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DECIDING ON DIFFERENT HINTING TECHNIQUES IN ASSESSMENTS FOR INTELLIGENT TUTORING SYSTEMS

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Abstract. *Intelligent Tutoring Systems (ITSs) must take advantage of their high computing capabilities and capacity for information retrieval in order to provide the most effective methodologies for improving students' learning. One type of ITS provides assessments to students and some help as a hint, when they do not know how to solve a problem. Our thesis is that the type of hinting techniques used without changing the contents can influence the learning gains and aptitudes of students. We have implemented some hinting techniques as an extension to the XTutor ITS. We found that some hinting techniques can produce a significant increase in students' knowledge with respect to others, but the improvement and direction of the comparison depended on some other factors such as the topics to which it was applied. We conclude that proper adaptation of hinting techniques based on different information of the systems will imply better student learning gains. In addition, the results of a student survey, which includes the students' ratings of the different hinting features they interacted with, leads to high variances, which reinforce the idea of the importance of adaptation of hinting techniques in these types of systems.*
Keywords: Adaptive systems, Decision support, Intelligent tutoring systems, Educational technology

1. **Introduction.** The adaptation of different aspects of the user experience depending on different parameters is useful in hypermedia systems [1]. Paper [1] distinghishes two general different types of adaptation: presentation (regarding different contents) and navigation (regarding the different links available to follow). Adaptive hypermedia systems can be applied in education to adapt the content and the links, and can take into account the user model [2]. The quality of an educational system can be improved by introducing intelligence and adaptation [3]. Therefore, the proliferation of a wide spectrum of adaptive systems in education is not surprising [4-6].

It is important to improve the quality of the learning/teaching process, and the introduction of assessments plays a key role [7-9]. There are several strategies in computer assisted assessment. In this work, we focus on the provision of hints. The underlying concept behind it is that a student can request some help from the Intelligent Tutoring System (ITS) when he/she is not able to answer a given problem in the assessment. This forces the student to make discoveries during the learning process. Several authors have reported on the benefits of this strategy ([10-12]). Based on this concept, there are several possibilities and techniques related to hints, and some hinting tutors have been implemented [13-17]. Frequent ways of measuring the efficiency and quality of these systems in the literature have been introduced through the measure of the students' learning gains and students' surveys.

Specifically, several authors reported on the importance of adaptation within hinting systems, and that one of the most important decisions of such systems is how to respond when a student asks for help [18,19], making, in that way, the adaptation decision. We can distinguish two general decisions in such systems: what to adapt and which parameters to use, and how to combine them in order to make the adaptation decisions. All of these works [18-21] adapted hint contents, but [18] was based on Bayesian networks that took into account the student knowledge level and the student mental state, while [19] used the Item Response Theory based on the student knowledge level, article [20] based the adaptation on the division of students in clusters depending on their knowledge levels, and article [21] was based on hints that depended on previous responses of other students.

Other works have proposed a cognitive model of students' behavior within a hinting system, and they have addressed the correlation between student behavior and learning gains [22-24]. This information can be taken for further research for the implementation of adaptive hinting systems, so that student behaviors can be modified in order to obtain the best learning gains. This type of adaptation based on student behavior has also been proposed for other types of learning systems [25]. Hence, these works proposed a model to retrieve students' actions within a hinting system, and the adaptation would be based on these parameters of student behavior.

The works presented in the previous paragraphs did not address the adaptation based on different hinting techniques (e.g. having penalties for viewing hints or not) which is a specific type of navigation adaptation according to the classification in [1]. Instead, some of the works adapted the contents of the hints, while other works focused on the adaptation based on student behavior.

The problem we focus on this paper is about the adaptation of hinting techniques in such systems without changing the contents, and we try to have some insights regarding the following questions: Is the adaptation of hinting techniques useful? For which hinting techniques does it make sense to implement adaptation? Which factors may influence the adaptation of hinting techniques? Is it possible to apply adaptation of hinting techniques successfully, even without a complex cognitive model? May it make sense to make adaptation decisions of hinting techniques depending on students' opinions?

In a similar way to other works which deal with adaptation within hinting systems, it is important to make proper adaptation decisions in order to increase students' learning gains. In our research, these adaptation decisions focus on the innovative aspect of the hinting techniques which was not studied before. If we achieve an increase in students' learning gains, then a more effective learning process is obtained, which is crucial in today's information society.

Specifically, this paper compares the effect on the learning gains between different hinting techniques implemented in Intelligent Tutoring Systems and knowing the students' opinions about such hinting techniques. This information can be used for selecting the most appropriate hinting techniques for the Intelligent Tutoring Systems depending on several factors, or for using adaptation to guide students to the best learning path. We have implemented an extension of the Xtutor (http://xtutor.org) Intelligent Tutoring System (ITS) for the provision of hints in problem-based learning which include different hinting techniques that are in the state-of-the-art systems and some other new functionalities, based on our own ideas. The details of our implemented hinting module are described in [26] and an overview is provided in Section 2 of this paper.

Regarding this work, two lab experiences (editions 2007 and 2008) have been designed in the context of a Computer Architecture Laboratory course, as part of the Telecommunications Engineering degree.

The remainder of this paper is organized as follows: Section 2 explains an overview of the XTutor system with the hint extension we implemented. Section 3 enumerates the objectives or research questions. The methodology and design criteria of the lab experiences are presented in Section 4. Sections 5 and 6 are devoted to explaining the results and making an analysis of the two main global objectives: the comparisons of the learning gains between different hinting techniques of the tutor (Section 5), and the survey of the importance of different hinting techniques (Section 6). Section 7 compares and relates the obtained results with respect to previous works. Section 8 focuses on the applications of the results, the limitations and future work. Finally, Section 9 exposes the conclusions.

2. **Overview of the Xtutor System with the Extension of Hints.** XTutor is a web based server developed at MIT (Massachusetts Institute of Technology). We have implemented an extension to include different strategies related to hints for the assessment problems. The details of this extension hinting module, as well as the different hinting features that it implements, based on a newly-created specification, are provided in [26].

Students received multiple choice, multiple response and fill in the blank exercises. Each exercise has an associated score. A student can try to solve an exercise several times, but each incorrect attempt by the student may imply a decrease of scoring points. Students can select hints for each exercise. The exercises with hints can be created with the help of an authoring tool [27], which generates final XML files that describe the hinting materials according to the specification. The generation of XML files that describe educational applications enables several advantages and there are many educational applications that use it, such as e.g. for the description of educational games [28] or some other educational services [29].

Figures 1 and 2 show an exercise of the lab experiences with different hints in two specific moments of a student's interaction. Initially (Figure 1), the student receives a problem about inter-process communication, for which the student must select the true sentences. There are a total of four sentences and the corresponding boxes can be selected (if true) or unselected (if false). This is a multiple response exercise. Each student incorrect attempt has a penalty of three points on the scoring. The student can request a hint, pressing the plus button, and then we can see the image of Figure 2. When it happens, another four plus buttons appear that represent four hints, which students can select. In this case, there is an item of information that only a maximum of two hints can be selected out of the four, but there are not any penalties on the scoring for viewing such hints. Students can select the hints by pressing the plus buttons and then other problems would appear as hints that would try to help in the resolution of the initial problem. In this case, to help students decide which hints to select, there is some meta-information regarding the topic of each hint before the hint is viewed.

3. **Objectives.** The two main objectives of this research are the following:

Objective 1. Comparing the Learning Gains by Changing Different Hinting Techniques. Determine if some hinting techniques of the Intelligent Tutoring System can increase the students' knowledge level more than others without changing the contents, and if this knowledge improvement is always in the same direction or if it may depend on some other factors such as the topics to which it is applied. Specifically, the comparisons of increase of knowledge between the different hinting techniques were the following:

- Penalize for viewing hints or having no effect on the scoring for viewing hints (in both cases without a maximum limit of the hints to select).

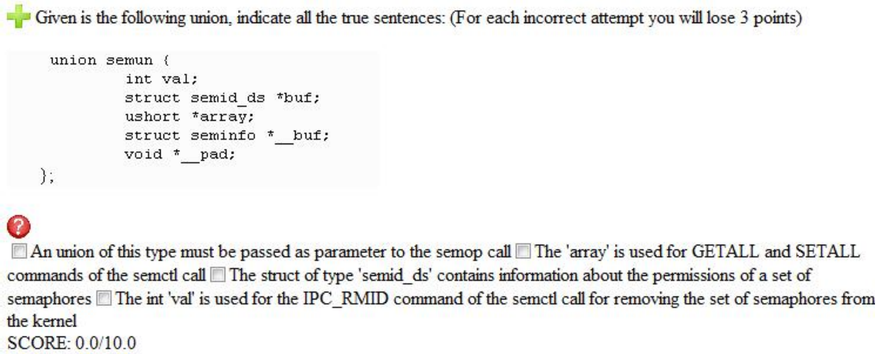

FIGURE 1. Exercise with hints executing within Xtutor (1^{st} phase of the interaction)

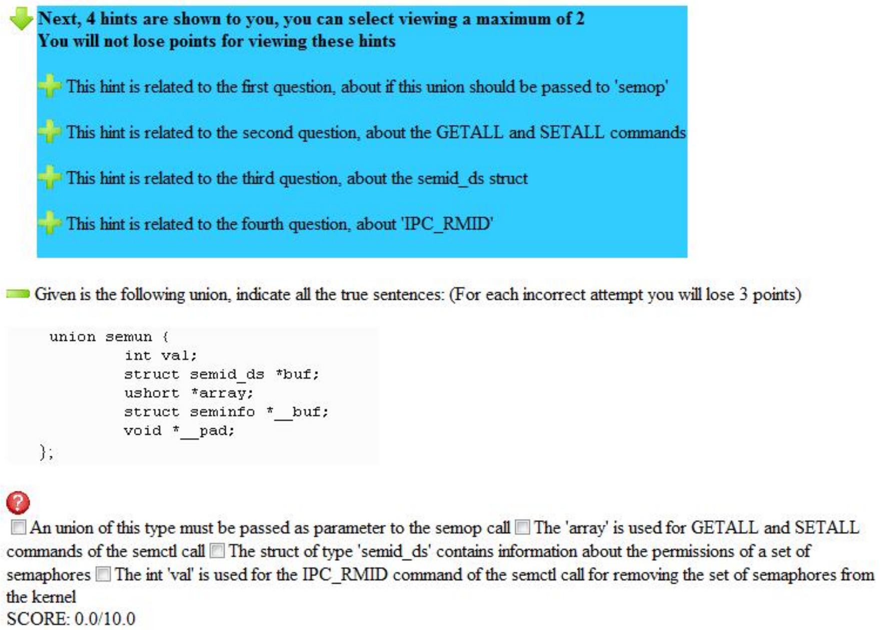

FIGURE 2. Exercise with hints executing within Xtutor (2^{nd} phase of the interaction)

- Penalize for viewing hints but with an unlimited number of hints to select or having no effect on the scoring for viewing hints but with a limitation of the maximum number of hints to select.
- Penalize for incorrect hint resolution, reward for correct hint resolution or having no effect on the scoring for hint resolution.
- Hints directly available, or only available as a response to an incorrect student's attempt.
- Being able to select all the hints minus one, or being able to select only one hint (without any penalties in any case).
- A combination of techniques that give hints without any effort on the part of the student or cost (hints directly available, without any penalty in the scoring for viewing the hints, and with a reward for answering hints correctly) or a combination of techniques that imply an effort or cost for students (hints only available as a result of an incorrect answer, with a penalty in the scoring for viewing the hints, and with a penalty for answering hints incorrectly).

Objective 2. Analyze Students' Opinions about the Importance of Different Hinting Techniques. The specific sub-objectives of this block are the following:

- Know students' opinions about the importance of each of the hinting techniques that they interacted with during the experience.
- Know if most students' opinions are in the same direction, or if there is a lot of variance.
- Know if students' opinions were according to the techniques that produced better acquisition of knowledge.

4. **Methodology.** A total of 55 students participated in the 2007 edition for the purposes of the research described in this paper, while 47 students participated in the 2008 edition.

In both editions, we performed one controlled lab experience that lasted for two hours. All exercises and hints were provided in English and Spanish as there are different language groups. The lab experience was presented to the students as a voluntary activity (without influence on the final course grade). During the two hour lab session students worked individually, each one with an assigned computer. The topics covered in the sessions were Shell script (S), Makefile (M), Inter-Process Communication (I) and the FAT file system (F). Every exercise designed in the experience in every phase was related to only one of these four topics, so there were not any exercises that covered more than one of these topics.

Phases of the Experiences. Figure 3 shows the phases of the 2007 edition:

- *PHASE 1: Introduction. Explanation of the lab experience and distribution of passwords (Time: five minutes).*
- *PHASE 2: Pre-test (Time: ten minutes).* The pre-test was a set of eight initial problems without hints, covering all the topics.
- *PHASE 3: Problems with hints provided by the XTutor hint system (Time: 50 minutes).* In this phase, each student visualized an index with 16 problems covering all the topics. Each problem has one or more hints, with different techniques or strategies related to hints. These problems with hints were offered by the XTutor system with the hint module extension.
- *PHASE 4: Post-test (Time: ten minutes).* The post-test was a set of eight final problems without hints, covering all the topics. The problems of the post-test and pre-test were different, but they had the same difficulty level and structure.
- *PHASE 5: Problems with hints provided by teachers (Time: 20 minutes).* In this phase, students viewed the same 16 problems as in PHASE 3, but in this case the system did not provide any hints related to these problems. Instead, students were able to request hints from the teachers. In actual fact, this PHASE 5 was not required for the purposes of the research exposed in this paper but it was included because of other research questions not covered in this paper.
- *PHASE 6: Survey to Students (Time: ten minutes).* Students filled in a form about different issues of the hinting functionalities which they interacted with.

The phases for the 2008 edition were the same as for the 2007, but PHASE 5 of interaction with teachers was removed. In this way, some phases of the 2008 edition increased their assigned time, and the number of problems to solve: the pre-test and post-test contained a total of ten questions (instead of eight) with an estimated time of 12 minutes (instead of ten minutes). In a similar way, the phase of interaction with the XTutor hinting module lasted for 65 minutes (instead of 50 minutes), with a total of 20 problems with hints (instead of 16).

Design of the Pre-test and the Post-test. The pre-test and post-test were carefully designed so that both had the same difficulty level and there were no questions repeated between the post-test and pre-test. In this way, the two tests were counter-balanced across participants, and the positive differences between post-test and pre-test cannot be

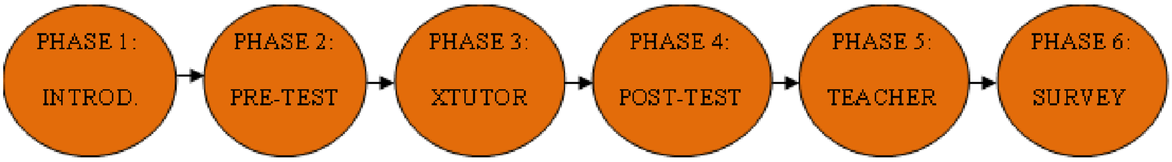

FIGURE 3. Different phases of the 2007 edition lab experience

explained as a consequence of an easier post-test or because of repeated or very similar questions. Therefore, the positive differences should be explained by the effect of the students' interactions with the hinting tutor. In addition, in order to achieve the research objective of comparing the increase of knowledge depending on different hinting techniques, we compared the differences between learning gains between students that interacted with exercises with specific hinting techniques and other students that interacted with the same exercises but changing the hinting techniques. In this way, even assuming that there were some differences in the difficulty level of the post-test and pre-test, the differences in learning gains between the application of some hinting techniques and others cannot be explained as a consequence of a difference in the difficulty level of the pre-test and post-test, because in any case all the students received the same pre-test and post-test and what we are interested in measuring is the relative difference between students that interacted with different hinting techniques but not in the absolute values of each learning gain. So, if there is a difference depending on the hinting techniques, it should not be explained by the post-test being easier than the pre-test.

Different Hinting Techniques for the Intelligent Tutoring System. There were a total of five different hinting strategies, each one with a set of possible hinting techniques. The possible hinting strategies were the following:

- Cost for viewing hints without maximum limit to select. The possible hinting techniques were to set a penalty on the scoring for viewing a hint or without any penalty on the scoring for viewing hints.
- Cost for viewing hints with a possible maximum limit to select. The possible hinting techniques were: a) there are n hints with previous meta-information. The student can select as many hints as he/she wants to, but there is a different penalty on the scoring for viewing each hint. b) there are n hints with previous meta-information. The student can only select a maximum of k hints (with $k <= n$), but there is not any penalty for viewing hints.
- Effect on the scoring for solving hints. The possible hinting techniques were: a) some of the hints are other exercises, for which there is a penalty in the initial problem for solving hint exercises incorrectly. b) some of the hints are other exercises, for which there is a reward in the initial problem for solving hint exercises correctly. c) some of the hints are other exercises and there is neither a reward nor a penalty for solving hint exercises correctly or incorrectly.
- Availability. The hinting techniques were: hints are available to students at the beginning or hints are only available as a result of an incorrect student attempt.
- Maximum limit to select. The hinting techniques can be that all hints minus one can be selected or only one hint can be selected among all. These types of exercises were only available in the 2008 edition.

Assigning of Students to Hinting Techniques for each Group of Topics. In the 2007 edition, students were divided into 3 groups: A, B and C. All the students (with independence of the group they belonged to) received the same initial exercises and the same contents of hints, but they received different hinting techniques for each topic depending on the group they belonged to. The number of students for each of these groups was not the same. There were a total of 16 students for group A, 24 for group B and 12 for group C (they do not total 55 that is the number of students in the experience, because three students' data were discarded as they arrived late to the session).

Table 1 shows groups A, B and C, and for each cell where the groups appear we can see the type of topics which hinting techniques were provided to such group. In this way, for the Shell Script and IPC topics (S+I), the students in group A interacted with a set of exercises with hinting techniques that required an effort or cost for students (penalties for viewing hints and hints only available as a response to an incorrect attempt) and with penalties for incorrect hint resolution; while students in group B interacted with a set of exercises with hinting techniques that did not require any effort or cost for students (without penalties for viewing hints and hints being directly available) and with rewards for correct hint resolution; while students in group C interacted with a set of exercises with hinting techniques that required an effort or cost for students and without influence for hint resolution. On the other hand, for the Makefile and FAT topics (M+F), students in group A interacted with a set of exercises with hinting techniques that did not require any effort or cost and with rewards for correct hint resolution; while students in group B interacted with a set of exercises with hinting techniques that required an effort or cost and with penalties for incorrect hint resolution; while students in group C interacted with a set of exercises with hinting techniques that did not require an effort or cost and without influence for hint resolution.

In the 2008 edition, there were not three different groups of students with different hinting techniques depending on the topic like in the 2007 edition, but the design of the experience changed the way of assigning hinting techniques to students in the PHASE 3 of interaction with the XTutor hinting module. As we had five different hinting strategies (as explained in the previous section), and four of the strategies with two variations, and another one with three variations (penalty, rewarding or no effect for hint resolution), then we had a total of 48 sets of combinations. Each combination of hinting techniques can be applied to each different topic. Thus, for the 2008 edition, we used the 48 possible combinations for S+I and M+F.

5. **Results and Analysis.**

The 2007 Edition. Table 1 shows different descriptive statistics (giving the means and the standard deviations) of the pre-test, the post-test and the increase of knowledge between post-test and pre-test for each group of students (A, B or C) and divided into two branches of topics (on one hand S+I, on the other hand M+F). The pre-test is a score between the range 0 and 10, as well as the post-test (so their means must be between these ranges), so the increase of knowledge (this is the difference between post-test and pre-test) must be between the range –10 and 10. Greater positive values indicate greater increase of knowledge during the students' interactions with the Intelligent Tutoring System.

Applying the normality tests and the variance homogeneity test for the six samples of increase of knowledge (the six that correspond with the filled data of Table 1), we can assume variance homogeneity (with the Levene test), but we cannot assume normal distributions for any of the six populations according to the Kolmogorov-Smirnov and Shapiro-Wilk tests. For this reason, and as the number of data of all the samples is not big enough (see the size of groups A, B, C), then we cannot apply the ANOVA or the t-test in order to compare the increase of knowledge of the different samples, and we must use alternative non-parametric statistical methods.

Applying the non-parametric Kruskal-Wallis test for the three different groups of hinting techniques on the one hand for S+I, and on the other hand for M+F (there are four groups

TABLE 1. Descriptive statistics for each group of hinting techniques for the 2007 edition

Sets of hinting techniques applied in the Intelligent Tutoring System	Corresponding Subgroup / Descriptive Statistics about S+I	Corresponding Subgroup / Descriptive Statistics about M+F
-Penalizing for viewing a hint -Penalizing for viewing hints that can be selected based on meta-information -Penalizing for incorrect resolution of problems that are hints -Hint only available as a response to an incorrect attempt	Group A / pre-test: Mean:2.66 Std. Dev: 1.92 post-test: Mean: 5 Std. Dev: 2.74 Increase of Knowledge: Mean: **2.34** Std. Dev: 4.13	Group B / pre-test: Mean: 3.85 Std. Dev: 2.08 post-test: Mean: 7.6 Std. Dev: 1.88 Increase of Knowledge: Mean: **3.75** Std. Dev: 1.80
-Without penalty for viewing a hint -Without penalty for viewing hints that can be selected based on meta-information -Rewarding for the correct resolution of problems that are hints -Hint directly available at the beginning	Group B / pre-test: Mean: 4.58 Std. Dev: 2.92 post-test: Mean: 6.67 Std. Dev: 1.75 Increase of Knowledge: Mean: **2.08** Std. Dev: 3.1	Group A / pre-test: Mean: 3.75 Std. Dev: 2.74 post-test: Mean: 6.09 Std. Dev: 2.41 Increase of Knowledge: Mean: **2.34** Std. Dev: 2.32
-Penalizing for viewing a hint -Penalizing for viewing hints that can be selected based on meta-information -Without penalty nor rewarding for resolution of problems that are hints -Hint only available as a response to an incorrect attempt	Group C / pre-test: Mean:2.29 Std. Dev: 2.25 post-test: Mean: 5.42 Std. Dev: 3.17 Increase of Knowledge: Mean: **3.13** Std. Dev: 2.64	
-Without penalty for viewing a hint -Without penalty for viewing hints that can be selected based on meta-information -Without penalty nor rewarding for resolution of problems that are hints -Hint directly available at the beginning		Group C / pre-test: Mean: 4.79 Std. Dev: 3.45 post-test: Mean: 6.67 Std. Dev: 2.22 Increase of Knowledge: Mean: **1.87** Std. Dev: 2.17

of hinting techniques, but we can see from Table 1 that for each topic there are only data for three of them), we obtained for S+I a value of 0.885 for the chi-square statistic and p=0.642. As $p > 0.05$, then we cannot refuse the hypothesis that the means are equal among the three different populations that interacted with different hinting techniques for S+I. But we obtained for M+F a value of 7.908 for the chi-square statistic and p=0.019. As in this case $p < 0.05$, then we can refuse the hypothesis that the means are equal among the three different populations that interacted with different hinting techniques for M+F, and we can conclude that there were statistically significant differences among the means depending on the hinting techniques the students interacted with.

Applying the Mann-Whitney test to compare, two by two, the three groups for each one of the topics' divisions, we obtained that there were not any statistically significant differences between the means of increase of knowledge in the three possible comparisons for the S+I topics (second column of Table 1). Nevertheless, applying the Mann-Whitney test for the three groups with respect to M+F (third column of Table 1), we obtained a statistically significant difference between the means of groups A and B (Mann-Whitney U = 119, Wilcoxon W = 255, Z = –2.168, p = 0.030), and also for the means of groups B and C (Mann-Whitney U = 76, Wilcoxon W = 154, Z = –2.451, p = 0.014), but there was no statistically significant difference between the means of groups A and C (Mann-Whitney U = 87, Wilcoxon W = 165, Z = –0.457, p = 0.647) so we cannot refute the hypothesis of equality of means for groups A and C.

Therefore, from the experience of the 2007 edition, we have found the following statistically significant differences of increased knowledge for the M+F topics depending on the set of hinting techniques that were provided:

(1) The union of techniques that require an effort and cost for students (penalizing for viewing hints, and hints available only as a response to an incorrect attempt) and the technique of having score penalties for incorrect hint resolution gave better results in

a statistically significant way than the union of techniques that does not require any effort or cost for students and the technique of having score rewards for correct hint resolution.

(2) The union of techniques that require an effort and cost for students and the technique of having score penalties for incorrect hint resolution gave better results in a statistically significant way than the union of techniques that does not require any effort or cost for students and the technique of not having any effect on the scoring for hint resolution.

The 2008 Edition. The first column of Table 2 shows the sets of hinting techniques applied to exercises with hints in the Intelligent Tutoring System. Each row represents a strategy and it can have two values: 0 or 1. Each value represents a specific hinting technique whose meaning is explained in Table 2. The possible values are 0 or 1 to be able to apply the desired correlation. These hinting techniques are used as variables for such a correlation.

We calculated the partial correlation between each one of the hinting strategies applied and the learning gains (for S+I topics and also for M+F), taking out the side effects of the students' initial knowledge levels for S+I or M+F (measured as their grades in the pre-test) and taking out the effect of the rest of hinting strategies applied. Thus, for one of the hinting strategies of the first column of Table 2, we take out the effect of the rest of variables of the first column. Specifically, the point-biserial partial correlation was calculated, because we set the correlation between a continuous variable (the increase of knowledge for S+I or M+F) and a dichotomic variable (which two possible values are the two different hinting techniques related to a specific hinting strategy). The correlation is partial because we need to remove the side effects of other variables that can influence the final result. In this case, these other variables that can influence are the other hinting strategies applied and the students' initial knowledge level.

Table 2 shows the results of the point-biserial partial correlation for each one of the listed variables, taking out the effect of the rest of variables that can influence the result and with respect to the increase of knowledge for S+I (second column of Table 2) but also for M+F (third column of Table 2).

Table 2. Partial correlation between the increase of knowledge and the different hinting techniques for the 2008 Edition

Sets of hinting techniques applied in the Intelligent Tutoring System	Increase of Knowledge on S+I	Increase of Knowledge on M+F
Cost for viewing a hint without a maximum limit to select (0 if there is no effect on the scoring for viewing hints; 1 if there is some penalty on the scoring for viewing hints)	–0.382 (p=0.020)	0.350 (p=0.034)
Cost for viewing a hint with a possible maximum limit (0 if there is no effect on the scoring for viewing hints but there is a maximum limit to select; 1 if there is some penalty on the scoring for viewing hints but without a maximum limit of hints to select	0.089 (p=599)	0.054 (p=0.749)
Availability (0 if the hints are only available as a response to an incorrect answer; 1 if the hints are available at the beginning to be selected)	0.010 (p=0.953)	–0.223 (p=0.184)
Maximum limit of hints to select (0 if students can select all the hints minus one; 1 if students can only select 1 hint)	–0.056 (p=0.743)	0.084 (p=0.623)
Effect on the scoring for solving hints (0 if there are not effects on the scoring for solving hints correctly or incorrectly; 1 if there is some effect on the scoring for solving hints)	0.357 (p=0.030)	–0.501 (p=0.002)
Type of effect on the scoring for solving hints (0 if there are penalties for incorrect hint resolution; 1 if there are rewards for correct hint resolution)	–0.019 (p=0.930)	0.239 (p=0.284)
Students' initial knowledge level for the correspondent topic	–0.490 (p=0.002)	–0.451 (p=0.005)

Next, there is an analysis of the results for the 2008 edition for each one of the hinting strategies applied (we consider statistically significant when p is less than 0.05). The two hinting strategies compared where there were statistically significant differences were the following:

(1) Cost for viewing a hint without a maximum limit to select: It gave better results in a statistically significant way for the increase of knowledge of M+F to apply penalties for viewing hints rather than not to have any effect on the scoring for viewing hints ($r=0.350$, $p=0.034$). Nevertheless, it was the opposite for the increase of knowledge of S+I, being better in a statistically significant way not to have any effect on the scoring for viewing hints rather than to apply penalties for viewing hints ($r=-0.382$, $p=0.020$). From these results, we can conclude that the variation of the hinting strategy related to the cost for viewing a hint without a maximum limit to select, influenced the final results of the students' increase of knowledge. In addition, we can observe that the way of such influence was not always the same, because we obtained different results for S+I and M+F. As the results were statistically significant in both cases, but in the opposite direction depending on the topic (S+I or M+F), then we can assure that there are some other factors that influence one technique being better than another.

(2) Effect on the scoring for solving hints: We found that it was better in a statistically significant way for the increase of knowledge of S+I to apply some effect on the scoring (either rewards or penalties) for correct or incorrect hint resolution rather than not having any effect on the scoring for hint resolution ($r=0.357$, $p=0.030$). Nevertheless, the opposite resulted for the increase of knowledge of M+F, being better in a statistically significant way not to apply any effect on the scoring for hint resolution rather than having some effect on the scoring for hint resolution ($r=-0.501$, $p=0.002$). Based on this, we can conclude that the variation of the effect on the scoring for hint resolution, influenced the final results of the students' increase of knowledge. In addition, we can observe that it did not influence in the same direction, because we obtained different results for S+I and M+F. As there were statistically significant differences in both cases, but in the different direction for S+I and M+F, then we can assure that there are some other extra factors that make a hinting technique better than another in certain conditions.

We cannot look for these other factors among the variables used in the partial correlation because their effect is already discarded with such partial correlation. Such other factors might be the type of topic (in this case S+I or M+F), the design of exercises/hints and the specific profile of each student (in this profile, the students' initial knowledge level of the topic is not taken into account, because the effect of this variable was already discarded with the partial correlation).

For the rest of hinting strategies there were no statistically significant differences either for S+I or for M+F. But there are some tendencies in the samples about which hinting techniques might be better with certain probability p. The fact of not having statistically significant differences does not mean that there is not a correlation between the variables, but we would need more samples to discern it with certain probability. Furthermore, the hypothesis that both variables are not correlated for this case may be also valid, but varying the topic, and/or the design of exercises/hints, and/or the students' profile, then it may result in a correlation between the increase of knowledge and a specific hinting strategy. In any case, these hypotheses should be corroborated by future experiments.

Finally, we analyze the partial correlation between the increase of knowledge and the students' initial knowledge level (last row of Table 2). The correlation between these two variables for S+I ($r=-0.490$, $p=0.002$), and also for M+F ($r=0.451$, $p=0.005$), resulting that a greater students' initial knowledge level for a topic, implied a lower increase of knowledge after interacting with the exercises with hints, and a lower students' initial knowledge level for a topic, implied a greater increase of knowledge after interacting with the exercises with hints. After an analysis, we conclude that the causes of this effect are two mainly: 1. Students with a lower initial knowledge level have a greater margin to improve (for example, a student with an initial knowledge level of 8 out of 10, can only increase his/her knowledge by two points because the maximum mark is 10); 2. The system was more beneficial for students with a lower initial level.

Analysis of the Combination of the Results in the 2007 and 2008 Editions. Next, there is an analysis which takes into account the data obtained from both editions (2007 and 2008). First of all, as from the 2008 edition we found that lower students' initial knowledge levels for a topic implied a greater increase of knowledge and vice versa, then it must be taken as a fact for the analysis of the results of the 2007 edition. In addition, we will analyze if the statistically significant differences found for the 2008 edition are consistent with the results of the 2007 edition. Next, there is an analysis for each one of the three possible combinations for the S+I topics, and the other three possible combinations for M+F in the 2007 edition.

Comparing groups A and B for M+F, we conclude that the cause of the statistically significant difference in learning gains cannot be explained as a result of the students' initial knowledge level in the topic, because this students' initial knowledge level was similar in both groups. We can see that the results of the 2008 edition are consistent with those of the 2007 edition. This is because for M+F, it was better in a statistically significant way to penalize for viewing hints without a maximum limit, and we observed a tendency (but not one which was statistically significant) for it to be better to make hints available only as a result of an incorrect attempt. On the contrary, we found a tendency (but not one which was statistically significant) to be better to give a reward for correct hint resolution, and we did not observe any tendency related to the aspect of penalizing or not for viewing hints with a possible maximum limit. If we use the data results of the 2008 edition for analyzing the results of the 2007 edition, we can see that there are two factors in one direction (one of them significant) against one factor in the opposite direction. Therefore, it is more probable to have the relationship that was finally found in the 2007 edition.

Comparing groups A and B for S+I, we conclude that there was a slight difference (not statistically significant) in favor of the same set of hinting techniques that resulted better for M+F. As we observed that the students who interacted with high cost and effort hinting techniques had a considerable lower students' initial knowledge level, we can conclude that the slight difference in favor of the group that interacted with high cost and effort hinting techniques, cannot be explained for S+I by the fact of the high cost hinting techniques being better. Indeed, taking into account the initial students' knowledge levels, the better hinting techniques would be the low cost ones. We can see that the result of the 2007 edition is consistent with the 2008 edition results, because for the 2008 edition it was better in a statistically significant way for S+I not to have effect on the scoring for viewing hints without a maximum limit, but there was no other remarkable tendency between the comparisons of the rest of hinting techniques that compounded the set for both groups.

Comparing groups A and C for M+F, as there was a difference between the students' initial knowledge levels between both groups, this might imply that the direction of the learning gain would be reversed if we discarded the factor of the students' initial knowledge level, it being better not to have any effect on the scoring than giving rewards. If we take the 2008 edition results as a starting point, we can observe that it was better (statistically significant) for M+F not to have any effect on the scoring, and we found that there was a tendency (not statistically significant) for it to be better to give a reward rather than penalizing for hint resolution. Therefore, it was expected to be better for the 2007 edition the group without any effect on the scoring. If we discarded the effect of the students' initial knowledge level, this would be the observed tendency for the 2007 edition, which is the expected outcome.

Comparing groups A and C for S+I, this is the only situation that the data obtained for the 2008 edition cannot predict the results of the 2007 edition. As a hypothesis, we formulate that the difference on the effect of this hinting strategy may lie in the different students' profiles.

Comparing groups B and C for M+F, part of this difference on learning gains in this direction should be explained by the effect of the different students' initial knowledge levels because the group that interacted with high cost hinting techniques had lower students' initial knowledge levels. But this can only explain a part of the difference, and the rest of the difference should be explained by the effect of the different hinting techniques applied. If we take the results of the 2007 edition as a starting point, we conclude that it was better in a statistically significant way for M+F to apply some penalties to the scoring for viewing hints without a maximum limit, and there was a tendency (not one which was statistically significant) to be better to have hints available only as a response to an incorrect attempt. Nevertheless, we observed a tendency (not one which was statistically significant) to be better not to have effect on the scoring for hint resolution, and there was no any tendency with respect to penalizing or not for viewing hints with a possible maximum limit. Applying deduction from the data of the 2008 edition, then as there is the combination of two factors of hinting techniques (one of them statistically significant) in one direction of learning gains, against one factor in the opposite direction, then the relationship that was found for the 2007 edition is consistent with this.

Comparing groups B and C for S+I, we can conclude that the results of the 2008 edition are consistent with the data results of the 2007 edition, when analyzed in a similar way.

6. **Results and Analysis of the Students' Opinions Regarding the Different Hinting Techniques.** In the 2007 edition, students filled in a survey about the importance of the different hinting techniques they used in their interaction with the Intelligent Tutoring System. The questions are shown in the first column of Table 3. Students rated each of the survey questions on a scale from 1 to 7. The second column of Table 3 shows the mean of the students' answers, while the third column shows their variance.

First of all, it is very important to note the high variance of the results in each one of the questions. Most of them reach variance values higher than 3, so the average deviation is high taking into account a scale from 1 to 7. This implies that there are different opinions among different students regarding the hinting techniques. Therefore, it implies different student profiles, and different ways to consider the importance of the different hinting techniques. This may imply a need for system adaptation, and the need to adapt the different hinting strategies depending on the different student profiles, so the hinting techniques for a specific problem would vary depending on the specific students.

With respect to the different techniques related to hints, as a general rule students considered slightly (as all the values are between 3.88 and 4.93) more important such techniques that imply a low effort for them and such techniques that do not imply any penalties for them (an exception to this rule is the penalty for incorrect attempts which students rated highly). Sometimes, this criterion matches with the techniques that may lead to more acquisition of knowledge, but not always. For example, from the 2007 edition (which was the same year in which the edition of this survey was performed) high cost hinting techniques and penalizing for incorrect hint resolution for M+F were better in a statistically significant way than low cost hinting techniques and reward for correct hint resolution. Nevertheless, students rated in the survey the hinting techniques that implied less cost and effort for them (such as hints directly available rather than only available as a response to an incorrect attempt, they did not consider specially important penalizing for viewing hints, and it obtained higher scoring to reward for correct hint resolution rather than penalize for incorrect hint resolution) as more important.

Table 3. Survey results showing the importance of each of the system functionalities related to hints

Question	Average (Scale from 1 to 7)	Variance
Hints for the problems available at the beginning	4.93	3.2
Hints for the problems only available as a result of an incorrect answer to a problem	4.49	3.29
Hints that are only text	4.81	2.78
Hints that are other problems	4.37	3.36
Several hierarchical hint levels (concept of hints about hints)	4.73	3.15
Hint sequence (hints that are several problems in different steps)	4.72	2.94
Showing several hints for which only a maximum can be selected	3.91	3.32
Hints depending on the student profile	4.01	3.91
Penalizing for viewing hints	4.03	3.2
Penalizing for incorrect attempts	4.88	2.97
Increasing the scoring for answering hints correctly	4.55	3.52
Penalizing for answering hints incorrectly	3.88	3.55

In a similar way, we observe a tendency on the part of students to rate the techniques that imply an easier learning path that helps them reach the final solution more quickly, as slightly more important, rather than other learning paths, that imply a more complete process and might imply a greater increase of students' knowledge. There were some questions on the survey about hinting techniques for which there were no experiments in this experience to discern which resulted better. In relationship with these other hinting techniques we can say the following:

- Students rated as slightly more important the hints that are only text instead of hints that are other problems. The hints that are only text might mean lower effort for the students, but maybe the students might learn more by doing other problems that help as hints to solve the initial exercises.
- Students rated lowly the hinting technique of setting a maximum limit of hints to select. To set a maximum limit of hints to select based on some meta-information implies an effort on the part of students, but might also mean more careful thinking on their part, which may in turn imply a better learning gain.

Finally, there are some other techniques that we can formulate to be good for the acquisition of knowledge, and also make life easier for students, as they are techniques of low cost and effort. These features obtained positive rates from students. Such hinting techniques are the sequence of hints (explaining step-by-step helps students) and hierarchical hints (this helps students because it provides them with several cues, giving increasingly more detailed help, which allows them to acquire the knowledge).

7. **Relationship of This Work with Respect to Prior Research.** In references [22-24], the authors show the correlation of different students' behaviors with respect to their learning gains. They found that different student behavior mistakes, such as 'help abuse', 'help avoidance' and other 'miscellaneous bugs' are negatively correlated with learning gains. But our point of view is different, as we focus on the comparisons of the learning gains depending on different hinting techniques, but not on the comparisons of the learning gains based on different users' behaviors when using the same hinting technique for each exercise. In references [22-24], the authors did not vary what we have called

hinting techniques. In addition, we do not distinguish between the different students actions based on a cognitive model, but we only consider the type of specific exercises, students' initial knowledge and the hinting techniques. So our cognitive model would be very simple, but despite of that fact we obtained some statistically significant differences by changing only the hinting techniques without taking into account other parameters of the students' cognitive model.

But there is a strong connection between our work and those researches. From our work, we know that, sometimes, some hinting techniques are better than others, but the tendency may vary depending on some factors. Those factors (such as the different student profiles, the topics, the design of exercises/hints, etc.) may imply that students make more or fewer behavior mistakes as those commented in [22-24]. That is to say that because of the design of a specific exercise with hints, students might be more conditioned to make 'help abuse', 'help avoidance' or 'miscellaneous bugs'. Or that because of the topic, if only a few students know about such concepts, then some types of 'help abuse' possibilities are discarded because students need help for such concepts as most of them have a lack of them. Or that depending on the students profile, students can make more or fewer mistakes of one type or another, or none.

On the other hand, the different hinting techniques may influence the students' behavior. We have found (from other research carried out simultaneously) that penalizing for viewing hints, giving hints only as a response to an incorrect answer, and penalizing for incorrect hint resolution decrease in some cases the amount of hints that students select. In this way, for situations where, depending on the factors which have been commented on, there is a greater probability of 'hint abuse', then it is recommended to apply such commented techniques in order to try to reduce the 'hint abuse' and this would be of benefit with respect to the learning gains. But if, for instance, the factors change and there is a greater probability of 'hint avoidance', then the hinting techniques that encourage the requesting of more hints (such as hints directly available to select, not penalizing for viewing hints, rewarding or not having effect on the scoring for hint resolution) would be better because such techniques make students select more hints, making a decrease of the 'hint avoidance', so the learning gains would be greater.

In addition, the ideal students' learning path for each case might vary, so we can make the hypothesis that it could have variations from the model proposed in [22]. The factors that might vary the ideal model are the already commented. For example, the ideal learning path might not be independent of the hint content: if the hint is very good, then the best thing would be for the student to view it even if he/she might not view it in a regular situation, or if the hint is very bad, then the best thing would be for the student not to view the hint even if he/she has no grasp of the concept. Sometimes, teachers do not know that they designed a hint in a bad way, so they do not have this information from scratch. The model of reference [22] could be seen as an ideal students' behavior model from the point of view of the student, when the student does not know for example what the hint is about, but the real best learning path might be different depending on other factors that a student might not know *a priori*. Or the ideal model may change because of the specific students. There can be some students that learned even if they made apparent behavior mistakes like "try abuse" because of their learning style. If the model changes for each case, then the best behavior would change for each case.

With the methods described in our work, we can modify the hinting techniques so that they result in a final direct benefit in the students learning gains, without taking into consideration any cognitive model or the factors that might influence the ideal student behavior, or the accuracy of the prediction of the ideal student behavior. With this approach, we do not react to each student's behavior possibility but we react considering the topic, the type of exercise or the design of the exercise. Therefore, the considered parameters for adaptation in our work are different from [22-24], including the different hinting techniques.

There are some works that provided personalized hints depending on the students' profile. For this adaptation, several techniques were used, such as Bayesian Networks students' models [18], the Item Response Theory [19], the division of students into clusters depending on their knowledge levels [20] or hints that depend on the previous responses of other students [21]. In any case, these works provided systems with adaptive exercises or adaptive contents for the hints, but they did not adapt the hinting techniques that we have explained in this paper. We have proved in this paper the need to adapt these hinting techniques as this can be of benefit for students' learning gains.

In our work, we have compared different hinting techniques. There are other works that compare the increase of knowledge depending on the semantics of the hints provided [30] or if the hints are worked-out examples or not [31]. In our case, however, we do not vary either the semantics of the hints provided or if they are worked-out examples or not (both aspects are fixed in our comparison, because the contents of the hints are similar, and what changes are the hinting techniques).

8. **Applications, Limitations and Future Work.** The results presented have direct implications for their use in practice. The first implication is that the adaptation of hinting techniques makes sense for assessment adaptive systems and the teaching/learning process can be improved with the inclusion of such features in those systems. Therefore, it makes sense to build an intelligent tutoring system that adapts not only the contents but also the hinting techniques.

The results presented show that these adaptations make sense at least for some of the analyzed hinting techniques (for which there was a statistically significant difference). Nevertheless, we have not found statistically significant differences in learning gains regarding other different hinting techniques. But this does not imply automatically that these types of adaptation do not make sense for them. Indeed, the reason might be that we could need to vary the type of exercise or topics to find some statistically significant differences for these other hinting techniques. In the future, we would like to design new experiences to have more data with other different exercises or topics in order to discern if there are any differences in the learning gains depending on the selection of such other hinting techniques.

In addition to the hinting strategies exposed in this paper, other new hinting strategies and their effect in the learning gains could be studied. Such other strategies are for example the number of levels in a hierarchical hint, the effect of a sequence of hints or changing the number of points for rewarding for correct hint resolution, and the number of points for penalties for incorrect hint resolution.

Another direct application of the results is to implement an adaptive hinting system that adapts the different hinting techniques based on methodology that is quite similar to that exposed in this paper. In this way, the adaptive hinting system would have a pre-test, a phase of student interactions with exercises with hints changing the hinting techniques and a post-test. The Intelligent Tutoring System would measure the different learning gains between post-test and pre-test for each student, and it would correlate the different learning gains with respect to the different hinting techniques applied divided by each specific exercise. In this way, after a training period, the system would know which hinting techniques resulted better for a problem with hints or a set of problems, and the system could decide which hinting techniques to present based on that data. In any case, the adaptive system would continue learning from each student interaction even after the training phase.

Regarding the student survey about the importance of different hinting techniques, we know from the results that there are different student opinions and preferences. As there is no uniform opinion, then it might make sense to adapt hinting techniques depending not only on the type of problems or topics but also on the students' opinions. Nevertheless, it should be proved in future work that these student opinions are correlated with their learning gains regarding the different hinting techniques. Indeed, the student survey model could be extended in order to know more students parameters so as to make decisions about the different hinting techniques.

With the results obtained in this work that suggest that the benefit of the different hinting techniques would depend on factors such as the problem topics, design and type of problems or the students' preferences, we can think about an application that extended the already commented adaptive system in a way that measures the learning gains and correlates these learning gains with respect to the different hinting techniques applied for a specific exercise, and which also correlates these learning gains with respect to the different users. In this way, we could know which hinting techniques might be better for a specific exercise, as well as which hinting techniques result better for a specific student. For future interactions of the student with the system (or of similar students), the system would make the decision about which hinting techniques to use based on what resulted better in the accessed exercise, but also by taking into account what resulted better for this specific student. Each factor might have a weight in the decision. Those systems could use different techniques for making the final decisions based on machine-learning decision-making techniques such as those presented in [32] or [33].

The commented methods for adaptation of hinting techniques are based on the comparison of parameters with learning gains. As part of the possible applications, other approaches can be also considered for the adaptation of hinting techniques without the use of the learning gains (so a pre-test and post-test would not be necessary in the system). For example, local decisions based on student behaviors inspired by some cognitive model (e.g. [22-24]) could be applied. The idea would be to analyze the influence of the hinting techniques in the student behaviors and apply the hinting techniques in order to obtain desired student behaviors that can produce better learning gains. We are presently conducting research in this direction to analyze the behavior effect of the hinting techniques depending on different factors. In this scenario, the results presented in this paper could be used to propose some modifications to the cognitive models about behaviors according to the obtained learning gains of this work. Another useful approach for adaptation of hinting techniques could be to extend the student survey and try to predict student behaviors, student preferences, etc. so that the systems would not need to monitor student actions or preferences, but predict from scratch by a survey. We are also conducting some research in this line in order to try to predict student behaviors based on an extended survey, addressed to students, concerning hinting techniques (extended survey with respect to that presented here about the importance of different hinting techniques).

Therefore, there are several ways in which the results of this work can be applied to achieve a useful adaptive system that adapts different hinting techniques. We have already implemented a prototype adaptive system for achieving adaptive hints that use semantic web techniques [34], but at present it only adapts some hint contents. As a future project, we would like to extend the system so that it can adapt the different hinting techniques. The final criteria and parameters for adapting the hinting techniques might use several of the different approaches which have been commented on in this section.

9. **Conclusions.** We have carried out two lab experiences with an Intelligent Tutoring System with approximately 100 students, each one of two hours in duration, regarding different hinting techniques. A summary of the main conclusions obtained are:

(1) The modification of some of the Intelligent Tutoring System's hinting techniques has an effect on the students' learning gains. Therefore, the selection of the hinting technique that is more suitable for each case cannot be made randomly, and learning systems should pay attention to which hinting techniques they provide to students.
(2) What results in better learning gains are not always the same configurations of hinting techniques for Intelligent Tutoring Systems, and this depends on several factors. For this reason, there is a need for adaptation of the hinting techniques.
(3) There is a high diversity of student responses regarding the different survey's answers related to hinting techniques. This is another clue to the need for adaptation of the hinting techniques.
(4) The adaptation of the hinting techniques (in order to obtain the best learning gains for each case) might depend on the topics addressed, the design of exercises/hints, or the students' profiles.

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