Investigating the Influence of Affective State on Help-Seeking: A Study with Novice Programmers

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Abstract. *The research investigates how specific affective states, such as frustration, boredom, and anxiety, influence help-seeking behaviors in programming problem-solving activities. Carried out with 73 beginner programming students divided into two CS1 classes, the study uses an interactive learning environment to collect and analyze data from student interactions. The results reveal that negative affective states are significantly associated with the search for hints that offer ready-made answers to problems. One of the conclusions from these results is that negative affective states can motivate students to prefer quick and less challenging solutions, emphasizing the importance of considering the affective dimension in the design of interactive learning environments.*

Resumo. *A pesquisa investiga como estados afetivos específicos, como frustração, tédio e ansiedade, influenciam os comportamentos de busca de ajuda em atividades de resolução de problemas de programação. Realizado com 73 alunos iniciantes em programação divididos em duas turmas CS1, programação introdutória, o estudo utiliza um ambiente de aprendizagem interativo para coletar e analisar dados das interações dos alunos. Os resultados revelam que estados afetivos negativos estão significativamente associados à busca por dicas que oferecem respostas prontas para os problemas. Uma das conclusões obtidas destes resultados é que que estados afetivos negativos podem motivar os alunos a preferir soluções rápidas e menos desafiadoras, enfatizando a importância de considerar a dimensão afetiva no design de ambientes de aprendizagem interativos.*

1. Introduction

The first experience of learning programming for many students is often frustrating, sometimes leading to high rates of academic failure on the part of these students [Bennedsen and Caspersen 2019]. In this sense, some of the authors point to the difficulties of introductory programming, treating it as a subject considered difficult to learn and teach [Sheard et al. 2009]. Thus, as part of the attempt to clarify possible factors that motivate these alarming rates, some studies focus on the influences of affective states, particularly negative ones, such as frustration, boredom, and anxiety, impacting novice programmers [Kinnunen et al. 2007]. Other studies link the affective state

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of confusion and boredom to poor performance in introductory programming courses [dos Santos et al. 2022].

From another perspective, it can be seen that, for novice programmers to achieve good performance in programming problem-resolution activities, there may be a search for help. In other words, these students will demand hints or feedback from a human or virtual tutor. Therefore, feedback is considered an important resource in the teaching-learning process, particularly in problem-solving activities, helping students identify shortcomings, evaluate their learning progress, as well as progress throughout the course [Bennedsen and Caspersen 2019].

Given the context above mentioned, some computing education researchers have been looking for ways for computing teachers to better support their students [Joni et al. 1983]. Still, it is often a challenge for computing educators to recognize performance indicators decreasing and help students overcome learning problems. For example, within the affective dimension, it appears that a state of confusion occurs when a student receives unexpected feedback [Yang et al. 2016]. With the spectrum of possible ways a student can react to difficulties (both affective and behavioral), it is important for educators to know which behaviors and affective states they should be most attuned to. In this sense, it is necessary to understand the affective states most related to the help-seeking behavior of novice programmers. Therefore, in this article, we developed an experimental study with the objective of investigating how specific affective states, such as frustration, boredom, and anxiety, influence help-seeking behaviors in programming problem-solving activities, specifically addressing the following research questions:

Research Question 01: What are the most frequent **positive** affective states in novice programmers who seek cognitive feedback during programming problem-solving activities?

Research Question 02: What are the most frequent **negative** affective states in novice programmers who seek cognitive feedback during programming problem-solving activities?

By answering these two research questions, we present results that are potentially suitable to provide support for the task of developing feedback in future research, given that it is crucial to progress in the course to provide effective and adapted feedback to these students.

2. Contextualization and Related Work

Virtual learning environments, such as intelligent tutoring systems, often allow students to have control over deciding when and how to use the system's intelligent and non-intelligent feedback features[Aleven and Koedinger 2000]. This means that students must judge when feedback is needed and the appropriate way to apply the feedback.

Smart hint messages and feedback can help students reduce unproductive time and thus learn more efficiently [Anderson et al. 1989]. When read carefully, the content of the messages can help students fill gaps in their knowledge. In this way, the student is a better judge than the system when deciding whether help is needed, as the system is not yet able to access the students' thoughts and may not have a complete enough domain model [Aleven and Koedinger 2000]. Although there are systems that decide when to provide feedback to the student, systems that allow students to judge the appropriate time are still very common.

For some authors, the system should intervene as little as possible and help should only be provided upon request [Burton and Brown 1979]. However, to do this, the student will have to judge for himself situations such as, for example, a mistake is just a slip and easily repaired or it is due to lack of knowledge or the result of guesswork [Baker et al. 2004]. Furthermore, there is consensus that students have different characteristics and skills, with evidence that such skills are not mastered by everyone. Therefore, it is not clear that putting control in the hands of the learner is always the best strategy [Aleven and Koedinger 2000].

2.1. Affective States in Problem Solving

The investigation of on affective states aspects within the learning process, particularly in tutoring systems, represents a continually evolving area of research. Extensive efforts have been directed towards understanding the intricate relationship between cognitive aspects and emotional states [Barrett 2009]. In the domain of computer programming, novice programmers commonly encounter both cognitive and emotional challenges [Grover and Basu 2017, Pardos and Heffernan 2014]. Cognitively, beginners often struggle with problem-solving tasks, including the formulation, execution, and evaluation of solutions [Medeiros et al. 2018].

However, the learning hurdles in programming extend beyond the cognitive realm and permeate the affective dimension. Emotions have garnered significant attention in academic contexts, with boredom, confusion, pleasure, and frustration being prominent focal points [Pekrun et al. 2016]. Consequently, a novice programmer's problem-solving endeavors can be significantly influenced by a spectrum of affective and mental states. For instance, unexpected feedback can induce confusion among students [Yang et al. 2016]. Moreover, shifts in affective states often manifest in cognitive performance, with studies linking affective states to novice programmers' final performance [Ovans , Kumar and Pal 2008]. High-arousal states like pleasure or fear have been associated with enhanced programming performance [Khan and Siddiqi 2007]. Additionally, a study during the COVID-19 pandemic shed light on the affective state of motivation among programmers [Tek and Ertekin 2018].

In a study by Bosch and D'Mello [Bosch and D'Mello 2013], the prevailing emotions among novice programming students were investigated, alongside their relationship with behavior and academic performance. Participants assessed various emotions during the programming process, ranging from basic emotions to learning-related ones. Results indicated that students commonly experienced a state of flow/engagement, followed by confusion, frustration, and boredom. Similarly, Chetty and Van Der Westhuizen [Chetty and Van Der Westhuizen 2013] explored students' emotional experiences when grappling with challenging concepts. Emotions such as anxiety, fear, confusion, and despair were identified as typical responses to difficult concepts. Recognizing these emotions is crucial for educators in providing appropriate support during challenging learning moments.

Against this scenario, numerous researchers have endeavored to develop solutions for identifying novice programmers' emotional states during programming activities. Vea et al. [Vea et al. 2017] developed a model to detect negative emotional states, particularly boredom, confusion, and frustration, among C++ learners. The detection relied on participants' typing patterns and mouse movements, although detection of reduced frustration levels proved challenging. Another study employed machine learning algorithms to predict emotional states among university students engaged in programming tasks of varying difficulty levels [Liu et al. 2018]. Features derived from keyboard and mouse logs were utilized for emotional state classification, albeit some researchers caution against relying solely on log measures to capture emotional processes accurately [Munshi and Hussain 2018]. Self-reports have also been explored as an alternative approach, with Harley et al. [Harley et al. 2013] reporting a 75% agreement rate between self-reports and video-based emotion detection. Thus, this article considers the emotional states reported by students within the learning environment during its utilization.

3. Methods

The research described in this article is part of a project carried out in four distinct stages: development of the virtual learning environment, approval of the project by the ethics board, data collection, and analysis of this data.

The developed learning environment will be detailed in Section 3.1. In this environment, programming students can record their affective states as they solve the proposed problems. Affective states that can be recorded include negative affective states (frustration, boredom, and anxiety), positive affective states (pleasure, motivation, confusion, and challenge), and neutral states. It is important to mention that half of these emotional states were identified as being relevant during the learning process [Craig et al. 2004], which led several other learning environments to adopt part of this set in their approaches [Karumbaiah et al. 2019]. Furthermore, it is important to highlight that, given that this research involves collecting and analyzing data from interactions with students, the researchers submitted the project to the local ethics committee, which approved the study. Only after this approval did the research proceed to the subsequent stages, which included data collection and analysis. The following subsections will detail the materials and methods used to conduct this research. This includes information about the study participants, the data collection instrument used, and how the data obtained was processed.

3.1. Materials

The ADA environment [1], serves as a learning platform for introductory programming courses. Developed with a focus on pedagogical effectiveness, ADA adheres to a well-defined conceptual framework comprising key elements: class, sessions, problems, alternatives, attempts, hints, code, subjects, and affective state. In ADA, a class is associated with a group of students and problem-solving sessions. Four hints and multiple alternatives accompany each problem. Students are encouraged to make multiple attempts at problem-solving. The platform offers various features geared toward facilitating programming learning.

One crucial feature is the problem solver, enabling students to submit partial or complete solutions for each problem. For partial solutions, students address specific questions related to problem-solving techniques, while for complete solutions, they write actual programming code. Another notable feature is the provision of hints to aid students

[1] https://ada-projeto.vercel.app/

in their problem-solving journey. Hints are categorized into different levels, each offering increasingly specific guidance corresponding to the problem's stage. Beginning with abstract hints, the progression leads to more direct suggestions, ultimately guiding students to the solution. Importantly, students can request hints at any time during problem-solving, enhancing their learning experience.

3.2. Experiment

The research described herein was conducted during the first semester of 2023 and involved students from two second-year technical high school classes situated in the interior of Northeast Brazil. The experiment spanned eight sessions, evenly distributed between the two classes. Initially, 112 students participated in the first block of sessions (averaging 57 students per class), followed by 99 students in the second block (averaging 49.5 students per class), 91 students in the third block (averaging 45.5 students per class), and concluding with 73 students in the last block (averaging 36.5 students per class), comprising 40 females and 33 males. The age of students ranged from 16 to 18 years old, with 31 identifying as of African descent and 42 as white or of Asian descent.

3.2.1. Procedure

The problem-solving sessions were conducted in person in two computer laboratories, at different times, with one student per computer. Each laboratory was organized into five vertical rows of seven computers. In addition to the students, two researchers were present in each laboratory. The experiment was applied throughout the computer programming classes (sessions).

For each class, the experiment took place in three stages: pre-test, intervention, and post-test. In the pre-test, the first session was subdivided into 30 minutes for presentation and 70 minutes for problem-solving. During this period, the objectives of the study were explained to the students, consent forms for participation in the experiment, by ethics committee guidelines, were distributed, and a comprehensive explanation of the tool's functionalities was provided. Special emphasis was placed on explaining the meaning of each affective state. In addition, students used ADA to register. After the introductory session, participants engaged in two more sessions (100 minutes) of problem-solving using the ADA environment.

4. Results and discussions

In this Section, we present the results and discussions through exploratory analysis of our dataset and follow with a discussion addressing the research questions announced in the introduction of this article.

4.1. Exploratory Data Analysis

In the exploratory data analysis, we investigated the relationship between the requested hints and the reported affective states, taking into account the number of problem-solving attempts and the students involved.

Figure 1 illustrates the correlation between the percentage of requests for each hint level and various affective states. Our analysis reveals that during states of frustration

(19.0%), anxiety (56.8%), and boredom (38.3%), there is a higher percentage of requests for hints 1 and 4. Conversely, in the emotional state of confusion, there is a notable increase in the percentage of requests for hint 4.

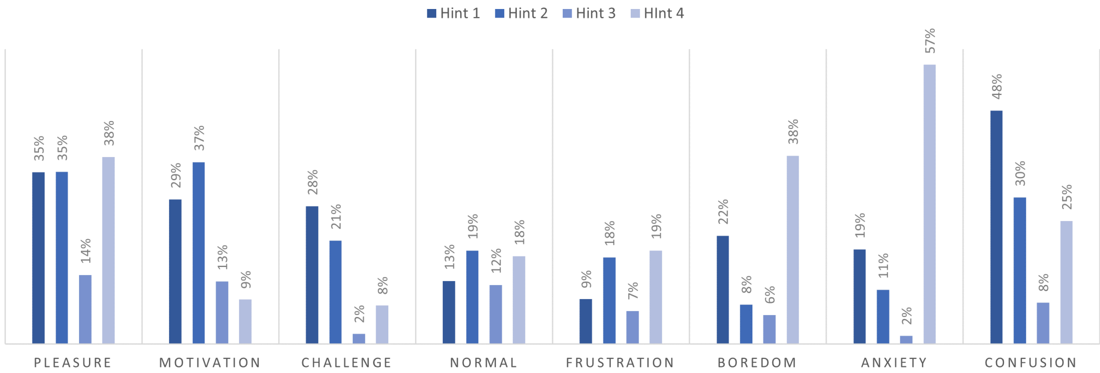

Figure 1. Percentage of Hint Requests by Affective State

Figure 3 shows the distribution of the number of students who requested each level of hint during a given period. The numbers indicate how many students chose to request a specific hint, with Hint 1 being the most requested hint, followed by Hint 4. Hint 2 and Hint 3 received fewer requests compared to the others. Furthermore, the figure shows that only three students did not request any hints during the period analyzed. The figure reveals interesting patterns of student behavior about the hints provided, especially considering that hint 4 contains the answer to the problem. Notably, hint 4 was requested by 53 students, representing a significant proportion of the total requests. This suggests that many students chose to access the full answer directly, rather than exploring the more subtle hints (Hint 1, Hint 2, and Hint 3) or attempting to solve the problem independently. On the other hand, hints Hint 1, Hint 2, and Hint 3 were requested by a smaller number of students, indicating a relative preference for a quick solution rather than a deeper resolution process.

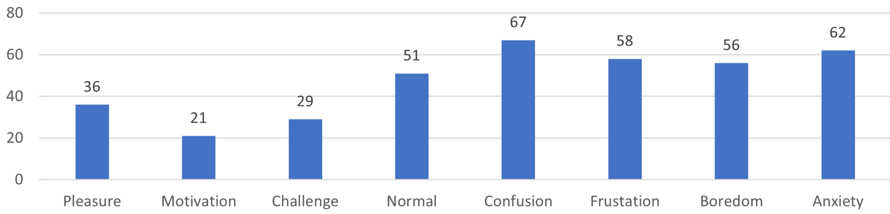

Figure 2. Number of Students by Affective State

Figure 2 provides a detailed view of the affective states reported by students during a specific period. Notably, a variety of emotional states are observed, from pleasure and motivation to confusion and anxiety. While positive affective states, such as pleasure and motivation, have a relatively smaller number of students associated with them, affective states that indicate challenge or discomfort, such as confusion, frustration, boredom, and anxiety, have a higher number of students. This distribution suggests areas of possible difficulty or stress in the learning process that require attention and intervention.

Table 1. Average number of attempts by type of hint and affective state

Hint	Pleasure	Motivation	Challenge	Confusion	**Positive**	Frustration	Boredom	Anxiety	**Negative**
Hint01	2.42±0.87	2.37±0.77	1.68±0.84	2.46±0.75	1.49±1.77	2.42±0.72	2.53±0.71	1.33±0.77	2.39±0.72
Hint02	1.11±0.33	1.71±0.94	1.34±0.78	2.55±0.57	1.42±0.17	2.24 ±0.24	3.28±0.74	1.45±0.35	0.31±1.29
Hint03	1.70±0.43	1.41±0.77	2.00±0.30	1.89±0.75	2.71±2.07	2.75±1.87	2.85 ±2.48	2.91 ±2.01	2.82±1.98
Hint04	3.12±2.43	3.76±2.05	3.88±3.08	3.68±2.90	3.71±2.87	4.19±2.43	4.36±2.87	4.46±2.43	4.37±2.2.54

Table 1 provides a detailed view of the average number of problem-solving attempts by affective state and type of hint requested, which can be useful for understanding how students interact with the learning environment and how their emotions influence this process. Let's examine some relationships between the data presented in the table and the academic literature on the subject:

Impact of Positive Affective States: It is observed that positive affective states, such as pleasure and motivation, are associated with a lower average number of attempts across all hints. This suggests that students tend to make fewer attempts when they are experiencing these emotional states, which may indicate greater confidence or satisfaction with their initial solutions. For example, for the hint Hint01, the average number of trials for the pleasure state is approximately 2.42, while for the motivation state, it is approximately 2.37. These values are lower compared to negative affective states;

Response to Negative Affective States: In contrast, negative affective states, such as frustration and anxiety, are associated with a higher average number of attempts across all hint. This suggests that students tend to persist and make more attempts when they are experiencing these emotional states, in an attempt to overcome difficulties or uncertainties. For example, for the hint Hint01, the average number of trials for the frustration state is approximately 2.42, while for the anxiety state, it is approximately 2.39. These values are higher compared to positive affective states;

Variation between Types of hints: Furthermore, we can observe variations in the average number of attempts between different types of hints for each affective state. This suggests that the effectiveness of the hints may vary depending on the student's emotional state. For example, for the confusion state, the average number of trials is higher for the hint Hint02 compared to other hints. This may indicate that the hint provided by Hint02 may not be as effective in helping students overcome confusion compared to other hints.

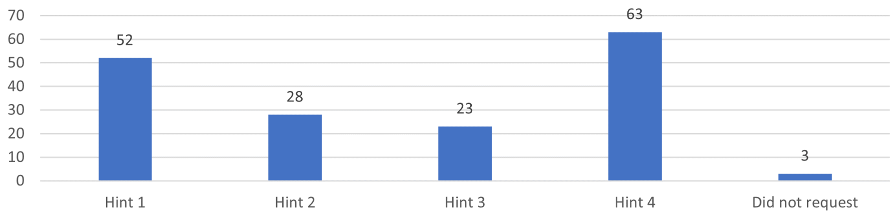

Figure 3. Number of Requests for Hints

4.2. Analysis of Research Questions

To analyze the correlation between hint level request levels and affective states. To do this, we calculated the Spearman correlation coefficient between the variables.

Table 2. Spearman correlation between hint levels and affective states

	Hint01	Hint02	Hint03	Hint04	Pleasure	Motivation	Challenge	Normal	Confusion	Frustration	Boredom	Anxiety
Hint01	1.0											
Hint02	0.28	1.0										
Hint03	0.221	**0.988****	1.0									
Hint04	0.280	**0.60****	**0.988****	1.0								
Pleasure	0.496	0.492	0.437	0.492	1.0							
Motivation	0.192	-0.095	-0.118	-0.095	-0.233	1.0						
Challenge	0.496	0.492	0.437	0.492	**1.000***	-0.233	1.0					
Normal	0.443	0.386	0.325	0.386	**0.831***	-0.323	**0.831***	1.0				
Confusion	0.439	0.501	0.466	0.501	**0.966***	-0.3	**0.966***	0.791	1.0			
Frustration	-0.068	0.485	0.494	0.485	0.019	0.119	0.019	-0.077	0.006	1.0		
Boredom	0.193	**0.961****	**0.975****	**0.961****	0.414	-0.112	0.414	0.298	0.432	0.51	1.0	
Anxiety	0.287	0.400	0.382	0.400	**0.789***	-0.444	**0.789***	**0.861***	**0.851***	-0.099	0.338	1.0

$*p < 0.05; **p < 0.01$

Before analyzing positive and negative affective states separately, we will do a complete analysis of Table 2. In this table, we present the correlation coefficients between hint and affective states. In this Table, the asterisks indicate the statistical significance of the correlations, with $p < 0.05$ and $p < 0.01$. All correlations between hint and positive affective states are statistically significant, indicating that these associations did not occur by chance. Let's carry out a complete analysis of the results:

Positive Correlations between Hint and Positive Affective States: Hint01, Hint02, and Hint04 show positive correlations with positive affective states such as Pleasure, Motivation, and Challenge. This suggests that students who requested these hints tended to report higher levels of these positive affective states during the learning process. Furthermore, the hint Hint03 also has a moderate positive correlation with the Challenge state.

Negative Correlations between Hint and Negative Affective States: Hint01, Hint02, and Hint04 have negative correlations with negative affective states such as Confusion, Frustration, Boredom, and Anxiety. This suggests that students who requested these hints tended to report lower levels of these negative affective states. However, hint Hint02 shows a moderate correlation with Confusion and Anxiety states, indicating a possible association with higher levels of these negative affective states.

Strongest and Weakest Correlations: The strongest correlations are observed between hint and positive affective states, especially with Pleasure, Challenge, and Motivation. On the other hand, correlations with negative affective states are more varied, with some hints showing positive and others negative associations.

Impact of Hint on the Learning Experience: Analysis suggests that appropriate selection and use of hints can play a significant role in promoting positive affective states and reducing negative affective states during learning. Hints that are strongly correlated with positive affective states, such as Pleasure and Challenge, may be more effective in promoting a positive and motivating learning experience.

In summary, the analysis suggests that the hints provided to students have a significant impact on their affective states during the learning process. Careful selection of hints can contribute to a more positive and engaging learning experience while helping to mitigate negative affective states such as Confusion, Frustration, and Anxiety.

RQ 01: What are the most frequent **positive** affective states in novice programmers who seek cognitive feedback during programming problem-solving activities?

Table 2 presents Spearman correlations between the hints provided and the students' positive affective states. Let's analyze the main findings: (i) **Positive Correlations between hint and Positive Affective States**: The hints Hint01, Hint02, and Hint04 present moderate positive correlations with the state of Pleasure, ranging from 0.28 to 0.496. Furthermore, there is a significant correlation between the Hint03 hint and the state of Pleasure, with a value of 0.221; (ii) **Strongest Correlations with the State of Pleasure**: hints Hint01, Hint02, and Hint04 have stronger correlations with the state of Pleasure, indicating a more direct association between these hints and the students' positive experience; (iii) **Correlations with Challenge**: The hint Hint03 also presents a moderate correlation with the Challenge state, with a value of 0.437. This suggests that this hint may be related to the feeling of positive challenge among students.

In summary, this analysis shows that some specific hints are positively correlated with positive affective states, such as Pleasure and Challenge. This suggests that these hints can be effective in promoting a more positive and engaging learning experience for students.

RQ 02: What are the most frequent **negative** affective states in novice programmers who seek cognitive feedback during programming problem-solving activities?

Table 2 presents the Spearman correlations between specific hints provided and the negative affective states reported by students. The analysis reveals several noteworthy findings regarding the relationship between these hints and students' emotional responses during their learning process.

Firstly, the hints Hint01, Hint02, and Hint04 demonstrate negative correlations with negative affective states such as confusion, frustration, boredom, and anxiety. This indicates that students who sought these hints tended to experience lower levels of these negative emotions while engaging with the learning material. In contrast, Hint03 also exhibits some negative correlations with these states, although these correlations are generally less pronounced compared to the other hints. Secondly, among these correlations, Hint02 stands out with moderate associations with confusion and anxiety. This suggests that students who actively sought Hint02 may have encountered higher levels of confusion and anxiety during their learning activities, possibly indicating areas where additional support or clarification might be beneficial.

Additionally, Hint03 shows a moderate correlation with the state of frustration, implying that students who utilized this hint may have experienced elevated levels of frustration during their learning process, possibly due to challenges or difficulties encountered. Overall, these findings underscore the complex interplay between the types of instructional hints provided in educational environments and students' emotional responses. Understanding these correlations can help educators and instructional designers tailor their support strategies more effectively, aiming to mitigate negative affective states and enhance the overall learning experience for students.

The analysis indicates that specific hints are linked to lower levels of negative affective states such as Confusion, Frustration, Boredom, and Anxiety, whereas other hints may be associated with higher levels of these negative affective states. This underscores the importance of carefully selecting and utilizing hints, as they can significantly impact reducing negative affective states and fostering a more positive learning experience for students. The positive correlations observed between the hints (Hint01, Hint02, and Hint04) and positive affective states such as Pleasure, Motivation, and Challenge suggest that strategically implementing these hints in Virtual Learning Environments (VLEs) can notably enhance student motivation and engagement. When students feel positively challenged and enjoy the learning process, they are more likely to persevere through difficult tasks and achieve a deeper comprehension of the content. Conversely, the negative correlations between these hints and negative affective states like Confusion, Frustration, Boredom, and Anxiety are pivotal. By mitigating these negative emotions, students can improve their focus and grasp of the material, potentially leading to reduced dropout rates and enhanced knowledge retention. This underscores the transformative potential of well-designed hints in creating supportive and effective learning environments tailored to individual emotional and cognitive needs.

These findings have significant implications for the design and implementation of VLEs: (i) **Feedback Personalization**: Based on the research findings, VLEs can be configured to provide specific hints whenever they detect negative affective states in students. For example, if the system identifies that a student is confused or frustrated, it can automatically offer a tip that has historically and empirically helped reduce these feelings. This creates a learning environment that is more responsive and adaptable to students' individual needs, promoting a more positive and effective learning experience;(ii)**Real-Time Monitoring and Adaptation**: VLEs can continuously monitor students' affective states using technologies such as behavior analysis, keyboard and mouse input, or even biometric sensors. With this real-time information, the system can dynamically adjust the type and level of support offered, increasing support when a student is struggling and decreasing it as the student progresses successfully; (iii) **Development of Pedagogical Strategies**: Educators can use these findings to develop more effective teaching strategies. By understanding which hints are most effective for promoting positive affective states like motivation and enjoyment, teachers can integrate these strategies into their teaching materials. Furthermore, knowledge about which tips are most effective in reducing negative feelings such as frustration and confusion can enable educators to intervene more quickly and effectively, providing personalized support to students based on their emotional and cognitive needs.

5. Conclusion

In this article, we present an experimental study involving students in a programming course for beginners, developed with a focus on problem-solving activities, analyzing hints, and feedback resources. More specifically, we focus on affective factors and their correlations with requests for help and feedback.

Analyzing the correlations between the hints provided to students and their affective states reveals significant insights into the influence of these hints on the learning experience. The results indicate that certain hints are associated with positive affective states, such as Pleasure, Motivation, and Challenge, suggesting that they can contribute to a more positive and engaging learning experience. Furthermore, some hints showed negative correlations with negative affective states, such as Confusion, Frustration, and Anxiety, highlighting their potential to reduce these unwanted emotional states during the teaching-learning process. These findings highlight the importance of customizing hints to individual learners' needs and highlight their role as an effective tool for improving the quality of the learning experience.

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