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The Interplay of Affective States and Cognitive Processes in an Open-Ended Learning Environment: A Case Study

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Abstract: Affective states play a pivotal role in learning processes, yet little research has addressed the relations between cognitive processes and affective states, particularly when middle school students work in Open-Ended Learning Environments (OELE). This study seeks to understand these relations and link them to learning outcomes over time using continuous data streams. Leveraging a mixed-method approach, we conducted a case study with six students, analyzing approximately 80 minutes of data per student. Affective states are derived using a comprehensive analysis employing validated valence-arousal scales and a quadrant-based interpretation of educational emotion associated with the affective state. Utilizing D'Mello and Graesser's Affective Dynamics in Complex Learning, the study compares the relations between affective state patterns and cognitive processes of students who completed and could not complete the map-building task. Additionally, we analyze affective state shifts as students progress through the tasks across two different days, shedding light on the potential links between affective states and success in map building.

Introduction

Recently, there has been a lot of interest in investigating students' affective states within computer-based learning environments. This interest stems from the hypothesis that these environments can scaffold complex learning tasks, thus helping students better regulate their affective states. Various studies have noted the interplay between students' affective states and their cognitive processes has been noted in (Karimah & Hasegawa, 2022). Baker *et al.* (2010) observed that sustained emotions like boredom during a learning session are strongly correlated with low performance. Similarly, confusion and frustration were found to have a detrimental impact on performance, especially during complex learning and problem-solving activities (D'Mello & Graesser, 2014; Ashwin and Guddeti, 2020). Conversely, certain studies have suggested that confusion might benefit learning, particularly for individuals aged 18 to 50 (D'Mello *et al.*, 2014). Most studies to date are not focused on school-age children. Many employ manual observation and annotation techniques (e.g., BROMP; Baker *et al.*, 2020). These methods observe a specific student for 20 seconds, assigning a single affective state for that entire duration, and employing a round-robin pattern of observation, potentially missing the nuances of continuous affect transitions for the students. Apart from the cognitive process, some studies consider coherent chunks, i.e., by establishing the relation between outcome (effectiveness) and affect over a set of actions that are related to one another. However, these studies considered interaction log data and discourse analysis for coherence effectiveness and emotion (sentiment) mapping.

In this paper, we explore the relationships between students' academic affective states (Pekrun & Stephens, 2012) described by a two-dimensional emotion model (D'Mello & Graesser, 2007; Russell,1980), and cognitive processes in an Open-Ended Learning Environment (OELE) named Betty's Brain (Biswas *et al.*, 2016). Students create causal maps to teach Betty about scientific processes. We refer to Completed Task (C) for those who successfully finish creating a correct map (explained in a later section), while Not Completed Task (NC) refers to those who can not complete the given task in the specified time. Unique to this research is our analysis of the relation between students' affective states, their cognitive processes, and their performance on learning tasks. We study how the affect-cognition relations change from one day to another, using additional variables such as coherence and effectiveness within the same learning context, a facet often overlooked in prior studies. This investigation provides a comprehensive mapping of a validated valence-arousal scale to academic affective states using a quadrant-based analysis. In more detail, we leverage our past work for conceptualizing cognitive processes (Kinnebrew, *et al.*, 2014), and High-Speed Face Emotion Recognition to delineate students' affective states on a common timeline. We use this timeline to address the following research questions:

RQ 1: Is there a relationship between Students' Affective States and Performance when they work in OELEs?

RQ 2: Is there a relationship between Students' Affective States, Cognitive Processes, and Performance?

The broader goal is to explore the relationship between affective states and cognitive processes in the framework of Self-Regulated Learning (SRL), which is described as a combination of Cognitive, Affective, Metacognitive, and Motivation (CAMM) processes (Azevedo *et al*., 2017).

Theoretical framework and literature review

SRL is described as the ability of learners to monitor and manage their CAMM processes (Azevedo, *et al*, 2017). Our theoretical framing in this paper studies the relationship between students' cognitive processes (Biswas, *et al*, 2016) and D'Mello and Graesser's (2012) affective dynamics in complex learning to study the relations between cognitive processes and affect when students learn and solve problems in the Betty's Brain environment. Following Winne's (2018) Information Processing Theory, we adopt a sequential framework to characterize students' learning processes. We define students' primary cognitive processes in terms of their seeking information (Reading), constructing and refining their knowledge (Map Building), and checking the correctness of their maps (Quizzing).

D'Mello and Graesser's (2012) Affective Dynamics in Complex Learning focuses on *cognitive disequilibrium*, a condition of uncertainty experienced by students when they encounter difficulties or obstacles to their learning. This concept is critical for learning with understanding because it entails a process where learners fluctuate between disequilibrium and equilibrium. Confusion among students indicates a state of disequilibrium. If the confusion is not resolved, it can lead to frustration and, eventually, boredom, leading to a lack of engagement with the learning content. Resolving this confusion, on the other hand, provides opportunities for learning and benefits students in regaining cognitive equilibrium, therefore, preserving their engagement and progress toward their learning objectives.

Previous studies have examined discrete affective states that occur during the process of complex learning, as evidenced by both observations and self-reports (Baker et al., 2010; D'Mello, 2013; D'Mello & Graesser, 2014; Taub *et al*., 2021). In their study, Baker et al. (2010) employed a combination of self-report measures and observation methodologies to investigate affective states. The researchers identified engaged concentration and confusion as the two predominant affect states. They also discovered that boredom emerged as the most persistent state, indicating the need to prioritize early detection and mitigation of this phenomenon. In a meta-analysis, D'Mello (2013) emphasized the need to direct attention toward affective states such as confusion, frustration, and boredom, as they have been recognized as negative affective states. In contrast, D'Mello & Graesser (2014) found that confusion and Taub et al (2021) found that frustration had positive effects on the use of effective cognitive processes and learning. These studies provide evidence for the correlation between students' affective states and their learning outcomes and cognitive processes.

Research on automatic emotion recognition has mainly focused on discrete academic affective states, yet there is a limited exploration of this in Online Educational Learning Environments (OELEs) using student data (Gupta et al., 2019; Ashwin & Guddeti, 2020). Current studies have not fully addressed the wide range of emotional dynamics or considered how affective states change over time. Furthermore, there is a gap in understanding whether emotional patterns differ between students who complete learning tasks and those who don't in such environments. By examining the correlation between cognitive processes, affective states, coherence (as a regulatory measure), and task effectiveness, we may uncover valuable insights into how students learn in OELEs.

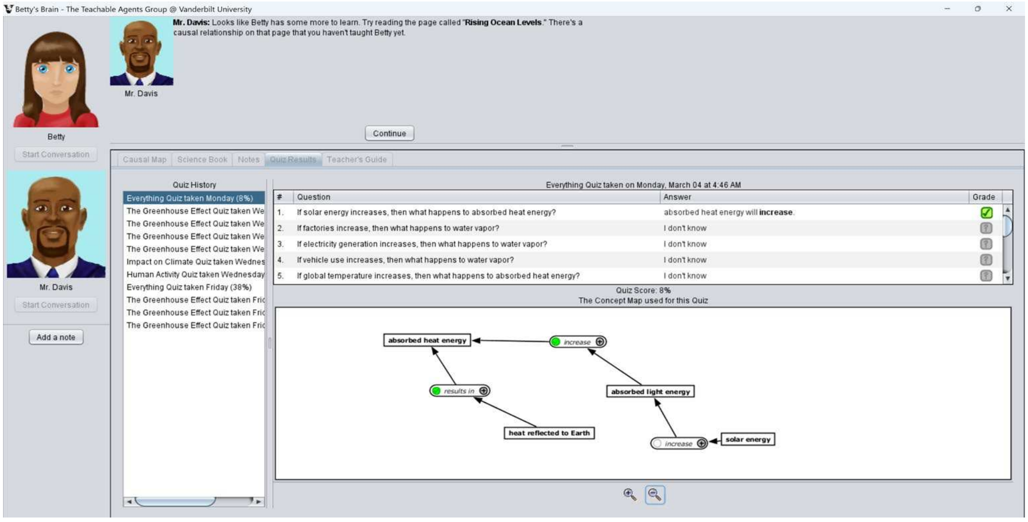
Methodology

Learning environment and context

Betty's Brain, an OELE designed for middle school students, uses a learning-by-teaching approach to help students learn cognitive and metacognitive skills (Biswas *et al*., 2016). Students in this interactive learning environment teach a virtual character, generically called Betty, by building causal models of scientific processes. Figure 1 below shows the system interface and illustrates the resources and tools the system provides students to learn, build, and check their models. The resources include a *science book*, a set of hypermedia resource pages that provide the domain knowledge students need to teach the agent. Students read sections of the book and identify concepts and causal (i.e., cause-and-effect) relations between concepts. They use the *causal map building tool*, a visual interface with a drag-and-drop menu, to teach their agent. The interface provides students with a visual representation of their causal map. The menu allows students to add, delete, and modify concepts and links. Other tools, such as the *query* and *quiz tools* allow students to probe their agent's knowledge of the science concepts and relations, by asking her to take a quiz. Quiz results direct students to errors in their current causal map. Effective learners can use this information to make immediate map corrections or to determine which sections of the book to read next. Overall, the quizzes help students track their agent's progress and by implication, their own scientific knowledge.

Figure 1

Betty's Brain Sample Screenshot of Quiz View Page with Feedback from Mentor Agent



Cognitive processes, coherence, and effectiveness

Students' primary actions, such as 'Read', 'Quiz', 'Build', and 'Notes', are logged and interpreted as basic cognitive operations that they can perform to build and test their causal maps. Table 1 lists the cognitive processes (CP) and their 1-1 links to actions that students can perform in the Betty's Brain environment.

Table 1

Cognitive Processes in Betty's Brain

Cognitive Process (CP)	Description & Recorded Actions in environment
Information Acquisition (IA)	Reading through hypertext pages to gain knowledge of the scientific topic: READ
Solution Checking (SCH)	Taking a quiz to check the correctness of their causal map. This is linked to students' evaluating their progress by looking at quiz results, the agent's feedback linked to the current results: QUIZ
Solution Construction (SCO)	Adding, Deleting, and Modifying concepts and links to build and refine the causal map: BUILD
Information Recording (IR)	Taking notes, for future reference typically as students read the resources: NOTES

We analyzed the cognitive processes of students learning about climate change topics in our study using screen recordings, eye-tracking, and interactive log data extracted from the Betty's Brain logs that was converted from JSON into a CSV format. We performed a case study analysis, including six students (age range 10-12), who were evenly divided between those who could complete (C) the causal map of the climate change phenomena (as defined by the classroom teacher) at the end of three working sessions and those who could not (NC). We excluded day 1 (when students were mostly familiarizing themselves with the environment), but included data from days 2 and 3. We chose days 2 and 3 for analyses because the students extensively engaged with the system to build their causal maps during this period. Each student worked approximately 40 minutes per day on the system. This produced approximately 8 hours of screen recording videos.

We used the definitions presented in Table 1 to identify and categorize time the periods when students worked on specific cognitive processes in the Betty's Brain environment. We used a mixed method analysis.

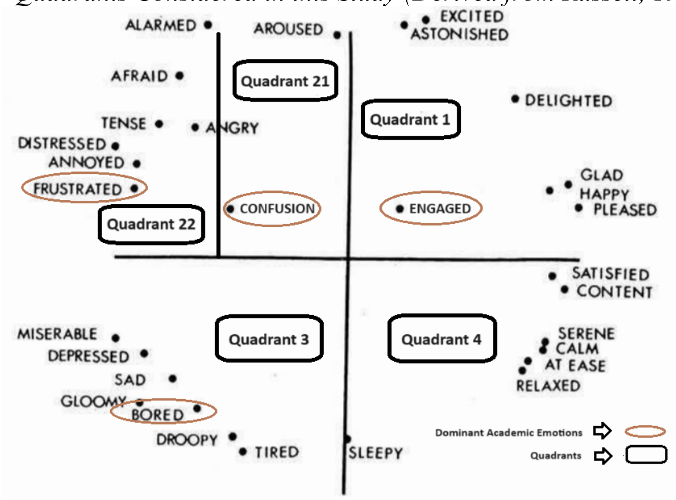
Cognitive process labeling used the log data to map the primary recorded actions into cognitive processes. We also noted the start and end time of each action from the screen recordings. An overlay of eye tracking from previous work (Rajendran *et al.*, 2018), helped us further refine our labeling of the cognitive process and their associated time intervals. This analysis provided us with a comprehensive and precise insight into students' cognitive processes in Betty's Brain. For example, it allowed us to accurately identify operations like BUILD by combining concurrent manual observation of the corresponding screen recordings.

Coherence focuses on the notion of support, i.e., when students perform an action *x* in the environment before action *y*, does *y* use the information generated by action *x*? If it does, then *x supports y* and *x and y are coherent*. Coherence of cognitive processes is an indirect measure of effective metacognitive monitoring and regulation by the students (Kinnebrew, et al, 2014; Schwartz, et al, 2009). In addition, to assess a student's cognitive processes, we also define the notion of *effectiveness* that judges whether a map-building action moves the student's causal map closer to the correct solution (Kinnebrew, et al, 2017). Overall, students with higher proportions of effective actions were considered to have a higher mastery of the related cognitive skills. This work only applies the effectiveness measure to the map building (BUILD) process. More details of the coherence measure and its use in Betty's Brain is discussed in earlier work (Segedy et al, 2015).

Affective states recognition

Emotion Classification Theory explores a range of primary affective states such as boredom, confusion, frustration, delight, and engagement, which can be effectively depicted along a valence-arousal scale (see Fig. 2). Russell's circumplex theory further organizes these affective states onto a two-dimensional scale, where specific affective states are positioned based on their relationships with each other (Russell, 1980). This model visualizes emotional concepts in a circular format, with valence (positive to negative) on the horizontal axis and arousal (calm to excited) on the vertical axis, with values ranging from -1 to 1. Within this framework, we have four distinct quadrants: confusion and frustration occupy different regions in the second quadrant, surprise, delight, and happiness in the first, boredom in the third, and sleepiness in the fourth quadrant. The ability to recognize confusion and frustration in educational settings is particularly emphasized in existing literature due to their significant impact on learning outcomes. (D'Mello & Graesser, 2007; Russell, 1980; D'Mello, S., 2013).

Figure 2
Quadrants Considered in this Study (Derived from Russell, 1980)



The initial two-dimensional circumplex employs the degree of an angle to position affective states on a valence-arousal scale. In contrast, the Affect Grid and Self-Assessment Manikin seek to precisely locate affective states within each quadrant, determining where expressions fall within the possible range of -1 to +1 for both valence and arousal (Russell *et al.*, 1989). Building on D'Mello & Graesser's (2007) findings, we capitalize on the insight where confusion is placed towards the neutral in the second quadrant and frustration is situated near anger. Frustration and its related affective states, encapsulated in quadrant 2.2 with valence values from -0.5 to -1, though more beneficial than boredom, might not offer the same educational advantages as confusion (D'Mello et al., 2014; Baker et al., 2010). This study introduces a refined framework, establishing five distinct quadrants to capture these nuanced affective states.

Affective States Recognition: The deep learning algorithm, HSEmotion (High-Speed Face Emotion Recognition) utilized the pre-trained model enet_b0_8_best_afew.pt, which was trained on the VGGFace2 dataset with 3.31 million images across 9131 subjects. We trained PyTorch models using SAM (Sharpness-Aware Minimization) to enhance generalization by minimizing loss value and sharpness simultaneously, exhibiting robustness to label noise. We detected facial regions in images with MTCNN (Multi-task Cascaded Convolutional Networks). We trained the affect recognition model on different datasets, ensuring representation of the specific age group in our study (Savchenko, 2023; Zhang *et al.*, 2016). We followed the preprocessing steps, as outlined by Ashwin and Guddeti, 2020, to ensure consistency and accuracy in vision data analysis. We based emotion predictions on videos at 30 frames per second. Valid affective states persisted for at least 5 seconds (150 frames), filtering out fleeting affective states. Predictions required at least 60% visibility of the face for consideration, disregarding instances with less visibility. The architecture can detect affective states with only 30% visibility of the face. However, our analysis focused on predictions from instances with over 60% face visibility. We excluded predictions where the face was not in the frame or if visibility was less than 60%. Once we obtained the valence-arousal values for each frame, they were mapped onto quadrants in Figure 2. Ten random batches of valence-arousal values were manually validated for each student at various intervals to ensure accuracy and consistency in the data, confirming the correctness and reliability of the collected information.

Results and analysis

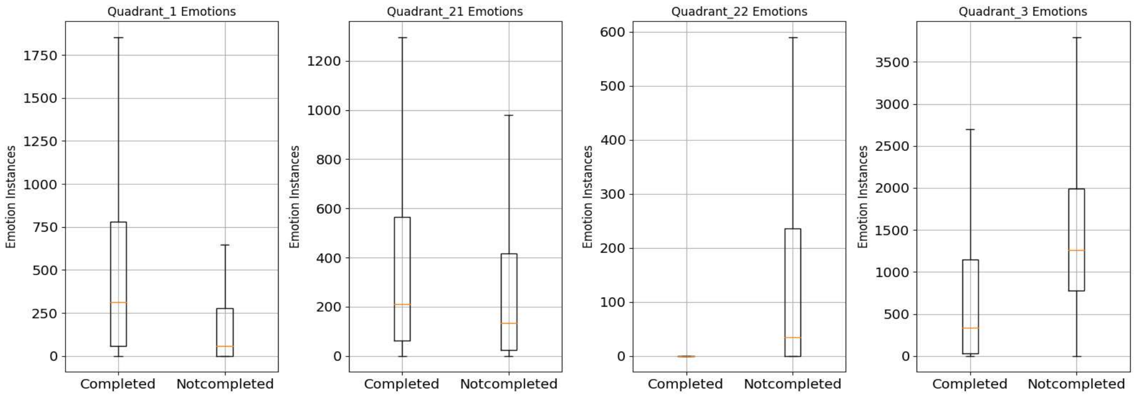
Given the small number of subjects, the nonparametric Mann-Whitney U Test was used for statistical analysis to explore the significance of our research questions.

RQ 1: Relationship between students' affective states and performance

Comparing the Affective States in Each Quadrant for Students who Completed and Did Not Complete the Task

Figure 3

Distribution of Instances of Affective Sstates in Each Quadrant for Completed and Not Completed

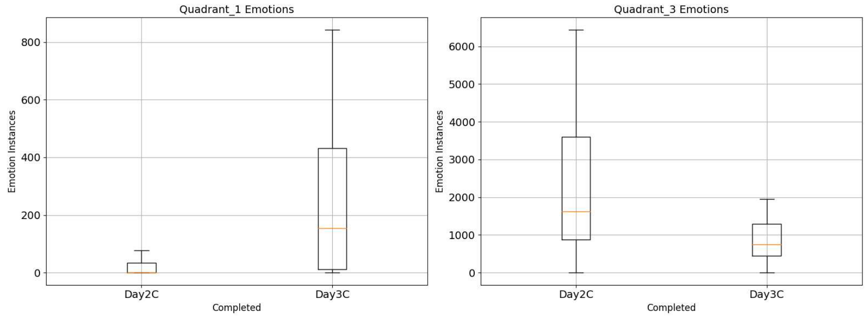


To answer RQ 1, we compared the number of affective states occurrences between the C and NC groups. Figure 3 shows the number of instances for students who completed their causal maps (C) and those who did not (NC). For Quadrants 1 (Q1) and 21, we observed significant differences in emotional occurrences between C and NC. Quadrant 1 had a Mann-Whitney U statistic (MWUS) of 25989.5 (p = 2.72E-07), indicating significantly higher affective state occurrences for C in Q1. Similarly, Quadrant 21 (MWUS of 23310 p = 0.00443), had significantly higher affect instances for C. Quadrants 22 and 3 also demonstrated notable differences in emotional instances between C and NC. Quadrant 22 (MWUS of 7779, p = 2.51E-37), produced considerably lower emotional instances for C. Similarly, Quadrant 3 (MWUS of 10350, p = 2.69E-16) also had significantly lower emotional occurrences for C. These statistical outcomes highlight distinct emotional patterns between C and NC across Quadrants 1, 21, 22, and 3 with the C students showing higher positive affect and the NC students showing more negative affect. In summary, the higher performing students (C) showed more positive affective states during the study than the low performing students (NC).

<u>Overall Instances of affective states for each student for Days 2 and Day 3</u>

The MWUS for emotional instances within each quadrant for C and NC on days 2 and 3 revealed distinct differences. Quadrants 1 and 3 displayed significant disparities for the C students, as shown in Figure 4. Quadrant 1 showed a MWUS of 322.5 (p = 5.35E-05), indicating higher instances of positive affective states for the C students on day 3 when compared to day 2. Conversely, Quadrant 3 exhibited a MWUS of 1021 (p = 0.00064), representing significantly lower emotional instances for C students from day 2 to day 3. However, Quadrants 21 and 22 showed no substantial variations between the C and NC students for both days, signifying similar occurrences of affective states for the two days. In contrast, for students who did not complete the map building task (NC), there were no significant differences observed in emotional instances across all quadrants (1, 21, 22, 3) for both days. Although variances existed, none of these differences achieved statistical significance.

Figure 4
Distribution of Instances of Affective States in Quadrants 1 and 3 for Completed Task



RQ 2: Relationship between students' affective sstates, cognitive processes and performance

For IA processes*,* Quadrant 1 displayed an MWUS of 440.5 (p = 0.00031), indicating a significant difference between the groups where C students had higher affect instances compared to NC students. Conversely, Quadrants 22 and 3 showed MWUS of 1494.5 (p = 1.75E-12) and 1432 (p = 0.0000011) respectively, representing significantly lower affect instances during the IA processes for C students compared to NC students. During SCO, Quadrants 1 and 21 exhibited MWUS of 104 (p = 0.014) and 76.5 (p = 0.0015), respectively, indicating significantly higher affect instances for C students than their counterparts. Quadrants 22 and 3 showed MWUS of 286.5 (p = 0.00082) and 279 (p = 0.028), respectively, representing significantly lower affect instances again for C students in comparison to NC students. Regarding the SCO process, only Quadrants 22 and 3 exhibited MWUS of 3704 (p = 2.35E-13) and 3178 (p = 0.00022), signifying significantly lower affect instances for C students as compared to NC students. For the SCH process, Quadrant 1 and Quadrant 21 displayed MWUS of 1851 (p = 0.0019) and 3383 (p = 0.003591), respectively, indicating significantly higher affect instances for C students in contrast with NC. Also, as compared to NC students, C students had a significant lower affect instances in Quadrants 22 and 3 revealed MWUS of 4150 (p = 1.88E-12) and 3843 (p = 0.0000025).

To summarize, occurrences for Q1 (containing instances of delight) and Q21 (containing instances of confusion), both representing positive affective states, were notably higher for C than for NC. However, statistically significant differences were observed only for Solution Checking and Solution Construction cognitive processes, suggesting that the affective state is reflective of the observed progress toward completing the map. Conversely, instances in Q22 (representing instances of frustration) and Q3 (representing instances of boredom) (negative affective states) were comparatively lower for C when compared with the NC. These differences were evident and statistically significant, signifying that negative affective states are closely related to the difficulties or lack of success that students have in their map completion task. Overall, the results indicate significant differences in affective states across the cognitive processes, especially for quadrants that contain delight, frustration, and boredom affective states. However, Q21 (representing instances of confusion state), described as the cause for cognitive disequilibrium, does not show a significant difference between the C and NC students for most cognitive processes. This may be a clear indication that those who completed the causal map task overcame their cognitive disequilibrium states and moved toward more effective map-building strategies, whereas those who are unable to complete their maps could not switch to more effective map-building actions.

The discernible variations in emotional states across different cognitive processes shed light on the potential influence of affective states on task completion within cognitive-affective learning environments. Further analysis and interpretation of these results, using coherence and effectiveness, are detailed in subsequent sections.

Discussion with coherence and effectiveness

When high-performing students show notable shifts in affective states between Quadrants 1 and 21, especially transitioning from neutral or positive affect during Information Acquisition (IA) to Spatial Cognitive Organization (SCO), it may lead to ineffective actions in establishing correct causal links within a cognitive map. For instance, if a student exhibits a high number of instances in Quadrant 1 during IA (e.g., 1657 instances) but sharply drops to 1 instance during SCO, it suggests decreased engagement or positive affect during SCO, potentially affecting task effectiveness. During periods of SCO, if instances in Quadrant 1 decrease to 0 while Quadrant 21 maintains a significant level (e.g., 525 instances), and Quadrant 22 registers 0 instances, it indicates a shift from engagement to confusion. Observations of facial expressions corroborate this, showing signs of confusion and uncertainty about map errors. However, due to limited instances and changes in coherence and effectiveness aligned with quadrant shifts, statistical significance could not be established, hindering a comprehensive understanding of affective state transitions impacting cognitive processes.

We observed cases where the number of instances in Quadrant 1 was lower than that in Quadrant 21, even during a coherent and effective state. Qualitative analysis revealed that despite constructing correct links, the student appeared uncertain. This suggests a disparity between the expressed affective state and performance trajectory. Despite a higher instance count in Quadrant 21, indicating potentially negative emotions, the correctness of the link suggests a nuanced relationship between affective states and task performance.

Furthermore, there were instances where Quadrant 3 showed prolonged high instances, followed by a sudden reduction during Solution Checking (SCH) and SCO phases. Despite this, coherence and effectiveness remained high during SCH and SCO, continuing into IA. The decrease in Quadrant 3 instances during SCH and SCO suggests a shift from potentially negative emotions to a more neutral or positive state. Despite these fluctuations, the student's cognitive processes remained logical and effective.

Limitations: This study had limitations, including the relatively small sample size and the focus on a specific domain. This study did not consider categorical affective states like boredom within the third quadrant for analysis. Consequently, the affective states observed in the third quadrant might not solely represent boredom but could encompass other affective states characterized by negative arousal and valence. For instance, affective states such as sadness could be included in this quadrant, signifying a broader spectrum of negative affective states. The absence of detailed categorical affective states within each quadrant might limit the precise interpretation of emotional responses observed in the study. Moreover, this study primarily explores the correlation between affective states and task completion rather than delving into the causative factors behind the higher instances in the first quadrant for high-performing individuals. Understanding the root causes of increased affective state instances in Quadrant 1 among high-performing students remains an avenue for future research to elucidate the underlying mechanisms driving this relationship.

Conclusion

The study conducted within the Betty’s Brain interactive learning environment yielded multifaceted insights into the intricate relationship between students' affective states, cognitive processes, and task completion. Using mixed-method analysis, this study sheds light on the nuanced dynamics within a cognitive-affective learning ecosystem. Distinct affective states patterns emerged between completed and not completed tasks across various quadrants. Quadrants 1 and 21 displayed significantly higher affective state instances for completed task students, suggesting heightened engagement and potentially deeper comprehension. Conversely, Quadrants 22 and 3 exhibited lower emotional instances for completed task students, implying different affect responses associated with incomplete task students, possibly indicating disengagement or challenges in understanding. The association between cognitive processes and affective states presented noteworthy insights. Solution Checking and Solution Construction processes demonstrated higher affective state instances in completed task students, highlighting their potential role in task completion. Conversely, significant differences in affective states within Quadrants 1, 22, and 3 across various cognitive processes underscore the intricate relationship between affective states, cognitive actions, and performance outcomes. In summary, this study contributes to the evolving understanding of the intricate interplay between affective states, cognitive processes, and task completion within open-ended learning environments. Future research endeavors could explore a larger cohort and diverse domains to generalize these findings. Furthermore, incorporating interventions targeting affective state transitions and cognitive strategies aligned with effective and coherent task completion could enhance the understanding of how affective states influence learning outcomes.

References

Ashwin, T. S., & Guddeti, R. M. R. (2019). Unobtrusive behavioral analysis of students in classroom environment using non-verbal cues. IEEE Access, 7, 150693-150709.

Ashwin, T. S., & Guddeti, R. M. R. (2020). Impact of inquiry interventions on students in e-learning and

classroom environments using affective computing framework. User Modeling and User-Adapted Interaction, 30(5), 759-801.
Azevedo, R., Taub, M., & Mudrick, N. V. (2017). Understanding and reasoning about real-time cognitive, affective, and metacognitive processes to foster self-regulation with advanced learning technologies. In Handbook of self-regulation of learning and performance (pp. 254-270). Routledge Baker, R. S., D'Mello, S. K., Rodrigo, M. M. T., & Graesser, A. C. (2010). Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive–affective states during interactions with three different computer-based learning environments. International Journal of HCS, 68(4), 223-241.
Baker, R. S., Ocumpaugh, J. L., & Andres, J. M. A. L. (2020). BROMP quantitative field observations: A review. Learning Science: Theory, Research, and Practice. New York, NY: McGraw-Hill.
Biswas, G., Segedy, J. R., & Bunchongchit, K. (2016). From design to implementation to practice a learning by teaching system: Betty's Brain. *International Journal of Artificial Intelligence in Education*, *26*, 350-364.
D'Mello, S. (2013). A selective meta-analysis on the relative incidence of discrete affective states during learning with technology. Journal of educational psychology, 105(4), 1082.
D'Mello, S., & Graesser, A. (2007). Monitoring affective trajectories during complex learning. In Proceedings of the annual meeting of the cognitive science society (Vol. 29, No. 29).
D'Mello, S., Lehman, B., Pekrun, R., & Graesser, A. (2014). Confusion can be beneficial for learning. Learning and Instruction, 29, 153-170.
Gupta, S. K., Ashwin, T. S., & Guddeti, R. M. R. (2019). Students' affective content analysis in smart classroom environment using deep learning techniques. Multimedia Tools and Applications, 78, 25321-25348.
Karimah, S. N., & Hasegawa, S. (2022). Automatic engagement estimation in smart education/learning settings: a systematic review of engagement definitions, datasets, and methods. SLE, 9(1), 1-48.
Kinnebrew, J. S., Segedy, J. R., & Biswas, G. (2017). Integrating model-driven and data-driven techniques for analyzing learning behaviors in open-ended learning environments. IEEE Transactions on Learning Technologies, 10(2), 140-153.
Kinnebrew, J. S., Segedy, J. R., & Biswas, G. (2014). Analyzing the temporal evolution of students' behaviors in open-ended learning environments. Metacognition and learning, 9, 187-215. Pekrun, R., & Stephens, E. J. (2012). Academic emotions.
Rajendran, R., Kumar, A., Carter, K. E., Levin, D. T., & Biswas, G. (2018). Predicting Learning by Analyzing Eye-Gaze Data of Reading Behavior. International Educational Data Mining Society.
Russell, J. A. (1980). A circumplex model of affect. Journal of personality and social psychology, 39(6), 1161.
Russell, J. A., Weiss, A., & Mendelsohn, G. A. (1989). Affect grid: a single-item scale of pleasure and arousal. Journal of personality and social psychology, 57(3), 493.
Savchenko, A. (2023). Facial expression recognition with adaptive frame rate based on multiple testing correction. Proceedings of the 40th International Conference on Machine Learning (ICML) (pp. 30119-30129).
Segedy, J. R., Kinnebrew, J. S., & Biswas, G. (2015). Using coherence analysis to characterize self-regulated learning behaviours in open-ended learning environments. Journal of Learning Analytics, 2(1), 13-48.
Schwartz, D. L., Chase, C., Chin, D. B., Oppezzo, M., Kwong, H., Okita, S., ... & Wagster, J. (2009). Interactive metacognition: Monitoring and regulating a teachable agent. In Handbook of metacognition in education (pp. 340-358). Routledge.
Taub, M., Azevedo, R., Rajendran, R., Cloude, E. B., Biswas, G., & Price, M. J. (2021). How are students' emotions related to the accuracy of cognitive and metacognitive processes during learning with an intelligent tutoring system?. Learning and Instruction, 72, 101200.
TS, A., & Guddeti, R. M. R. (2020). Automatic detection of students' affective states in classroom environment using hybrid convolutional neural networks. Education and information technologies, 25(2), 1387-1415.
Winne, P. H. (2010). Improving measurements of self-regulated learning. Educational Psychologist, 45(4), 267–276. https://doi.org/10.1080/00461520.2010.517150
Winne, P. H. (2018). Cognition and metacognition within self-regulated learning. In D. H. Schunk & J. A.
Zhang, K., Zhang, Z., Li, Z., & Qiao, Y. (2016). Joint face detection and alignment using multitask cascaded convolutional networks. IEEE signal processing letters, 23(10), 1499-1503.

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