in decision making within a particular sample of tutoring sessions.

Method

The Tutors

Five experienced tutors who practiced in a variety of educational contexts (i.e., across academic disciplines and instructional settings) were studied. Three of these five tutors were examined about their experiences tutoring college students on a computer-based instructional system for improving mathematics knowledge and skill. One of the computer-aided tutors worked with student dyads, while the other two worked with individual students. In addition, to gain information about the variability or stability of tutoring constructs across settings and subject domains, we studied two tutors who worked with college students enrolled in a special program designed to support high-risk college students. One of these tutors worked with students on their writing assignments. The other remedial tutor helped students with math.

Data Collection Procedure

Sessions with tutors consisted of two phases, knowledge elicitation and rating grid. Prior to the knowledge elicitation sessions, tutors were asked to prepare a list of tutees with whom they had recently worked for a significant period of time and who were very familiar to them. The number of tutees listed by each tutor ranged from seven to thirteen. Tutors were advised to gather and bring any available notes and records of these tutoring sessions to use at the knowledge elicitation sessions.

During knowledge elicitation, each tutor was presented with a series of triads, each triad consisting of three of the names from the list of tutees known to that tutor. The names in each triad, the ordering of triads, and the sequencing of names within triads were randomly determined. Triads were examined by the tutor one at a time. For each, the tutor was told to think of the most important attribute that distinguished the two most similar members of the triad from the third "outlying" member. The distinguishing construct reported by the tutor was recorded along with what the tutor provided as an opposing construct (e.g., the construct "involved" was recorded along with what the tutor believed to be an opposing construct, "uninvolved"). This presentation of triads and identification of discriminating constructs continued until several constructs given by the tutor merely repeated previously reported constructs and no new constructs were emerging.

Tutors were also asked to recall tutoring sessions as a basis for specifying *what* evidence they observed that enabled them to discriminate among students on the basis of each construct, and to state *how* such discriminations influenced their tutoring of these students. Because this technique attempted to focus tutors' retrospective recall on a particular set of tutoring sessions and tutees, and also provided tutors with various memory aids (notes and records) to prompt specific memories, we believe the generated data fall within the "many-to-one" category (one verbalization for many actions), as defined by verbal protocol theory [Ericsson & Simon, 1984]. This theory supports the assumption that data obtained in this manner is veridical albeit less dense than what think-aloud methods would provide. The requirement to examine multiple tutors, multiple tutees for each tutor, and multiple sessions for each tutee, made think-aloud methodology a virtual impossibility.

Once a representative list of personal constructs was elicited from a tutor, a rating grid was developed so that the tutor could score all his or her tutees on all of the bi-polar constructs elicited by that tutor. A rating grid was constructed with the list of students in a row at the top of the page, and the bipolar constructs in a column on the left of the page. Each student was then rated by the tutor using a five-point semantic differential scale. Not all constructs were evaluative, but those thought to possess an evaluative component were arranged so that the highest rating (5) was given for the most positive characterization (e.g., "Very Careful"), while the lowest rating (1) would represent a negative judgment (e.g., "Very Careless").

Analyses and Findings

Based on the knowledge elicitation procedure, an average of 18 bipolar personal constructs were identified by each tutor as important to describing and discriminating among tutees. Tutors each rated their tutees on their personal construct scales, and these ratings were transformed into *z*-scores for input to SPSS for Windows. Cluster analyses were performed for each tutor. Cluster analysis is a statistical procedure that identifies homogeneous groups or clusters of cases based on values given for a set of variables.

Two types of cluster analyses were performed for each tutor. One analysis treated bi-polar constructs as cases. Clusters of bi-polar constructs were the output, which helped identify basic, underlying dimensions of judgment used to describe and rate tutees. The other analysis treated students as cases and thus created clusters representing groups of students who were similar in terms of how they were perceived by the tutor. Student clustering represented a search for naturally occurring student "types," or generic student "models" that might suggest distinctive instructional approaches or tutoring strategies.

Cluster Analysis 1: Dimensions of Judgment and Tutoring

Cluster analyses of bi-polar constructs revealed that five different experienced tutors working in various settings all described and categorized their students in terms of two essential traits: learning ability and motivation. Several other minor constructs were used by tutors in describing their students, but learning ability and motivation were dominant and universal clusters and were perceived by tutors as the most important. However, even though these same basic traits were used by all tutors when assessing students, there were differences among tutors in how these traits were specifically defined. For example, motivation for one tutor embodied academic assertiveness; for another it embodied cooperative attitude, and for yet another it involved sociability and friendliness. Learning ability for some tutors included considerations of competence with computers; for others, computer skills were a separate or irrelevant issue. For one (the most experienced) tutor, learning ability had a hierarchical structure and embodied both intelligence and cognitive effort. For other tutors, learning ability was a simpler, almost unidimensional trait.

Having judged and characterized tutees on the basis of their motivational state and academic ability, all tutors in this study reported adapting their tutoring accordingly. Tutors reported many different techniques and complex strategies for adapting their tutoring to students' motivational level and learning ability. The reasoning processes and tutoring decisions described by different tutors reflected noticeably different tutoring "styles" [Lepper & Chabay, 1988] that varied in terms of content, philosophy, and complexity. Style variations were unrelated to student population, content domain, and instructional setting. For example, similar styles that might be described as indirect, therapeutic and empathetic were exhibited by a female writing tutor in an authentic remedial setting and a male math tutor who worked with a computer in a laboratory setting.

In contrast to findings of conversational analyses of adult human tutoring, the results of this study strongly and consistently support Lepper's [Lepper & Chabay, 1988]; [Lepper et al., 1993] idea that student modeling by human tutors involves consideration of motivational, as well as cognitive, states of students. All tutors watched for motivational indicators and adjusted their tutoring. Moreover, three of five tutors reported that judgments of motivational/affective states were more important for their tutoring than were judgments of cognitive ability. Examples of complex strategies for dealing with low-motivation problems included a method of questioning designed to draw unengaged students into active thinking about their problem solving, and another method whereby the tutor and tutee swapped roles. Examples of simpler techniques were responding to low motivation by shortening tutoring sessions and attempting to personalize problems or assignments.

General Student Types

Analyses were performed to describe how each of the tutors naturally grouped students into clusters or types. [Fig. 1] through [Fig. 5] visually depict the student clusters for each tutor in terms of students' relative positions on grids representing the two main discriminating constructs (learning ability and motivation) that were similar across tutors. To obtain these figures, each student's scores on ability and motivation were calculated by averaging their ratings (provided by their tutor) on personal construct scales associated with the ability and motivation clusters. Based on these scores, each student was located on the grids shown in [Fig. 1] - [Fig 5], where each grid represents a separate tutor, the two dimensions depicted on each grid represent scaled measures of student motivation and ability, and each plotted number is a point representing an individual student. Circles were drawn to indicate those students who were grouped together by the cluster analyses of students (the single cluster outlined by a dotted line represents a group with relatively weak cohesion).

These figures illustrate some interesting similarities and differences among tutors with respect to how they grouped students as types. All four math tutors [Fig. 1, 2, 3, & 5] possessed a "problem student model" for those who were both unmotivated and less competent. No math student was perceived as having both high ability and low motivation. All math tutors also had a single, large "other student" category that subsumed

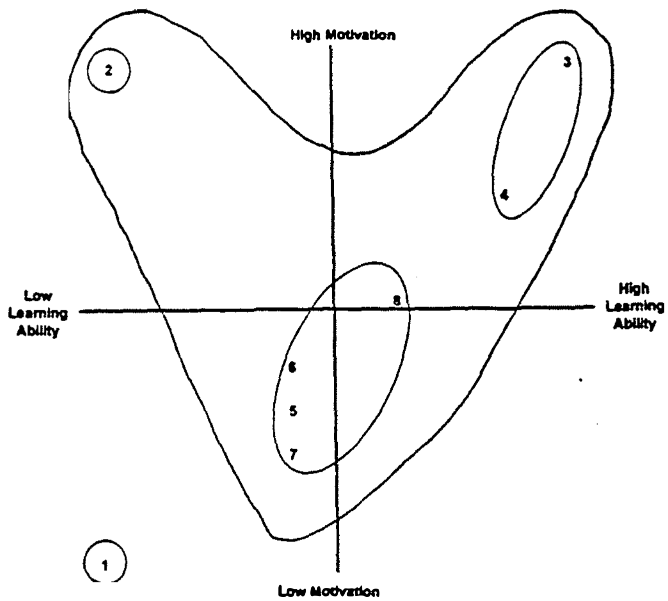

Figure 1: How Female Math Tutor in Computer Lab Setting Discriminated and Grouped Tutees

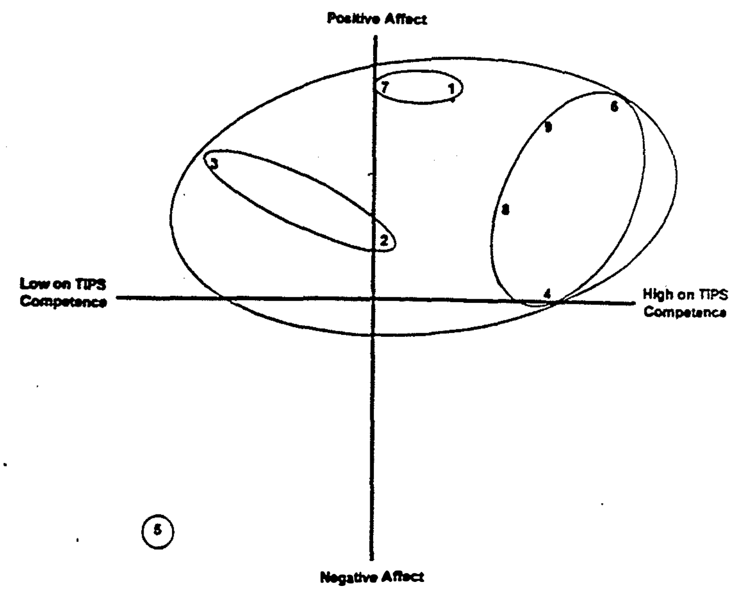

Figure 2: How Male Math Tutor in Computer Lab Setting Discriminated and Grouped Tutees

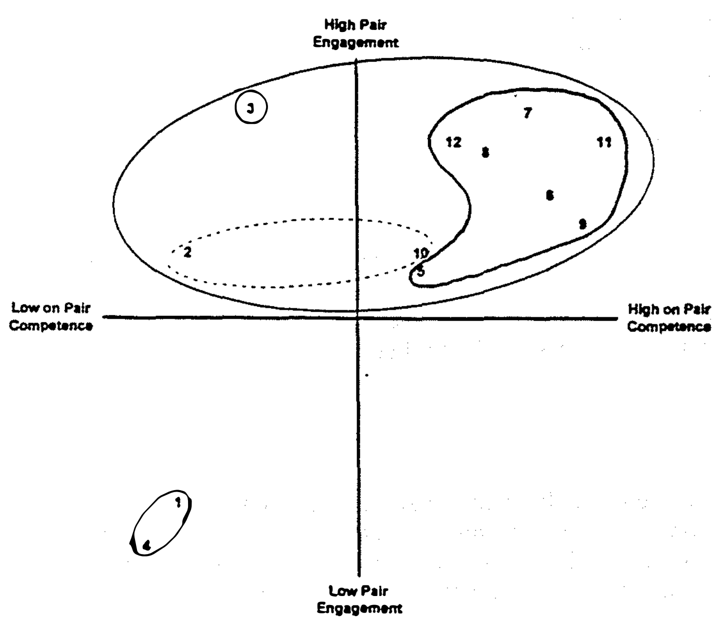

Figure 3: How Male Math Tutor in Computer Lab Setting Discriminated and Grouped Pairs

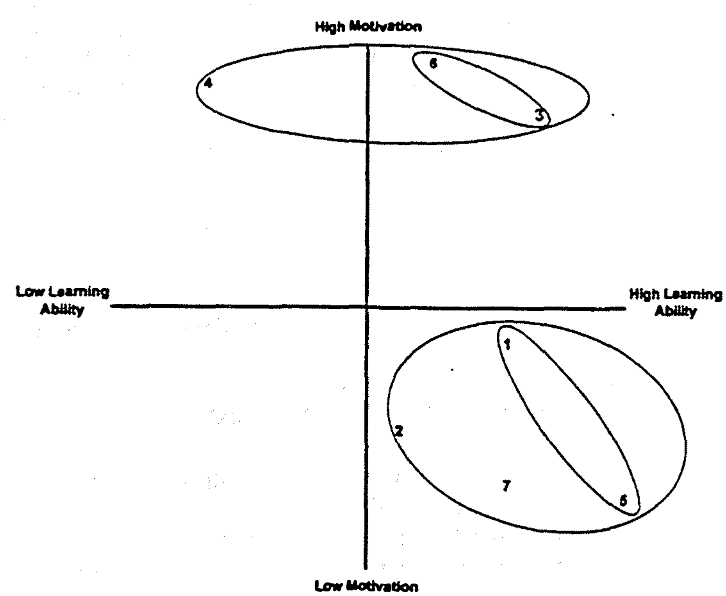

Figure 4: How Female Writing Tutor in Authentic Remedial Setting Discriminated and Grouped Tutees

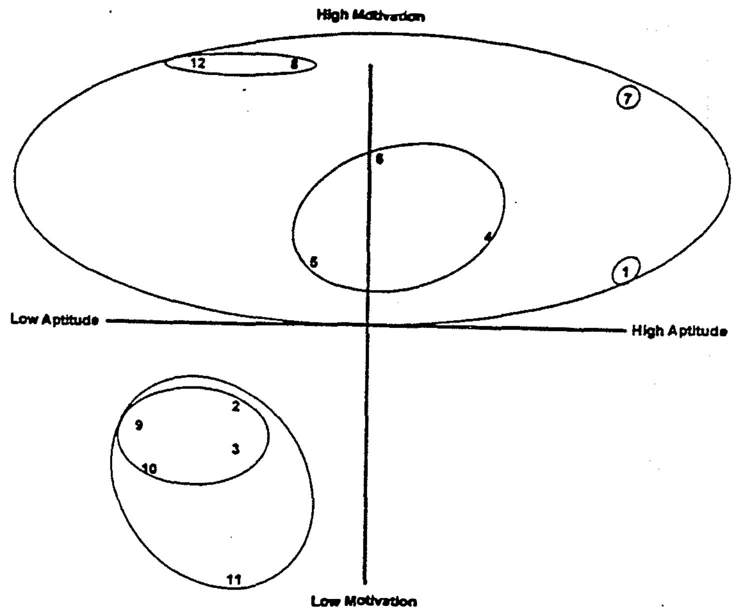

Figure 5: How Female Math Tutor in Authentic Remedial Setting Discriminated and Grouped Tutees

several sub-groupings. For tutors 2, 3, and 5, "other students" were all motivated but were distinguished from one another roughly on the basis of competence. Tutor 1 differed from other math tutors in that a number of moderately competent students were all perceived as being relatively less motivated. For Tutor 1, this middle cluster was labeled "typical students." The patterns for tutors 2, 3, and 5 suggest that a feasible strategy for designing intelligent computer-based instructional systems for mathematics would be to create a distinctive tutoring strategy assuming motivated students that could be modified on the basis of student competence. Another separate distinctive approach would be created for more difficult and unique students possessing both motivational and competence problems. The pattern suggested by tutor 1 also suggests the need for a distinctive "problem student" approach. How to deal with "other students" is not obvious, but one feasible design would involve creating a "typical student" tutoring strategy that could be modified on the basis of increases in motivation and/or ability.

Interestingly, the writing tutor [Fig. 4] differed from all math tutors by failing to identify any student as both unmotivated and incompetent, but by identifying numerous students as both competent and unmotivated. No math tutor viewed any competent student as unmotivated. Whether this deviation reflects a difference in domain, tutor perspective, or student samples poses an interesting question for further research.

Summary and Conclusions

Five experienced tutors representing several domains and settings all described and categorized their students with reference to the constructs, *learning ability* and *motivation.* Several other constructs were mentioned by tutors, but learning ability and motivation were dominant and universal and were primary discriminators for tutoring. However, there were between-tutor differences in how motivation and ability were defined.

Tutors described various techniques and strategies for adapting their tutoring to students' motivation and ability level. Their reasoning and decision processes revealed between-tutor style differences that were unrelated to student population, content domain, and setting, supporting Lepper's idea that tutoring "style" is an important form of instructional variation.

Comparisons of tutors with respect to how they clustered students revealed interesting similarities and differences. All math tutors, but not the writing tutor, possessed an implicit "problem student" category for those who were unmotivated and not competent. All math tutors also had a single large "other student" model that subsumed several sub-groupings defined largely by ability differences. No math tutor identified any student as both competent and unmotivated. By contrast, the writing tutor [Fig. 4] tended to view most students as competent, with the major discriminating factor being motivation. For this tutor, "problem students" tended to be perceived as capable but unmotivated.

In contrast to conversational analyses of adult human tutoring, results strongly suggest that student modeling by human tutors involves consideration of motivational, in addition to cognitive, student states. For three of five tutors, motivational assessments were more important for tutoring than judgments about cognitive ability.

To the extent that the problem of intelligent tutoring is conceptualized as one of (a) observing evidence that can be used to evaluate students in terms of constructs that are relevant to tutoring, and then (b) selecting tutoring responses, styles, or strategies that are appropriately adaptive to those evaluations, this study offers several interesting design suggestions for intelligent computer instruction. For example, naturally-emerging student groups suggest that systems might be programmed with distinctive tutoring styles for different types of students.

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