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Achievement Motivation, Performance Structure, and Adaptive Hypertext Learning

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Abstract. In the past, formal models of cognitive psychology successfully contributed to the development of computerized adaptive tutorial systems. Emotional and motivational aspects, however, were rarely considered, although a variety of studies demonstrated their significant influence on learning and performance. The aim of the current pilot study was to investigate whether the sound and empirically valid knowledge space theory is able to cover learning and performance in two different motivational states, which were hope for success and fear of failure. Moreover, within a factorial design these motivational states were combined with two different learning conditions. Pre-structured learning sessions within an adaptive tutorial system were contrasted with rather free text-based learning. The data collected with 104 high school students in the domain of elementary probability theory indicate that knowledge space theory is able to represent the responses obtained in a post-test for both motivational states, as well as for both learning conditions. These results lay out a promising route to integrating cognitive and emotional/motivational aspects into a comprehensive psychological model for adaptive tutorial systems.

Keywords. eLearning, adaptive tutorial systems, knowledge space theory, motivation

Introduction

Developing computer-based tutorial systems has a tradition that reaches back to the nineteen eighties. Triggered by the rapid evolution of technology, we are currently facing a boom of eLearning systems, which provide a powerful technology with the potential of enhancing human learning. This goal, however, is not reached if a purely technology-centered approach is followed.

Within a technology-centered approach the development focuses on cutting edge advances of multimedia technology, e.g. the integration of multimedia in communication technology or the development of virtual, interactive systems. However, pure technology-centered approaches failed to lead to lasting improvements in human learning [1]. In 1922 Thomas Edison predicted that motion pictures will supplant largely, if not entirely, the use of textbooks. In 1945 William Levenson predicted that radio receivers will be as common in the classroom as chalkboards and that radio instructions will be an integrated component of

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every day's school life (cited in [1], p. 19). The promises of 20th century computer technology were very much the same. However, technology-centered tutorial systems failed to produce better learning than traditional teacher-lead instructions [2]. These insufficiencies are possibly due to the fact that instead of technology adapting to human learning, humans were forced to adapt to new technology-driven systems. Consequently, the prediction that eLearning would revolutionize learning turned out to be false. eLearning still plays a subordinate role [3], and even in the currently booming market we are facing a number of prominent insolvencies of eLearning companies [4]. One reason for this might be that many systems only offer digitized contents, more or less refined with some psychological and pedagogical basics. They seem to be nothing more than rich media versions of their predecessors of the nineteen eighties. To develop more successful approaches, a comprehensive and profound cognitive-psychological basis is required.

Successful tutorial systems have to adapt to the human learner [5, 6]. The focus must be on using multimedia as an aid to human cognition [2]. eLearning platforms have to evolve from systems with strictly hierarchical content presentation to adaptive, personalized tutoring systems. Cognitive and educational psychology provided considerable contributions to foster this development [7, 8, 9]. Knowledge Space Theory (KST) suggested by Doignon & Falmagne [10] provides an appropriate psychological framework that can serve as a basis for implementing the required adaptivity of the learning system. We will briefly introduce KST below. Up to now emotional and motivational aspects, however, played a minor role in the development of these systems, and most often they actually were neglected. In order to integrate these factors into the outlined psychological framework, they have to be compatible with the cognitive model. The subsequently presented pilot study is a first attempt to address this issue.

A Brief Introduction to Knowledge Space Theory

Knowledge Space Theory (KST) is a well-elaborated formal psychological theory founded by J.-P. Doignon and J.-C. Falmagne [10]. It provides an intuitive and simple set-theoretic framework for representing and assessing knowledge.

The starting point is the notion of a so-called knowledge domain Q, which is nothing else but a set of problems taken from a certain content area, like, for instance, basic algebra consisting of problems involving additions, subtraction, multiplication, and division of positive integers. To provide an example, assume that the knowledge domain $Q = \{a, b, c, d, e\}$ consists of the five problems *a, b, c, d,* and *e*. Now, let the knowledge state of a person be represented by the set of problems the person is capable of solving. Then the knowledge state of an individual is simply a subset of the knowledge domain Q. However, if we look at the solution behavior that a sufficiently large number of subjects exhibits on these five problems then most certainly not all of the possible subsets (there are $2^{|Q|} = 32$ subsets in our example) will actually occur. A person who is capable of solving a problem that requires to multiply two positive integers will also be capable of solving a problem that only involves an addition of two positive integers. This means that from a correct solution to the first problem we can surmise a correct solution to the second problem. This kind of mutual dependency is captured in a so-called surmise relation, or prerequisite relation. The left panel of Figure 1 illustrates an example of a surmise relation, which is represented by line segments that connect some of the nodes corresponding to problems. For instance, from solving problem *c* we can surmise correct solutions to problems *a* and *b*, and an individual capable of solving problem *e* will solve all remaining problems, too.

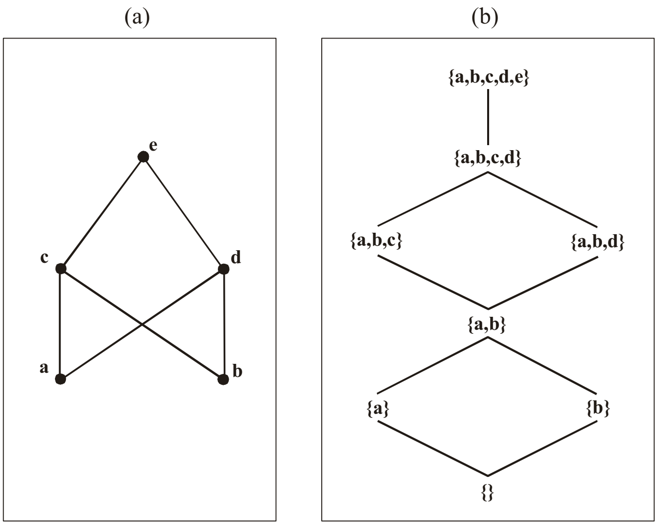

Figure 1. Panel a shows a surmise relation on the knowledge domain *Q = {a, b, c, d, e}*. The relation is represented by upwards directed sequences of line segments. Panel b shows the corresponding knowledge space.

The surmise relation restricts the possible knowledge states (i.e. subsets of solved problems). To comply with the surmise relation of Figure 1, for example, each knowledge state containing problem *c* should also contain problems *a* and *b*. The collection of the knowledge states corresponding to a surmise relation is called a (quasi-ordinal) knowledge space, which, for the given surmise relation is *{{}, {a}, {b}, {a, b}, {a, b, c}, {a, b, d}, {a, b, c, d}, {a, b, c, d, e}}*. Figure 1b provides a diagram illustrating this knowledge space. The upwards directed line segments (representing set-inclusion) may be interpreted as the possible learning paths leading from the naïve knowledge state *{}* to the knowledge state of full mastery *Q = {a, b, c, d, e}*. They may serve as a basis for personalized teaching that matches to the student's current knowledge state. If a student is in knowledge state *{a, b}*, for example, then content related to problems c or d should be presented next to allow for learning to take place (i.e. transition into knowledge state *{a, b, c}* or *{a, b, d}*, respectively). Knowledge spaces also form the basis for an efficient adaptive knowledge assessment. The rationale of the assessment procedure is exemplified below. Observing a correct response to problem d implies that, given the knowledge space of Figure 1, the corresponding knowledge state is one of *{a, b, d}*, *{a, b, c, d}*, or *{a, b, c, d, e}*. If then problem c is not

solved, we have uniquely identified the knowledge state to be *{a, b, d}* by presenting only two out of the five problems constituting the knowledge domain.
Knowledge Space Theory, as a formal approach to a psychological representation of knowledge, and various of its extensions [11, 12] have been implemented to provide adaptive knowledge assessment as well as personalized knowledge acquisition. Implementations in adaptive tutorial systems, for instance, include the research prototype RATH [13, 14, 15], AdAsTra [16], and the commercial eLearning platform ALEKS [11].

Emotional and Motivational Aspects of eLearning

Emotional and motivational aspects play an important role in acquiring new knowledge as well as for recalling previously learned knowledge in testing situations [17, 18, 19]. [20] emphasize the significant impact that emotional and motivational aspects have on cognitive structures, which, however, is commonly not reflected in the development of computerized eLearning systems.

There are some formal models that represent emotional and motivational concepts, and might provide a promising basis for an extension of the existing eLearning systems. In particular, we want to mention the Hull-Spence-Spielberger anxiety-performance theory [21, 22, 23, 24], and its competitors, the anxiety-learning theory by Albert [25] on the one side, and the achievement motive and risk taking behavior theory by McClelland and Atkinson [26, 27, 28, 29] on the other side.

As an example let us consider the model of Atkinson and McClelland, as it refers to well-known and extensively studied concepts. Atkinson distinguishes between an *achievement motive* and an *avoidance motive*. The tendency to achieve success T_S is computed as the product of the subjective probability of success P_S (hope for success), the achievement motive $M_{S,}$ and the anticipated positive effects of success I_S (e.g. the expected amount of pleasure)

$$T_S = P_S * (M_S * I_S). \qquad (1)$$

Similarly, the tendency to avoid failure T_F is defined as a product of the subjective probability of failure P_F, the avoidance motive M_F, and the anticipated negative effects of failure I_F (e.g. anger, shame)

$$T_F = P_F * (M_F * I_F). \qquad (2)$$

Consequently, the resultant motivational tendency T_R to tackle a task or to avoid it is

$$T_R = T_S + T_F = P_S * (M_S * I_S) + P_F * (M_F * I_F). \qquad (3)$$

In this formalization we may additionally assume that the more difficult a task is, the prouder is a person in case of success ($I_S = 1 – P_S$). Likewise, the easier a task is, the more ashamed is a person in case of failure ($I_F = - P_S$). Together with the fact that $P_F + P_S = 1$ (exactly one alternative will happen) we get

$$T_R = T_S + T_F = M_S * [P_S * (1 - P_S)] - M_F * [P_S * (1 - P_S)] \tag{4}$$

$$= (M_S - M_F) * [P_S * (1 - P_S)].$$

The predictions that can be derived from this formula are illustrated in Figure 2. According to the two plotted functions, persons with a relatively high achievement motive ($M_S > M_F$) will prefer problems with intermediate subjective success probability, while persons with a relatively high avoidance motive ($M_F > M_S$) are supposed to prefer problems with more extreme subjective success probabilities. These predictions may be contrasted with the navigation behavior that can be observed in eLearning environments.

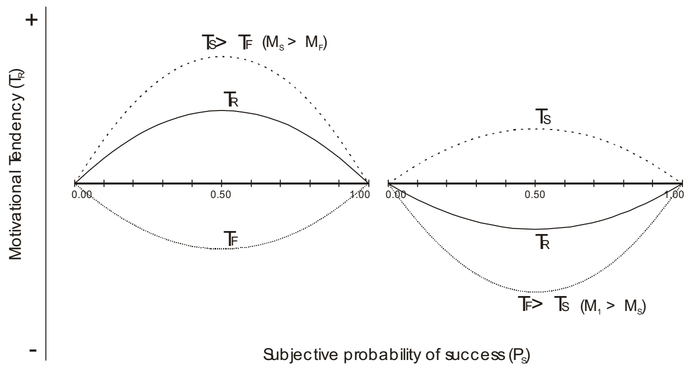

Figure 2. Illustration of the resultant motivational tendency in the model of Atkinson and McClelland.

The outlined motivational model focuses primarily on approach and avoidance tendencies. Supplementary studies have shown that, for the present context, the model will have to be extended to incorporate additional factors. The observed effects will not only depend on approach and avoidance tendencies [30, 31, 32] but also on situational controllability of behavioural results [33], and internal or external causal attribution [34, 35]. It is, however, beyond the scope of the present paper to provide a more detailed account of this issue.

Combining Cognitive Approaches with Emotional and Motivational Aspects

Combining cognitive models (like KST) with formal models of emotional and motivational factors seems to be a promising route to arrive at a more comprehensive psychological model of human learning in computerized environments.

So far, we have represented learning as a transition between knowledge states (e.g. from *{a, b}* to *{a, b, d}*). The probability of this transition, however, will not only depend on the current knowledge state, but also on the available relevant skills and competences. There are various extensions of KST that integrate these kinds of psychological constructs [12]. Moreover, probability of learning will heavily depend on emotional and motivational states, and these will strongly interact with cognitive states. A simple example may suffice to clarify this dependence. If a student successfully acquires new knowledge then this is likely to increase the motivation, which in turn may increase the probability of learning related content. Representing moderator effects like this calls for further extending KST. Introducing latent emotional/motivational states, however, requires that they are compatible with the structural assumptions in the knowledge space. This is completely in line with the fundamental compatibility of the underlying skill, or competence structures with the knowledge space [11, 12]. The question whether we are able to represent the observed solution behaviour under different motivational states within the same knowledge space has to be answered empirically. The subsequently presented pilot study takes a first step into this direction. Since most of the previous investigations on motivational and emotional aspects were conducted in non-computerized environments, the experiment includes different types of learning conditions, which are computer-based learning and common text-based learning. The experimental setup thus also allows for detecting possible interaction effects.

Method

Design

In a 2x2 factorial design we investigated two emotional / motivational states, hope for success (HS) and fear of failure (FF), and two learning conditions, learning within an adaptive tutorial hypertext system and traditional text-based learning. The experiment was divided into two parts, an initial session for assessing motivational states, and a subsequent learning and testing session. Parallel groups in both learning conditions were obtained by forming matched pairs with respect to motivational state (FF, HS).

Achievement was measured by a paper-and-pencil test administered after the learning phase.

Material and Apparatus

The Multi-Motive-Grid (MMG), a diagnostic tool proposed by [36], was applied to differentiate between the two different motivational states hope for success and fear of failure. It consists of 14 test items that resemble those of the TAT. The MMG is a reliable projective technique that uses standardized response categories instead of a free response format.

The two learning conditions consisted of the presentation of a course on elementary probability either in a print-out (text-based learning), or employing the adaptive tutorial system RATH (available at http://wundt.uni-graz.at/rath).

The research prototype RATH [13] is a relational adaptive tutoring hypertext WWW environment based on KST [10, 11] and a relational hypertext model [15]. The system adaptively responds to a students knowledge state. Contents, examples, and exercises are presented "just-in-time" according to the current state. Too easy and too difficult content is hidden. Thus, RATH guides a student adaptively through the structure of learning objects along one of the possible learning paths. RATH is a server-side application, i.e. students connected to RATH with school computers via network connections.

For traditional text-based learning (TBL) a folder was created that contained print-outs of the complete course including examples and exercises. The main difference between both learning conditions is that in the RATH condition students were adaptively guided by the system, while in the TBL condition students were free to explore each part of the course at any time, irrespective of the sequence of the material in the folder.

The learning material consisted of a course on elementary probability theory by Held [37]. He identified ten cognitive demands that are required to understand the learning material and, therefore, to solve all related problems. The ten demands comprise capabilities ranging from understanding simple *Laplace* probabilities to a general understanding of events and their probabilities. These demands were supplemented by an additional demand, the understanding of the concepts of random experiments, results, and events [13]. From the resulting eleven demands six problem classes (*A* to *F*) were constructed. Thus, the knowledge domain is given by $Q = \{A, B, C, D, E, F\}$. This knowledge domain is assumed to be structured according to the knowledge space illustrated in Figure 3. It shows the ten knowledge states (subsets of *Q*), and indicates the demands (numbers 0 to 10 labeling the arrows) that have to be mastered to be able to move from one state to another.

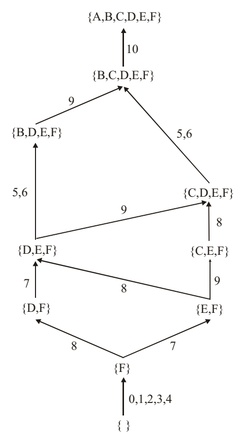

Figure 3. Diagram of the knowledge space on the knowledge domain $Q = \{A, B, C, D, E, F\}$ of problems on elementary probability theory. The numbers refer to the required demands. The diagram is taken from Hockemeyer ([13], p. 42). Please notice that the knowledge state $\{C, D, E, F\}$ is missing in the original figure of [37].

Achievement was measured by a paper-and-pencil test administered after the learning phase. The total of 18 problems created by [37] resulted from three instances for each of the six problem classes *A* to *F*. The problems were presented in an order individually randomised for each of the participants. The complete course and all the problems are in English language.

Subjects

To participate in the present study the subjects had to meet two requirements. On the one hand, they should be able to understand the used learning material (e.g. its form and content). On the other hand, it was necessary to reduce the amount of pre-knowledge to a minimum. Thus, we recruited a total of 116 students from six Austrian high school classes (7th and 8th grade). Due to drop-outs the presented results are based on 104 of these students. There were 64 female and 40 male students with an age range from 16 to 19 (M = 16.6, SD = 0.74).

Procedure

The study was conducted as a group experiment in the class-room of each of six high school classes, and consisted of two phases. In an initial session, after a general introduction, the students filled in a form querying personal data, like age, gender, pre-knowledge in elementary probability theory, mathematics, and English grades. After that the MMG was administered with a time limit of 30 minutes. According to the results of the MMG matched pairs were formed with respect to motivational state, which resulted in 21 pairs for the motivational state hope for success, and 31 pairs for the motivational state fear of failure. The members of each pair then were randomly assigned to one of the two learning conditions.

The time period between initial and main sessions was 7 to 16 days (identical for all students of the same high school class). The main session consisted of a learning phase that lasted 75 minutes. In the text-based learning condition the students were presented with a print-out of the course material, while in the computer-based learning condition they were able to work with the adaptive tutorial system RATH. Please remember that in the text-based learning conditions the students were free to explore the material in any order. In the RATH condition the students were forced to process the lessons, examples, and exercises according to the knowledge space illustrated in Figure 3..

After the learning phase and a ten minutes break, the students had take the same paper-and-pencil test in both learning conditions. For completing the test there was a time limit of 40 minutes.

Results

The main interest of this pilot study was to investigate whether KST can cover different motivational states (HS, FF) of a student in different learning conditions (RATH, TBL). Thus, we analysed the deviations of response patterns in the paper-and-pencil test from the underlying knowledge space proposed by Held [37]. For this we applied a strict criterion for deriving the response patterns over the problem classes from the obtained results. A problem class (*A* to *F*) was considered to be solved only if all of the three associated problems were solved correctly. Two indicators of goodness-of-fit of a knowledge space were used as dependent variables. The minimal symmetric distance is defined as the least number of differing elements that result when a response pattern is compared to all knowledge states in a given knowledge space. A minimal symmetric distance of 0 indicates that the response pattern is identical to a knowledge state, a value of 1 indicates that it coincides with a knowledge state only after adding or deleting a single problem, and so on. We consider the distribution of the minimal symmetric distance over subjects as well as its average. The second indicator refers to the compatibility of the order of the problem-specific solution probabilities with the assumed surmise relation. The number of solved problems is used as an additional variable indicating a level of achievement that is independent of the assumed knowledge space.

To analyse the deviations between the response patterns and the knowledge space we used the software tool *DI*, version 2.4.5 from the Knowledge Space Tools package by Held, revised by [38]. DI computes the minimal symmetric distances for each response pattern. Figure 4 shows the resulting average of minimal symmetric distances for all experimental conditions.

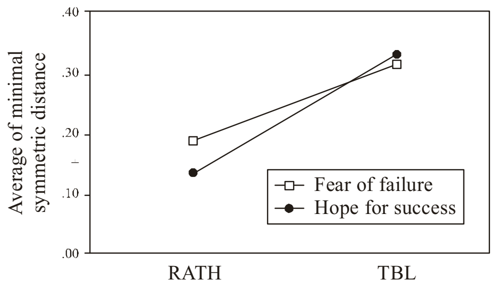

Figure 4. Average of minimal symmetric distances between response patterns and proposed underlying knowledge structure.

In the RATH condition smaller values result (FF: .19; HS: .14) than in the text-based learning condition (FF: .32; HS: .33), whereas in the HS and FF conditions the values are very close (.31 versus .35). Figure 4 seems to suggest a slight interaction between the factors.

Table 1 provides the distributions of the minimal symmetric distances for all experimental conditions. It shows that over all conditions a majority of response patterns coincide with knowledge states, ranging from 71.43% in the TBL/HS condition to 80.65% in the RATH/FF condition. The RATH condition seems to yield a somewhat higher percentage of patterns in accordance with the knowledge space. For a statistical test we lump together the categories with distances 2 and 3. Then the difference between learning conditions turn out to be non-significant in a chi-square test ($X2\ (2) = 3.51$, $p = .173$, Fisher's Exact Test $p = .210$). Moreover, there are no differences between motivational states FF and HS ($X2\ (2) = 0.67$, $p = .967$, Fisher's Exact Test $p = 1.000$). Applying a multinomial logit model with main effects provides a close to perfect fit between observed and predicted frequencies. Consequently, the resulting chi-square statistic (based on the likelihood ratio) leaves no room for an interaction effect ($X2\ (2) = 0.3503$, $p = .839$), contrary to what Figure 4 seems to suggest.

Table 1. Distributions of minimal symmetric distances for all experimental conditions. The table provides absolute frequencies and percentages (in parentheses) of response patterns for each distance.

	Distance	RATH	TBL
FF	0	25 (80.65)	23 (74.19)
	1	6 (19.35)	6 (19.35)
	2	0 (0.00)	2 (6.45)
	3	0 (0.00)	0 (0.00)
HS	0	18 (85.65)	15 (71.43)
	1	3 (14.29)	5 (23.81)
	2	0 (0.00)	1 (4.76)
	3	0 (0.00)	0 (0.00)

The results based on the problem-specific solution frequencies also provide ample evidence that there are no differences concerning the goodness-of-fit of the supposed knowledge space over experimental conditions. Figure 5 shows the obtained relative frequencies plotted in the graph of the respective surmise relation. For all experimental conditions these frequencies decrease the higher the 'difficulty' of the problem class, which is to be expected if the response patterns conform with the knowledge states. The results also indicate a slightly better performance in the TBL condition.

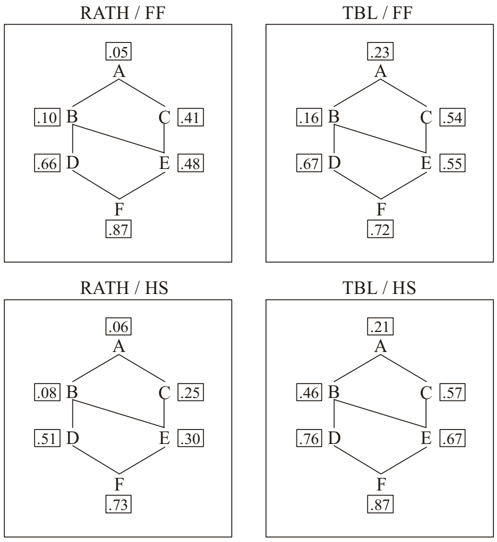

Figure 5. Surmise relation with problem-specific relative solution frequencies for all experimental conditions.

In order to evaluate the result of the test independent of the assumed knowledge space we consider the number of solved problems, relative to the total of 18 problems that were presented. Due to the time limits, however, the students were often not able to review the complete course. The actually covered content is evident from the associated exercises, which had to be completed in the learning phase. The number of exercises tackled and solved correctly within the time limit in the learning phase was very similar in all conditions, ranging from 63.44% in condition TBL/FF to 70.63% in condition RATH/HS. Thus, it is reasonable to confine consideration to those problems, the associated exercises of which have been tackled and solved. Table 2 provides the resulting average values for this case.

Table 2. Average number of solved problems conditional on tackling and solving the associated exercise in the learning phase. See text for details.

	RATH	TBL
FF	6.94	7.74
HS	5.43	9.29

An analysis of variance shows that there is no main effect of the motivational state ($F(1,100) < 0.001$; $p = 0.984$), while the main effect of the learning condition turns out to be significant ($F(1,100) = 6.129$; $p = 0.015$). There is no significant interaction between the factors ($F(1,100) = 2.623$; $p = 0.108$).

Discussion

While models of cognitive psychology significantly contributed to the development of adaptive tutorial systems in the past, emotional and motivational aspects were only rarely considered. A psychological model for a successful computerized adaptive tutorial system, however, has to cover all these aspects. The idea underlying the present paper is to build a starting point for integrating formal models of cognitive and emotional/motivational aspects into a comprehensive psychological model that can serve this purpose. We outlined Knowledge Space Theory (KST) suggested by [10, 11], a well-established cognitive model for computerized adaptive testing and teaching, and discussed the motivational model of Atkinson and McClelland as a candidate that may be used to extend KST in a proper way. Integrating latent emotional/motivational states, however, requires that they are compatible with the structural assumptions in KST. The research question whether we are able to represent the observed solution behaviour under different motivational states within the same knowledge space is addressed by the presented pilot study. It focuses on the motivational states hope for success (HS) and fear of failure (FF). For compatibility with previous investigations on motivational and emotional aspects, the experiment included different types of learning conditions, which are computer-based learning (RATH) and common text-based learning (TBL).

The results of the pilot study show that under all conditions the vast majority of response patterns coincide with a knowledge state of the assumed knowledge space. This means that the knowledge space suggested by [37] offers a considerably good fitting representation of the response patterns, and thus of the knowledge in the considered domain. Statistical analysis of the data in Table 1 reveals that the goodness-of-fit does not differ over experimental conditions. There is neither a main effect, nor an interaction effect of the two factors motivational state and learning condition. This conclusion is also corroborated by the fact that the order of the problem-specific solution frequencies is in line with the underlying surmise relation under all conditions (see Figure 5). The frequencies decrease with increasing “difficulty” of the respective problem class. This finding complies with the notion of the surmise relation. If solving problem a implies solving problem b then the number of students solving b has to be greater than or equal to the number of students solving a. The average number of solved problems (conditional on tackling and solving the associated exercise in the learning phase) exhibits no differences in the two motivational states. There is, however, an effect of the learning condition, but no interaction is present. This result is remarkable, because, although there are differences in the over-all level of performance, the assumed knowledge space was able to represent the obtained responses with the same high precision. We may call this property *sample invariance* of the knowledge space. It is an essential requirement for extending KST by introducing additional factors, like motivational states.

In order to conclude, the results of the presented pilot study strongly encourage the research program to integrate cognitive and emotional/motivational aspects into a comprehensive psychological model for adaptive tutorial systems. As we have only treated two prototypical motivational states, however, future research should address other emotional and motivational aspects. These may also include factors like controllability, or causal attribution. A further step then should aim at implementing such a comprehensive psychological model into a tutoring system.

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