The Mars and Venus Effect: The Influence of User Gender on the Effectiveness of Adaptive Task Support

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Abstract. Providing adaptive support to users engaged in learning tasks is the central focus of intelligent tutoring systems. There is evidence that female and male users may benefit differently from adaptive support, yet it is not understood how to most effectively adapt task support to gender. This paper reports on a study with four versions of an intelligent tutoring system for introductory computer programming offering different levels of cognitive (conceptual and problem-solving) and affective (motivational and engagement) support. The results show that female users reported significantly more engagement and less frustration with the affective support system than with other versions. In a human tutorial dialogue condition used for comparison, a consistent difference was observed between females and males. These results suggest the presence of the *Mars and Venus Effect*, a systematic difference in how female and male users benefit from cognitive and affective adaptive support. The findings point toward design principles to guide the development of gender-adaptive intelligent tutoring systems.

Keywords: gender effects, adaptive support, intelligent tutoring systems, affect, engagement, frustration.

1 Introduction

Effective adaptation to users during problem solving and learning is a longstanding goal of the user modeling community [17, 22, 30]. Adaptive learning environments, specifically intelligent tutoring systems (ITSs), are inspired by the adaptation of human tutors to student learners [5, 12]. This intelligent adaptation often focuses on knowledge and skill, relying on user modeling techniques such as knowledge tracing [17], constraint-based modeling [22], or reinforcement learning for strategies [11]. These models, which differentiate users primarily by the user-system interactions that unfold rather than by any characteristics of the user, have been proven highly effective not only for ITSs but more broadly within user modeling, e.g., detecting the manner in which learners interact with online content [6], modeling engagement with social games [7], delivering tailored content based on historical data [28], and estimating how much a student learns while browsing online materials [25].

While task characteristics can inform models of user interaction, recent findings suggest that characteristics of the *person* are more indicative of user behavior than characteristics of the *task* [23]. There is a growing body of evidence suggesting that individual characteristics such as personality profile [16, 29], cognitive processing ability [4], and level of expertise [13] influence the effectiveness of adaptive support.

Of all the learner characteristics that are known to influence the effectiveness of adaptive support, *gender* is one of the most widely recognized. Female and male students tend to differ in their receptiveness to feedback [1, 26], and although users of both genders have been observed to display strong affective responses to adaptive support, female students may particularly benefit from motivational scaffolding [10].

This paper examines the hypothesis that male and female students benefit most fully from different types of adaptive support. We focus on the crucial open question of how to most effectively balance *cognitive* support (pertaining to knowledge and problem solving) with *affective* support (pertaining to motivation, self-confidence, and engagement) [14, 27]. Design principles for cognitive and affective feedback have begun to emerge from the literature. For example, in addition to the effectiveness of task-based scaffolding mentioned above, there is evidence that adapting to affective states such as uncertainty [11] and confusion [16] leads to more effective tutoring. However, the results to date do not clearly provide a comprehensive set of design principles for gender-adapted problem-solving support.

Using an intelligent tutoring system that supports introductory computer programming, JavaTutor [21, 29], we conducted a study to examine the advantages and disadvantages of different forms of adaptive support for female and male students. Our study used four versions of JavaTutor: the *Baseline* version provided a problem-solving environment with learning tasks that built progressively upon each other, and the other three versions provided the same progressive learning tasks with additional adaptive support. The *Cognitive* version provided problem-solving feedback and hints, the *Affective* version provided motivational and engagement support, and the *Cognitive-Affective* version provided integrated cognitive and affective support. Results show that female and male users diverge in their responses to the different forms of support, particularly with respect to the important outcomes of frustration and engagement (discussed in detail in Section 2). We also compare these human-ITS conditions with a human-human tutorial dialogue condition from previously collected data within the same learning environment. The differences that emerge among these conditions by gender, taken in concert with findings from previous studies, reveal the *Mars and Venus Effect*, in which female and male users benefit differently from cognitive and affective adaptive support. The findings point toward design principles to improve future user-adaptive intelligent tutoring systems.

2 Related Work

This work builds upon related work on a body of empirical findings on gender and adaptive support during learning as well as on cognitive and affective support.

2.1 Gender and Adaptive Support for Learning

Previous studies have demonstrated that male and female students may benefit differently from adaptive support strategies. In a study with a mathematics tutoring system, female students tended to accept more of the tutor's feedback, spend more time referencing available learning aids, and engage in less gaming of the system than male students, especially when provided with an embodied tutorial agent [1]. Female students were also more engaged when provided with motivational scaffolding [2]. In studies with human tutors that work with mostly young adult learners in college, female students engaged longer and in more content-filled discussion with the tutor than their male counterparts [8, 26]. A study with learning companions found that female students' self-efficacy improved when the agent provided motivational scaffolding with corresponding nonverbal behaviors. Male students in that study were particularly frustrated when the agent displayed discordant verbal and nonverbal behaviors [10]. These studies have spanned age groups and reveal important conditions in which gender may influence the perception and effectiveness of support.

2.2 Cognitive and Affective Goals

It is widely recognized that the most effective adaptations take into account both cognitive and affective considerations of learners; yet, an inverse relationship has sometimes been observed between these considerations. In one study within a middle school group, as students became more comfortable with the task (an affectively positive outcome), the students learned less content (a cognitively negative outcome) [27]. In another study, the more frustrated a student became with the complexity of the task, the higher the learning gain displayed at the end of the activity [18].

When university students were offered content feedback, progress feedback, both, or neither, the amount of content feedback was directly correlated with the student's learning gain at the end of the session; further, these students tended to display higher levels of frustration and lower levels of engagement [20]. In another study with university students, more tutor encouragement and praise were associated with increased student self-efficacy but lower overall learning [9]. Additionally, students who were offered purely cognitive feedback had the highest learning gains, even over those who were provided both cognitive and motivational feedback.

This body of empirical findings highlights the complex relationship between cognitive and affective concerns. In addition, the categorization of affective states as "positive" or "negative" with respect to learning is not straightforward. There is growing agreement that some amount of student confusion is not detrimental [3], but rather necessary for learning [14]. Theories related to affect in learning provide insight into these phenomena: flow theory suggests that a balance between perceived skill and perceived challenge is the optimal psychological state for student engagement and learning gain [15], and the theory of cognitive disequilibrium proposes that students enter this often-productive state when attempting to understand new ideas [14].

The present study builds upon this body of prior research in order to better understand how to support students of different gender. Male and female students interacted with four different versions of an intelligent tutoring system, which provided cognitive, affective, cognitive plus affective, or no adaptive support. Their resulting learning gain, frustration, and engagement outcomes identify important differences between male and female users and could have far-reaching implications for the design of user-adaptive support.

3 Studies

To investigate gender-specific adaptive strategies, we conducted two studies in which male and female students interacted with one of several versions of a tutorial dialogue system. This section details the two studies. One is a human-human tutorial dialogue study in which human tutors and students interacted through synchronous problem-solving interfaces with textual dialogue. The second is a human-ITS study conducted in the same problem-solving environment with four different levels of automated cognitive and affective support.

We hypothesized that female and male students would respond differently to cognitive and affective support, and moreover, that there would be significant differences between the human-human and human-ITS studies based upon gender. This section presents the results of analyses to investigate these hypotheses. In particular, we examine the relationship between gender and the outcomes of learning gain, frustration, and engagement.

3.1 Participants, Learning Tasks, and Data Sources

In both the human-human and human-ITS studies, participants were undergraduate students recruited from an introductory engineering course in exchange for course credit. No previous computer science knowledge was assumed or required, and students who reported taking a formal computer science course in the past were not included as participants, since our goals were to investigate adaptive support for novices.

Using a problem-solving environment purpose-built for this project (Figure 1), the students completed a series of programming tasks centered on the creation of a simple text-based adventure game. The problem-solving interface displayed the learning tasks in the upper left, a code editing window beneath that, and the results of compilation or execution of the students' program at the bottom. On the right hand side of the interface was the tutorial support window with textual interactions. Students were presented with subtasks in a succession designed to support them in completing the text-based adventure game and in learning the target concepts (e.g., variables, conditional logic, and iteration). There were five separate problem-solving sessions, and the students' solution built on itself from session to session.

Prior to each tutorial session, each student was administered a content-based pretest. The pretest consisted of a set of multiple-choice and free response items closely aligned to the concepts and skills for that day's learning tasks. After working within the problem-solving environment (and receiving adaptive support while doing so if the student was in an adaptive support condition), students completed a posttest identical to the pretest.

After each problem-solving session, the students also completed a post-session survey intended to gauge their engagement and affective outcomes including frustration. The survey included a validated User Engagement Survey [24] and the validated NASA-TLX workload survey [19], which includes an item on frustration. The frustration item within the NASA-TLX workload survey was of particular interest for the current study as prior work has shown that frustration has a significant impact on student learning [3].

3.2 Human-Human Tutoring Study

In the human-human tutoring study, each tutor and student pair interacted through the remote tutoring interface (Figure 1) with problem-solving tasks and textual dialogue. Human tutors ($N = 5$) were primarily graduate students with prior experience in teaching or tutoring introductory programming. Tutors were not constrained to scripts or protocols, but were encouraged to provide problem-solving support for the task at hand as well as broader concept-knowledge support, both of which are types of cognitive scaffolding. The tutors were also encouraged to provide motivational scaffolding whenever they felt that it would be helpful in order to improve the student's engagement, interest, or affective state.

There were 67 students in the human-human tutoring study, 24 of whom (36%) were female. Their average pretest score was 50.87%, and their average posttest score was 76.67%, reflecting a statistically significant learning gain ($p < 0.0001$).

3.3 Adaptive Support Conditions Study

The human-ITS study included 78 novice computer science students, 23 of whom (31%) were female (two students did not report gender, and were excluded from the analyses on gender). Students were randomly assigned to interact with one of the four versions of the system during the same series of five problem-solving sessions that were utilized in the human-human study described previously. The *Baseline* version of JavaTutor consisted only of the problem-solving environment

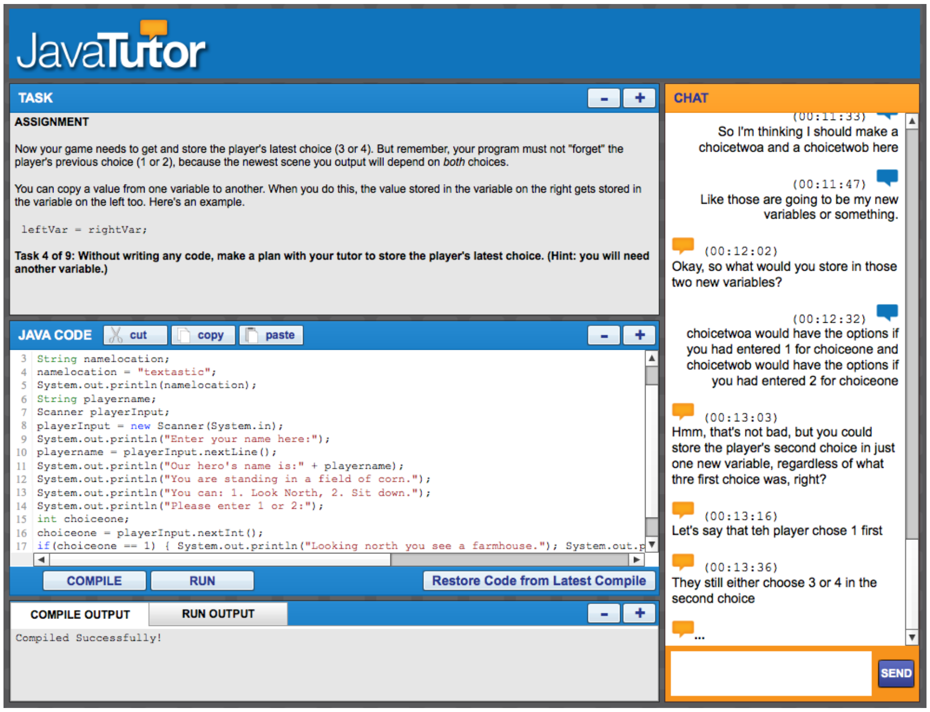

Fig. 1. The web-based interface for introductory Java programming.

with its series of subtasks, and no adaptive support; the adaptive support conditions were *Cognitive*, or problem-solving, support; *Affective*, or motivational, support; and a combination of both, which we refer to as the *Cognitive-Affective* condition. All of the adaptive support was delivered as textual utterances within the interface (Figure 1).

The adaptive support in JavaTutor was built over the past several years relying upon a combination of machine-learned models of effective human tutoring from the human-human study described previously, along with handcrafted models of affective support, since the human tutors did not extensively employ affective strategies, as we will discuss later. The timing and content of the support was determined by this suite of machine-learned classifiers and handcrafted policies, triggered by events such as success or failure of the students' program to compile, correct or incorrect programming task actions, or periods of inactivity. Examples of cognitive and affective support offered to the student by JavaTutor are displayed in Table 1.

In the human-ITS study, the average pretest score was 51.08%, and the average posttest score was 65.46%. This difference was highly statistically significant ($p < 0.0001$).

Cognitive Support	Affective Support
The Scanner lines allow you to get input from the player.	Alright, great work! You're doing a great job.
Note that variable names cannot contain spaces.	Congratulations on writing your first program!
There were no errors, so you have completed the task.	Don't give up! You'll get it if you keep trying.
Now, your variable has a value stored in it.	It's okay to make mistakes because each mistake is a chance to learn.

Table 1. Example cognitive and affective scaffolding utterances provided by the JavaTutor ITS to the students.

4 Analysis and Results

In order to compare the ways in which male and female students responded to cognitive and affective scaffolding across the conditions, we compared the outcomes between conditions and by gender.

Learning gain was calculated as the difference between a student's posttest score and pretest score for each tutorial session. Frustration score was taken from the Frustration Level scale of the NASA-TLX workload survey [19], administered after each session (Scale 1-100). Engagement scores were calculated as the sum of three sub-scales of the User Engagement Survey [24]: Focused Attention (perception of time passing), Felt Involvement (perception of involvement with the session), and Endurability (perception of the activity as worthwhile) (Scale 1-85). Each student's average learning gain, frustration, and engagement were computed as the average of these values for that student across all five tutoring sessions. The statistical comparisons reported in this section were conducted with the Tukey-Kramer test, which includes a correction for multiple hypothesis testing.

4.1 Learning Gains

The results in Table 2 reveal that students in the human-human tutorial dialogue study learned significantly more overall than in any of the human-ITS conditions ($p < 0.001$). Additionally, the *Cognitive-Affective* condition saw significantly lower learning gains than either the *Cognitive* or *Affective* conditions alone ($p < 0.05$). There was no significant difference in learning gain between genders under any condition ($p > 0.05$).

4.2 Frustration

As shown in Table 2, the human-human condition was significantly less frustrating than any of the human-ITS conditions ($p < 0.0001$). However, mirroring the

	Learning (1-100)		**Frustration (1-100)**		**Engagement (1-85)**	
	Female	Male	Female	Male	Female	Male
Baseline	10.14	14.03	***51.87**	**29.01**	63.13	59.69
Cognitive	16.13	15.01	***59.69**	**35.05**	58.47	57.85
Affective	10.86	15.87	31.74	39.42	**63.94**	**59.03**
Cog-Aff	9.42	13.44	27.31	39.24	58.50	56.63
Human	22.82	21.21	**19.54**	***13.30**	*51.61	*53.28
Overall	17.49	17.50	30.91	25.55	56.21	56.13

Table 2. Student learning gain, frustration, and engagement. Asterisks (*) denote significant differences between conditions; boldface denotes significant differences between genders. *Baseline*, *Cognitive*, *Affective*, and *Cog-Aff* denote type of ITS support; *Human* indicates human tutor support.

negative result of the *Cognitive-Affective* ITS condition for learning gain, the *Cognitive-Affective* condition was reported to be the most frustrating of all the ITS conditions ($p < 0.001$).

The results reveal significant differences in frustration across genders. Two of the ITS conditions, *Baseline* and *Cognitive*, as well as the *Human* condition, were more frustrating for females than males ($p < 0.0002$). These ITS conditions are the two in which no adaptive affective support was provided.

Across human-ITS conditions, female students were least frustrated when the automated tutor included affective feedback, that is, in the *Affective* and *Cognitive-Affective* conditions ($p < 0.0001$), while male students found all ITS conditions equal in terms of self-reported frustration ($p > 0.05$).

4.3 Engagement

As shown in Table 2, both male and female students reported lower engagement scores under the human condition than under any of the automated conditions ($p < 0.0001$). Importantly, the lower reported engagement in the human-human condition did not correspond to lower learning (in fact, the opposite was true).

Analogously to the finding with frustration, female students responded more positively to the *Affective* ITS condition than did males ($p < 0.05$), reporting higher engagement. The gender difference on engagement was not observed with the other ITS conditions.

5 Discussion

Results of this analysis confirmed that cognitive and affective support during problem solving were perceived differently by female and male students. First, while there were differences in learning between conditions, there were no significant differences in learning between genders. Male and female students achieved statistically equivalent learning gain in each condition, including all four human-ITS conditions as well as the human-human tutoring condition. The fact that female students learned at the same rate as male students under these conditions is consistent with some findings in previous studies suggesting that males and females may not need different *cognitive* support (e.g., [1]).

The findings are consistent with many prior studies comparing human tutoring to ITSs [17, 30]: students learned more with human tutors but also learned significantly with the ITS. However, perhaps counter-intuitively, the *Human* condition was more frustrating for females than males. This finding is likely due in part to the fact that despite encouragement to provide affective and motivational support to students, even our experienced tutors very rarely engaged in utterances that were not task- or concept-related. The scarcity of affective support in the *Human* condition may be the reason that female students were more frustrated with the human tutors than male students were. This notion is supported by the fact that female students found the two ITS conditions that had no affective feedback (*Baseline* and *Cognitive*) to be more frustrating than did male students.

Lower engagement scores were observed for students of both genders when working with human tutors than with ITSs. Human tutors' textual dialogue moves were more varied in nature than those provided by the ITS and therefore may have more easily taken the students' attention from the task, which may have reduced the feeling of involvement and focused attention. Interestingly, students participating in the human-human condition demonstrated a correlation between lower engagement scores and *higher* learning gain. This result, coupled with the lower learning for the *Cognitive-Affective* condition, is consistent with both theory and emerging empirical findings, which suggests that it is challenging to address simultaneously both cognitive and affective concerns. If cognitive scaffolding works, and affective scaffolding works, it is not necessarily the case that combining these two will work better.

The findings highlight important differences between males and females with regard to the importance of adaptive affective support. Female students were significantly less frustrated and significantly more engaged when provided with affective feedback than without. On the other hand, the presence of affective support did not significantly change the male students' frustration or engagement levels.

Design Implications. Although future studies will continue to elucidate the phenomena observed here, the current results suggest a set of design implications for gender-adapted systems. First, the current results taken in concert with prior findings from the literature indicate that in the face of limited resources for adaptive system development, creating separate cognitive support strategies by gender may not be necessary. Second, the results suggest that if system development resources are available to implement affective scaffolding in any form, it should be done: even if this scaffolding is not delivered in a gender-adaptive way, it benefits female users while not negatively impacting male users. Finally, the ideal design of gender adaptation appears to be greater affective scaffolding for females than for males, though identifying the ideal balance and types of support by gender is a crucial area for future study.

6 Conclusions and Future Work

A growing body of findings suggests that user gender should be considered as we design adaptive scaffolding for problem solving. This paper has reported on a study that examined the difference in outcomes, in terms of learning gain, frustration, and engagement, for female and male students engaged in learning to solve computer science problems. The results show that both groups benefited equally from all types of cognitive support studied, but that female students tended to become significantly more frustrated and less engaged than male students in the absence of affective support. The *Mars and Venus Effect* was observed not only with automatically generated ITS support, but also in a study with experienced human tutors. One clear design implication for adaptive systems is that we should take great care to support female students' affective states that are conducive to learning because, while we may measure statistically equivalent learning gain, the perception and memories taken away from the problem-solving experience will likely influence the students in the future.

There are several directions that are important for future work. As indicated by the results presented here, the disproportionate benefit of affective support for females is a phenomenon that is particularly important for future study. The current study has examined different types of affective support related to motivation and self-efficacy, but there are many highly promising types of affective support that hold great promise for users of both genders, and could continue to improve dramatically the effectiveness and personalization of intelligent learning environments. Additionally, along with gender, the community should examine ways in which learning environments can tailor their adaptive support to other influential learner characteristics, such as personality. Given the tremendous increase in at-scale learning and its corresponding collections of "big data" for problem solving, the user modeling field has the opportunity to learn fine-grained adaptive models that reach beyond one-size-fits-all task support and instead adapt highly to each individual. It is hoped that this line of research will tremendously increase the effectiveness of adaptive support for learning.

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