Do Learning Styles Influence the Way Students Perceive Interface Agents?

Eliseo Reategui
Faculdade de Educação
UFRGS
Rua Paulo Gama, 110
90040-060 Porto Alegre, RS
Tel: 55 51 33 08 37 39
eliseoreategui@gmail.com

Cláudia Zattera
Departamento de Informática
Universidade de Caxias do Sul
Rua Francisco Getúlio Vargas, 1130
95070-560 Caxias do Sul, RS
Tel: 55 51 32 18 21 00 ext. 2264
crzatter@ucs.br

ABSTRACT
This paper presents an interface agent, designed for a virtual learning environment, whose main capabilities are to communicate with users in natural language and to promote collaboration by inciting students to help each other. An experiment was carried out with 72 university students to assess the effectiveness of the interface agent regarding its ability to improve students' performance, to influence students' perception of their learning experience, and to involve students in collaborating with each other. Furthermore, the students were classified by their learning style, according to the Felder-Silverman model [6]. We then evaluated if different learning styles could produce different results because of the way students perceived the interface agent. The results of the experiment are presented here, as well as conclusions and direction for future work.

Categories and Subject Descriptors
H5.2 [Information interfaces and presentation]: User Interfaces. Graphical user interfaces

General Terms
Experimentation, Human Factors.

Keywords
Interface agents, recommender systems.

INTRODUCTION
The integration of interface agents with different types of communication skills in human-computer interfaces has spread both in academic and commercial spheres [15]. Within these applications, many recent examples can be found in Education. Ashori et al. [2], for instance, present a pedagogical agent, called Mentor, who acts as a teacher and interacts with other agents in order to monitor the progress of the students in learning activities. In MathGirls [10], an interface agent specially designed for the interaction with girls, helps young students in learning algebra, getting them to actually improve their performance. Other earlier experiments have also shown that the presence of the human figure can have a positive effect in the interactive experience of users. André et al. [1] verified that students considered a subject studied significantly less difficult and the presentation more entertaining in the presence of an interface agent. Moreno and Mayer [14] demonstrated that the inclusion of a pedagogical agent had a positive effect on students' interest and transfer.

However, none of these studies considered whether students may react differently to interactive interface agents depending on their ***learning style***. These styles define how people perceive and process information, how they interact with each other and learn. Among all the models that categorize people's learning styles, such as Kolb [11], Myers-Briggs [19], Riding [18], Felder & Silverman [6], we opted for investigating the latter. We believe that this model can provide guidance on how a particular interface agent may impact on different individuals using a virtual learning environment. Felder & Silverman's model is divided in four dimensions:

- *Active* and *Reflective*: People classified as *active* tend to learn better by practicing actively with the subject being learned, by discussing, and/or explaining it to others. People classified as *reflective* tend to think about the subject being studied quietly at first.
- *Sensing* and *Intuitive*: While *sensing* learners prefer to learn facts, *intuitive* learners often favor the investigation of new possibilities and relationships.
- *Visual* and *Verbal*: People classified as *visual* remember best what they see (such as pictures and diagrams). *Verbal* learners, on the other hand, prefer to learn through written and spoken explanations[1].

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[1] Although people are classified in the model either as *visual* or *verbal*, Felder and Soloman [7] state that people learn more when information is presented both ways. Other researchers have also come to the same conclusion, such as Richard Mayer [13] in his theory of multimedia learning.

- *Sequential* and *Global*: *Sequential* learners prefer to study in linear logical steps. *Global* learners favor to learn by looking at the subject in an almost random manner. Then, suddenly, they understand the meaning of what they were studying and relate it with other matters.

This paper presents an experiment carried out with 72 university students, contrasting their learning styles with the way they perceive an interface agent in a virtual learning environment.

Our agent had particular features, such as the ability to communicate in natural language and to promote collaboration by recommending students to interact with each other. Our premise was that the simple presence of an interface agent could have a distinct influence on the way students with different learning styles perceived the information present in the virtual learning environment.

The next section of the paper presents the interface agent employed in the experiment, detailing its mechanisms to communicate with the user in natural language. Section 3 explains the interface agent's technique for finding student tutors, based on performance, social and affective data. Section 4 presents the experiment designed to evaluate how the students with different learning styles reacted to the interface agent. Section 5 discusses the experiment's results and the use of personified interfaces, and the final section presents conclusions and directions for future work.

THE INTERFACE AGENT

Our interface agent had as a main goal to answer questions about algorithms and to promote collaborative learning by getting students to help each other. The knowledge base of the interface agent stored knowledge about algorithms, enabling it to assist students mainly in theoretical questions. The Artificial Intelligence Markup Language (AIML) was used to represent the agent's conversational knowledge [21], employing a mechanism of stimulus-response. The stimuli (sentences and fragments which could be used to question the agent) were stored and used to search for pre-defined replies. The most important AIML tags are:

<aiml>: indicates the beginning of a document.

<category>: the simplest knowledge unit in AIML. Each category consists of an input question, an output answer and an optional context. The question, or stimulus, is called the *pattern,* while the answer is called the *template*.

<pattern>: keeps a set of words which is searched for in sentences which the user may enter to communicate with the interface agent. The language that may be used to form the patterns includes words, spaces, and the wildcard symbols _ and *;

<template>: when a given pattern is found in the input sentence, the corresponding template is returned and presented to the user. In its simplest form, a pattern is a word and the template consists of plain text. However, the tags may also force the conversion of the reply into a procedure which may activate other programs and recursively call the pattern matcher to insert the responses from other categories.

The optional context of a category enabled the agent to remember a previous statement. This feature, together with the possibility of launching particular programs when a certain pattern is found, makes the AIML communication mechanism very distinct from a simple retrieval of questions and answers from a database.

In addition to the existing AIML tags, new ones were created to manage the agents' emotional appearance. For instance, we created the tag <humor> to control the image changes reflecting different moods of the interface agent (happy, calm, aggressive, etc). For each mood, several images were stored and selected at random, making the character more credible through a less repetitive behavior [8].

Therefore, when the user posed a question (stimulus), the character started the AIML Retrieval Mechanism in order to build an appropriate reply using the information, patterns and templates from the AIML database. A picture of the character was picked from an image database to match the sentence retrieved according to the humor tag.

In addition to being able to answer questions in natural language, the interface agent was also able to recommend students to interact with one another, as explained in the next section.

RECOMMENDING STUDENT TUTORS

Besides interacting with the user in natural language, the interface agent had the ability to identify students that could help others in certain activities proposed. The following information was used in this recommendation mechanism:

Mood: the mood of a person may vary several times a day, depending on a number of things that the person does. Even being successful in the majority of these actions, the mood of the person may be affected negatively, leaving the person with some sort of unpleasant emotional residue. The mood was used here to indicate whether the student could be recommended as a tutor in a certain moment, as a student in a bad mood could have more difficulty in helping others. The system did not try to infer the mood of the student, but it was informed at login time through a graphical interface, as shown in the figure 1. In this interface, besides the username (*usuário*) and password (*senha*) the user also had to inform how he/she was feeling through smiley faces that ranged from sad to very happy.

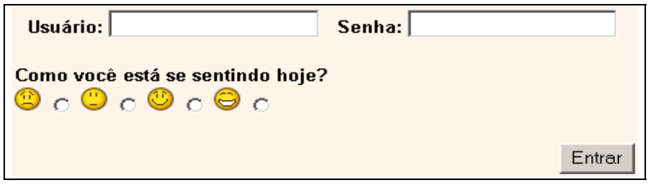

Figure 1: Login screen

According to the selection made by the user, the variable *mood* assumed values between [0,1], where 0 represented a bad mood and 1 a very good mood.

Performance: Represented the performance of the student in all the activities proposed. A higher number of tasks completed and higher marks denoted a better performance. Two relative performance degrees were used to infer the global performance level of the student. The first tried to measure the performance of the student during the whole course/discipline. The second tried to determine how well the student did in the particular topic for which help was being asked.

Acceptance degree: After a helping session, a small questionnaire was submitted to the student who got assistance, with the purpose of collecting information about the performance of the tutor. The questions presented were based on concepts from Social Networks and Sociometry, and could be answered by four qualitative values: "excellent", "good", "regular", and "bad".

Interaction average: This variable referred to the average of the total of communication attempts started by the student and replied by another one, and it could be computed as:

$$Ai = \frac{W1 * Ci}{GAi} + \frac{W2 * Cr}{GAr}$$

where Ai was the average of interactions of the student, Ci represented the number of communication attempts started by the student, GAi was the general average of communication attempts started by students, Cr was the number of communication attempts answered by the student and GAr was the general average of communication requests answered by students, while $W1$ and $W2$ were the weights attributed to consider the importance of each factor.

The final score of the student was obtained through a simple formula that computed the weighted sum of all the data considered for the recommendation of student tutors.

$$StudentScore = W1*Pf + W2*M + W3*Ac + W4*Ai$$

where Pf was the performance computed for the student, M corresponded to his/her mood, Ac was the acceptance level and Ai was the average number of interactions. In the specific case of the recommendation of student tutors, without trying to raise a discussion on the importance of each factor, all factors were multiplied by the same weight 1.

Promoting the interaction of students through the recommendation of student tutors is a collaborative learning practice supported by established pedagogical theories. It is said, for instance, that there is a higher intellectual demand when students are placed in collaborative situation than when they have to work on their own, and that group diversity may contribute positively to the learning process [20].

EXPERIMENTAL RESULTS

An experiment has been set up in order to evaluate the influence of the interface agent considering students' learning style. A total of 72 university students participated in the experiment, all of them enrolled in the discipline algorithms at the Computer Science Department of the University of Caxias do Sul, Brazil. The students were between 16 and 45 years old (mean average 21.2 and standard deviation 4,9). Out of the 72 students, 52 were men (72.2%) and 20 were women (27.8%). The students were informed that they would participate in an experiment related to what they were studying at that time. They were asked to solve a problem using the virtual learning environment ***Moodle***, where a course about algorithms was structured. The course contained all the topics covered in the discipline, including exercises and activities. Two interfaces were built for the course, one of them with the interface agent, and the other one without.

The students were divided into two groups:

- ***Group A:*** this was the control group, who worked with a standard ***Moodle*** interface without any interface agent (figure 2);
- ***Group B:*** this group used the virtual learning environment in which the interface agent was placed on the right hand side of the screen, as depicted in figure 3.

Figure 2: Control system without the presence of the interface agent

Figure 3: Interface agent introduced in the virtual learning environment

Both groups of students were asked to write an algorithm to generate prime numbers from 1 to 1000, using the Sieve of Eratosthenes – a method that was new to them. They had one hour to learn the method and to build the algorithm, and they could look for information about methods for finding prime numbers in the course itself.

During this process, the students could interact with one another. However, they were particularly instructed not to talk to each other aloud, in order to maintain the silence in the lab. Instead, they could interact with any other student logged in through the chat system available. Such guidelines were created to enable the monitoring of the students' interactions, which was necessary for the experiment.

Both versions of the interface created for the virtual learning environment were able to recommend the students to interact with other classmates, in order to promote collaborative learning. In case of the version with the interface agent, the agent itself made these recommendations. The version with no interface agent simply presented the recommendations as plain text, in the same place where the interface agent was located in the other version.

After finishing the algorithm, the students were asked to post their solutions online and to fill out the *Index of Learning Styles* questionnaire[2].

The following subsections present results on different research questions regarding the impact of the interface agent.

Verifying students' perception of their learning experience

After finishing their assignment, the students of both groups (A and B) were asked if they were able to learn the Sieve of Eratosthenes without the intervention of a teacher, by simply exploring the virtual learning environment and interacting with the interface agent (in the case of group B). Table 1 summarizes their answers.

Table 1: Students' perception about their own learning

	I did not learn at all	I did not learn a lot	I learned a little	I really learned	Total
Group A	10	3	1	21	35
Group B	2	1	1	33	37

This histogram presented in figure 4 shows the distribution of the answers for the same question.

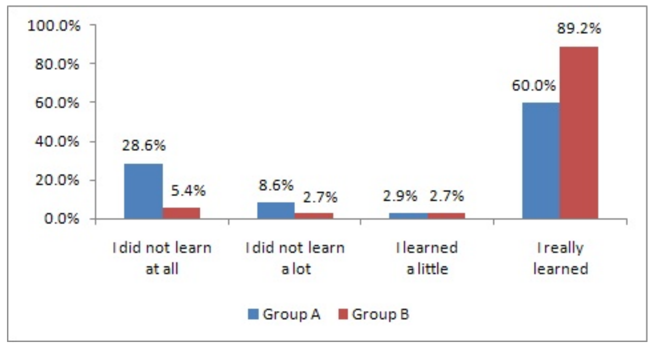

Figure 4: Students' perception about their learning

By looking at the results in figure 4, we can see that the vast majority of students in group B (89.2%) had the impression they really learned through their interactive experience with the learning environment and the interface agent. A much smaller proportion of students of Group A (60%) thought they truly learned by exploring the course in the virtual learning environment without the interface agent. Notice also a rather large number of students in this group stating that they did not learn at all (28.6%), against a much smaller proportion of students in Group B (5.4%).

The chi-square test was applied to the same dataset in order to verify whether the profile of the answers in each system was significantly different from the global profile of the totals computed above. The test result was significant, with $p<0.03$, attesting that in one or more columns the profile of answers was different from the global profile.

Table 2 shows the answers to this same question, according to the students' learning styles. However, here we re-binned the outcomes, integrating negative answers and positive ones. The purpose of this reorganization was to reduce the number of cells of the new contingency table, which had to consider now 8 different learning styles, and would produce very sparse results and a large number of null cells. Thus, the answers were integrated in the following way:

[2] The complete questionnaire can be found online in the following URL (june 2008): http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSpage.html

- *I did not learn at all*, and *I did not learn a lot* became ***I did not learn***
- *I learned a little*, and *I really learned* became ***I did learn***

Notice also that the total number of students in each dimension (*active/reflective*, *sensing/intuitive*, *visual/verbal, sequential/ global*) is always smaller than the total number of students who participated in the experiment (72 students). This happens because some of them remained in "grey" areas between two learning styles. In these cases, they could not be classified in neither of the categories.

Table 2: Students' answers according to learning style

	Group	I did not learn	I did learn	Total
Active	A	7 (70%)	3 (30%)	10
	B	0	13 (100%)	13
Reflective	A	0	3 (100%)	3
	B	2 (33.3%)	4 (66.7%)	6
Sensing	A	5 (38.5%)	8 (61.5%)	13
	B	2 (8.7%)	21 (91.3%)	23
Intuitive	A	0	2 (100%)	2
	B	0	0	0
Visual	A	6 (40%)	9 (60%)	15
	B	0	18 (100%)	18
Verbal	A	1 (50%)	1 (50%)	2
	B	0	0	0
Sequential	A	5 (45.5%)	6 (54.5%)	11
	B	0	9 (100%)	9
Global	A	0	3 (100%)	3
	B	0	2 (100%)	2

The majority of the students were *active*, *sensing*, *visual* and *sequential*. Among the *active* learners, 70% of the students in group A stated that they did not learn the Sieve of Eratosthenes method by doing the assignment, while only 30% of the students said they did learn. In group B, all the students claimed to have learned with the assignment (100%), which shows a positive influence of the interface agent. The chi-square test here gave a probability *p* tending to 0, indicating that the results were significant.

For the *reflective* students, all of them in group A said to have learned with the assignment. In group B, 33.3% said they did not learn, and 66.7% said they did learn. Here, we see a difference in the trend which favored the use of the interface agent. However, the probability computed for the chi-square test here was p=0.257, considering now only one degree of freedom. This means that the results were not significant (*p* should be smaller than 0.05 for significant results). We discuss more about these results in the next subsection.

Regarding the *sensing/intuitive* dimension, very few students were classified as *intuitive* – and all of them were in group A. For the students classified as *sensing*, 61.5% in group A stated that they did learn with the assignment, while a much larger proportion gave the same answer in group B (91.3%). Again we could see a difference favoring the use of the interface agent, although here the distinction between groups was not as big as in the *active learners'* group. Here, the chi-square test result was significant, with $p=0.03$. For the category *intuitive*, because of its extremely low number of students in our sample population (only 2 students), we did not carry any further analysis.

Concerning the *visual/verbal* dimension, the vast majority of students were classified as *visual*, with only 2 students being classified as *verbal*, both in group A. Thus, for category *verbal* no further analysis was carried out. For the students classified as visual, 60% in group A stated that they really learned, while in group B all of the students made the same statement (100%). These results once again favor the use of the interface agent. The result of the chi-square test here was significant, with $p= 0.003$.

As for the *sequential/global* dimension, very few people were classified as *global*, and there was no significant difference between their answers in groups A and B. For the students classified as *sequential*, group A was not so assertive about having been able to learn by exploring the virtual learning environment: only 54.5% said they did learn with the assignment, while in group B all of the students said they did learn. These results once again strengthen the hypothesis that the use of the interface agent may have a positive effect on the user's perception of their learning experience. The outcome of the chi-square test here gave a probability $p=0.02$, indicating a significant result.

Our next question was to verify whether the interface agent had an actual influence on the students' performance.

Assessing students' performance

The students' assignments were reviewed in order to asses their performance in solving the prime numbers problem. In this step, only the students with grades higher than 5.0 in their last examination were considered, as we knew that students with bad grades would not be able to solve the prime numbers problem neither with, nor without the presence of the interface agent. Thus, 28 students remained in group A (which we will call A') and 27 students remained in group B (which we will call B'). Table 3 shows, for each group, the averages of the students' grades in the discipline before making the assignment, and their grades in the actual assignment.

Table 3: Students' performance

	Average of grades in the discipline (0-10)	Average of grades in the assignment (0-10)
Group A'	8.16 (standard deviation 1.54)	2.73 (standard deviation 3.82)
Group B'	8.06 (standard deviation 1.62)	5.11 (standard deviation 4.55)

Although the students' grades in the discipline were very similar in both groups (8.16 in group A' and 8.06 in group B'), the students in group B' got higher marks in the assignment (5.11 against 2.73 for group A'). The high standard deviation in the assignment's grades, both in groups A' and B', was due to the fact that most of the students either did or did not understand the method for solving the prime numbers problem with the Sieve of Eratosthenes method. Table 4 shows the students' grades according to their learning styles.

Table 4: Students' answers according to learning style

	Group	Number of students	Grade Average (1-10)
Active	A'	8	1,57
	B'	12	5,46
Reflective	A'	3	3,33
	B'	5	6,80
Sensing	A'	8	0,62
	B'	15	4,93
Intuitive	A'	2	7,25
	B'	0	-
Visual	A'	14	1,93
	B'	16	5,40
Verbal	A'	1	10,00
	B'	0	-
Sequential	A'	9	2,72
	B'	5	5,90
Global	A'	3	3,17
	B'	1	0*

*the student handed in a blank assignment

The third column of table 4 shows that group A's averages are always smaller than those of group B'. The only dimensions where this is not observed are in the *intuitive* and the *verbal* categories, as there were no students classified as *intuitive* and *verbal* in group B' for these categories. The histogram in figure 5 shows the difference in grade averages observed for the dimensions where there were no null values for either group A' or B'.

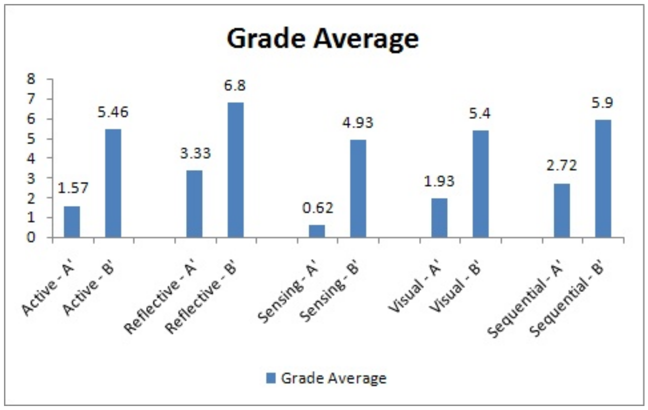

Figure 5: Students' grade averages for groups A' and B'

Although the highest grade averages can be found in the categories *intuitive* and *verbal* for students in group A' (please refer to table 4), the persisting difference showing higher scores in group B' demonstrate that the use of the interface agent had a positive influence in the students' performance for all categories in which there were a valid number of students for group B'.

Verifying how effective was the agent in promoting student collaboration

One of the most distinctive features of the interface agent developed in our research was its ability to promote collaboration by trying to get students to help each other. We monitored the student interaction while they made the assignment in order to assess how effective the agent was in getting them to collaborate. The information stored about the students' interactions was:

- the number of students who interacted in each group;
- the number of relevant interactions (as many conversations that took place through the chat tool were not related to the assignment);
- the number of students that indeed got help from their classmates.

Table 5 shows the results.

Table 5: Number of interactions between students

	Total number of students	Number of students who interacted	Number of relevant interactions	Number of students who were actually helped
Group A	35	26	24	20
Group B	37	18	18	14

The histogram in figure 6 shows a graphical representation of the data presented in table 5.

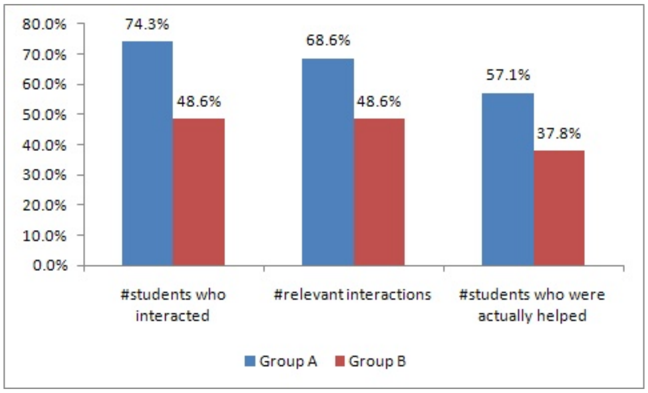

Figure 6: Students' interaction for groups A' and B'

The histogram demonstrates that the students that interacted the most were in group A, and their communication was also more effective as the students in this group talked more about relevant topics, and helped/got more help from other fellow students. Therefore, the introduction of the interface agent in fact did not help in promoting the collaboration among students. In fact, it produced the opposite outcome. The next section discusses these and other results, proposing further investigation on different topics.

DISCUSSION

The initial results in the experiment, regarding the students' perception on their learning experience, showed that the majority of students who considered they really learned through their assignment were students who used learning environment in which there was the interface agent. How can this be explained? Other previous research had already shown that students may consider a subject significantly less difficult and the presentation more entertaining in the presence of an interface agent [1]. Lester et al. [12] also showed the benefits of pedagogical agents, especially on what motivation is concerned. Here, our findings support this same hypothesis, i.e. that interface agents introduce social stimuli with a type of technology that is still unknown for students, and therefore intrigues them, makes them excited about their interactive experience and therefore motivates them in what they are doing.

Our second investigation question was whether the students learning styles had an influence on the way they perceived their learning experience – and whether the interface agent had an influence on their perception. In almost all of the dimensions (active, sensing, verbal, sequential, global) the use of the interface agent had a positive outcome on the way the students saw their own learning experience. The only situation where this did not happen was for reflective students. Although the results in the chi-square test were not significant for this particular analysis, we found interesting that a different trend seemed to be present here, and we believe this could be a subject for further analysis. A possible interpretation for this difference could be that, as active learners tend to like group work, the presence of the interface agent introduced a human component in the interface that had a positive effect. For reflective learners, who prefer to work on their own, the presence of this human figure (the interface agent) was a distracting factor that did contribute to their natural way of working and reasoning.

Our following investigation question was whether the interface agent had an actual impact on the students' performance, and not only on the way they perceived it. We realized from the results that group B', who interacted with the interface agent, had a much better performance than group A'. After the analysis of the students' learning styles, the same was observed, showing that the styles did not influence the students' performance (but again, no conclusion could be drawn for the categories intuitive and verbal, as there were no students in these categories for group B). Other previous research had already shown that the interaction with animated and static interface agents could affect students' learning [4]. If this is because of the actual help the agents bring, or because of the motivation they may produce in the users, it is not clear. Moreno and Mayer [14], for example, showed that a pedagogical agent could have a positive effect on students' interest. In MathGirls [10], it has also been demonstrated that students' performance got better with the introduction of a pedagogical agent. In fact, research on interest and motivation and their effects on learning already demonstrated, for a long time, that these are propelling forces that have to be present for learning to take place [9]. As for computational systems, Picard et al. [16] emphasized that new software should not only contemplate cognitive aspects, but also emotional aspects that may influence learning. Our results showed that the introduction of an interface agent could have a positive effect in a virtual learning environment, integrating cognitive and social-affective aspects that ended up by influencing the students' performance in a given assignment.

Our last investigation question tried to assess the effectiveness of the interface agent to promote student collaboration. The results of the experiment showed that the group of students who collaborated more was the one who used the virtual learning environment with no interface agent. Such a result surprised us at first, as our hypothesis was exactly the opposite. However, we realized that, given then circumstances, the students were not really encouraged to collaborate, as they were faced with a new and reasonably difficult problem, and they had a specific amount of time to finish their assignment. And it is also true that the presence of the interface agent may have intensified the pressure for students to finish their assignments on time, inhibiting them to interact with each other during the experiment. A similar effect has been reported by Rickenberg and Reeves [17], who showed that the presence of a character in a website could increase the user's confidence, even though it could also augment the user's anxiety.

CONCLUSION

This paper presented an experiment with a specific interface agent, which had as main features the ability to communicate in natural language and to incite students to collaborate with each other. The experiment carried out with the interface agent demonstrated that it had a positive impact in students' learning of a specific topic in algorithms, both in the students' perception of their learning experiences, and in their actual performance making a particular assignment.

In a certain way, these results confirm that interface agents may improve the communication between user and computer by introducing social stimuli, as claimed by De Angeli et al. [5]. Pandzic et al. [15] also demonstrated that people react more positively to services with animated characters then without. The authors also concluded that a service with animated characters is considered more human-like and provokes more positive feelings than another one with audio only.

Although it has been argued that questionnaires are not the best method to assess the effectiveness of novel interface approaches, we believe that the view users can give us through feedback forms can provide interesting insights on what works and what does not work in human-computer interaction. Such type of evaluation mechanism is still extensively used by the scientific community in the area, as in [3] where the authors found that animated characters could enhance consumer satisfaction by using affective usability questionnaires. Nevertheless, our results were based not only on questionnaires, but also on the analysis of the previous knowledge the students had in algorithms (we considered their grades in the discipline), and on what they learned in the experiment, by actually correcting their assignments.

The main contribution of this work has been to demonstrate that the model of interface agent developed in this research, which was capable of communicating in natural language and recommending student tutors, had a positive impact in students' learning. Another contribution has been to identify that students' learning styles did not influence the effectiveness of the interface agent, i.e. the agent had a positive impact for students with all learning styles - apart from *intuitive* and *verbal* learners, as there were no students in these categories in one of the groups tested. We could also conclude from the results of the experiment that the agent was not helpful in promoting student collaboration – and that it even had the opposite effect, inhibiting students' communication. However, because of the nature of the experiment, in which students had a certain amount of time to conclude an assignment, we believe that further investigation is needed. The interaction of the students with the interface agent and among themselves has to be monitored for a longer period to enable more categorical conclusions to be drawn in this respect.

For future work, our research group has been investigating how interface agents can be used not only to support students' work, but also to assist teachers. Evaluating the effectiveness of these agents in a distance education course will be one of our main goals, as in this modality teachers usually get overloaded with work because of all the communication with students that has to be done through the computer. We are trying to assign part of this work to an interface agent, who will organize the information to be presented to the teachers and who will also try to perform some of the tasks themselves, as sending warning to specific students about deadlines for posting their work, informing teachers about students' activity in the virtual learning environment, among other tasks.

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