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Investigating Secondary School Students' Academic Emotions in Data Science Learning

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Abstract: Cultivating students' data science knowledge and skills is pressing and challenging, given its interdisciplinary nature, students' limited prior knowledge, and teachers' insufficient training. In data science learning, students may experience various academic emotions. Understanding what emotions students experience, how these emotions are associated with their perceived learning, and under what conditions they experience intensive emotions is critical to informing the design of data science programs and better supporting students. This study collected 839 emotion survey responses from 67 secondary school students in two cycles of a two-day out-of-school data science program. The program engaged students in collaborative inquiries on authentic problems through data science practices with the support of teachers, researchers and facilitators. We found that frustration, interest, surprise and happiness positively predicted students' perceived learning, whereas anxiety negatively predicted perceived learning. Students experienced peaks of positive emotions after an expert's enthusiastic introduction talk to data science in the first cycle and after one-to-one face-to-face consultations with data science experts in the second cycle. However, sharing their progress and challenges with the data science expert in the first cycle and preparing for presentations in both cycles made them experience intense negative emotions such as anxiety, frustration, and confusion. These findings provide implications for designing data science programs to elicit students' positive learning experiences and reduce intensive negative emotions.

Keywords: Academic emotions, data science, secondary school, out-of-school program

1. Introduction and Literature Review

Preparing data-literate citizens who can play data scientist roles in the increasingly digitalized society is a pressing challenge (Finzer, 2013). Efforts have been made to offer after-school data science programs (Thompson & Arastoopour Irgens, 2022). However, challenges exist, which may influence students' emotions and learning. Emotions are coordinated processes, including affective and cognitive components in learning (Scherer, 2009). There are relationships between academic emotions and outcomes— typically, positive academic emotions motivate learners to engage in learning (Pekrun, 2006), whereas negative academic emotions may harm motivation and learning outcomes (Wortha et al., 2019).

However, little is known about what academic emotions secondary school students experience in data science programs and how emotions contribute to their learning. To address this gap, this study examines— RQ1: What emotions predict students' perceived learning in this out-of-school data science program? and— RQ2: What are the conditions when students experience intense emotions during the learning process in the program?

Data science is an interdisciplinary field at the intersection of computer science, math and statistics (Hazzan & Mike, 2023). Data science skills typically involve formulating investigative questions, collecting data, analyzing data, interpreting, and communicating results (YouCubed, 2022). Developing data science skills requires early intervention (English, 2014). However, the interdisciplinarity nature of data science creates challenges like accommodating different learners (Hazzan & Mike, 2023). Data science programs can be challenging for students with limited prior knowledge (Heinemann et al., 2018). These challenges may evoke students' negative emotional experiences in data science learning.

Academic emotions include epistemic and achievement emotions (Pekrun & Stephens, 2012). Epistemic emotions arise during knowledge-generation (Muis et al., 2018). This study considered seven epistemic emotions that have been empirically researched: happiness, curiosity, surprise, confusion, anxiety, frustration, and boredom (D'Mello & Graesser, 2011). We also considered another three emotions (interest, excitement and sadness), which might be more related to the learning content. According to Pekrun et al. (2023), when positive activating emotions like excitement increase and deactivating emotions like boredom decrease, students intend to place more effort into their work. Learning activities and students' emotions and engagement are correlated – for example, Volet et al. (2019) found that positive emotions come from scientific, hands-on, and social aspects during collaborative science learning activities. When students take part in deep reflections on their discussions, they experience positive emotions (Zhu et al., 2022). These studies suggest the need to study conditions in which students feel various emotions in data science learning.

2. Methods

The participants of this study were 67 secondary students from two cycles of an after-school data science program. In the first cycle, 24 secondary students from two secondary schools in Singapore participated. Their average age was 14.46 years old, with 13 students in secondary 2 (Grade 8) and 11 in secondary 3 (Grade 9). In the second cycle, 43 students from two secondary schools in Singapore and one in Hong Kong participated. Their average age was 13.91 years old, with 24 students in secondary 1 (Grade 7), 4 in secondary 2 (Grade 8), 12 in secondary 3 (Grade 9), and 3 in secondary 4/5 (Grade 10).

Table 1 shows the events that took place. Each group formed investigative questions on sustainability, searched for data, analyzed data, interpreted and communicated results. Each group consulted a data science expert and refined their investigations. Finally, they presented their inquiry to the community. In the first cycle, students analyzed data using a statistical tool, Common Online Data Analysis Platform (CODAP). In Cycle Two, Jeffreys's Amazing Statistics Program (JASP) was also taught.

Table 1. *Key Events of the Data Science Program*

Day 1 Activity	Day 2 Activity
C1ES1, C2ES1 Watch two videos about sustainability C2ES2	Community Metatalk (Reflect on what they had learned) C1ES9, C2ES7
Introduction talk to Data Science C1ES2, C2ES3	Data analysis. Consult data science expert. C1ES10, C2ES8
Introduction talk to sustainability C1ES3, C2ES4	Consult data science expert. Revise investigative question. C1ES11, C2ES9
Game to learn about regression	Revise investigative question C1ES12, C2ES10
Form groups based on common interest C1ES4	Prepare for presentation C2ES11
Explore trend, correlation, prediction C1ES5, C2ES5	Prepare for presentation C2ES12
Formulate group investigative questions (Cycle 1 only: Sharing by invited students) C1ES6	Prepare for presentation C1ES13, C2ES13
Data finding/ searching C1ES7, C2ES6	Presentation C1ES14, C2ES14

Demonstration of CODAP and JASP (Cycle 1 only: Data analysis) C1ES8	Write down group reflection C1ES15 Community Metatalk, Individual reflection C1ES16

Note. C1 stands for cycle one, and ES1 stands for emotion survey 1.

The data source was 839 emotion survey responses (two cycles). Students were required to self-report their emotions after major events. Through the online survey, participants rated the extent to which they felt anxious, frustrated, confused, curious, interested, excited, surprised, bored, happy, sad, and their perceived learning using a five-point scale (1= not at all; 5= very much). To respond to the first research question, a multiple linear regression was conducted, with perceived learning as a dependent variable and ten emotions as predictors. For the next research question, for each emotion in each cycle, we calculated the average emotion intensity rating of all individuals at each time point and analyzed activities before and after the intense emotions.

3. Results

3.1 Prediction of students' perceived learning

Table 2 shows the results of the multiple regression predicting perceived learning. Emotions could explain 17.60% of the total variation in perceived learning (F (10, 825) = 17.60, $p < .001$). Anxiety negatively ($p = .00 < 0.01$) predicts perceived learning. Frustration ($p = .03 < 0.05$), interest ($p < 0.001$), surprise ($p = .01 < 0.05$), and happiness ($p < 0.001$) positively predict perceived learning. Correlations between anxiety, surprise, happiness and perceived learning were weak, and the correlation between interest and perceived learning was moderate.

Table 2. *Multiple regression to predict students' perceived learning*

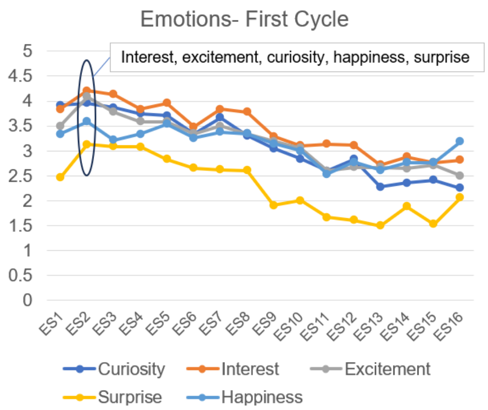
Model	Unstandardized Coefficient B	Standard Error	Standardized Coefficients Beta	*t*	Significance
(Constant)	2.68	0.20		13.12	<.001
Anxiety	-0.12	0.04	-0.12	-2.89	0.00***
Frustration	0.12	0.05	0.10	2.23	0.03*
Confusion	-0.08	0.05	-0.07	-1.76	0.08
Curiosity	-0.05	0.04	-0.05	-1.17	0.24
Interest	0.30	0.06	0.29	4.99	<.001***
Excitement	-0.11	0.06	-0.10	-1.90	0.06
Surprise	0.10	0.04	0.11	2.72	0.01**
Boredom	-0.06	0.04	-0.06	-1.56	0.12
Happiness	0.17	0.05	0.16	3.72	<.001***
Sadness	-0.08	0.05	-0.07	-1.68	0.09

Notes: *$p < .05$; **$p < .010$; ***$p < .001$

3.2 Conditions of Intense Emotions

In the first cycle, interest, excitement, curiosity, happiness and surprise were the highest, whereas boredom was the lowest after the introduction talk by a Data Science expert on the first day (C1ES2, see Figure 1a). During the second cycle, after the same talk (C2ES3, see Figure 2b), there was a sharp decrease in anxiety and frustration (from C2ES2 to C2ES3, see

Figure 2b). The speaker shared what a Data Scientist does in real-life. The enthusiastic tone and personally relevant examples could have led to positive emotions.



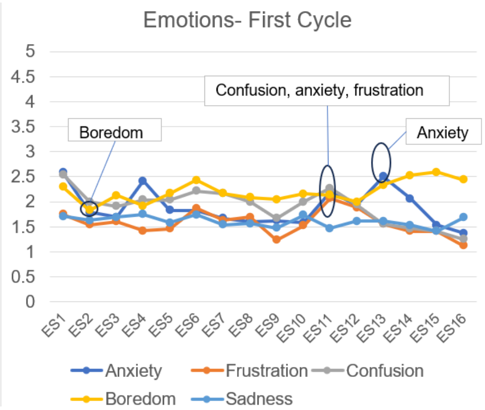
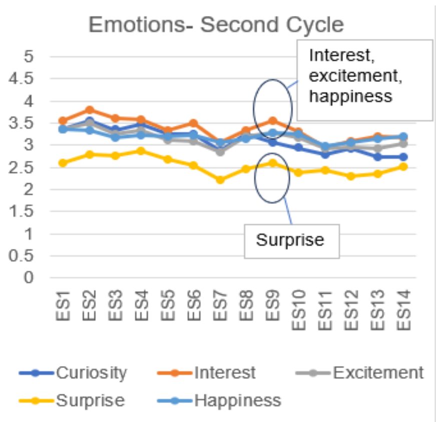


Figure 1a. Positive Emotions (First Cycle) *Figure 1b.* Negative Emotions (First Cycle)

In the first cycle, confusion, anxiety and frustration were the highest or second highest for the day after consultation with the data science expert (C1ES11, see Figure 1b). During consultation, all groups presented their progress to the expert and community. The expert asked questions and gave feedback. When the expert asked questions about a group's graphs, silence was observed, which could be attributed to not knowing how to answer them. Frustration and confusion could have arisen due to the inability to respond to questions. Furthermore, the feedback received could have been overwhelming and students might have felt challenged by the lack of time to refine their analysis. In the second cycle, however, after expert consultation, students reported the lowest anxiety level, second lowest sadness and boredom level (C2ES9, see Figure 2b), and highest positive emotions of—interest, excitement, happiness, and surprise —across the day (C2ES9, see Figure 2a). In this cycle, participants did not share their progress with the community during consultations, possibly leading to less pressure. As the experts approached them, participants tended to feel less bored or sad but more excited about conducting their interest-driven investigation.

Anxiety was the highest and second highest for the day before the final presentations at C1ES13 (see Figure 1b) and C2ES13 (see Figure 2b). It was probably due to having to explain their investigations in front of a large community. Students might also be worried about audiences' appraisal of their presentations, questions posed, and potential criticism.



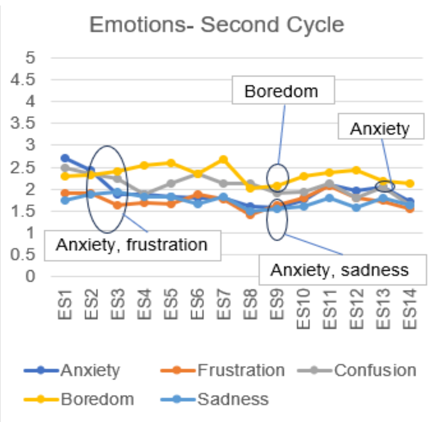


Figure 2a. Positive Emotions (Second Cycle) *Figure 2b.* Negative Emotions (Second Cycle)

4. Discussion

This study explored how different emotions predicted students' perceived learning and the conditions when they experienced intense emotions in data science learning.

The multiple regression analysis suggested that anxiety negatively predicted perceived learning, whereas interest, happiness, surprise, and frustration positively predicted perceived learning. Similarly, there were negative correlations found between anxiety, including test anxiety, and learning achievement (Van den Berg & Coetzee, 2014). Positive emotions (happiness, interest) enable students to participate in meaningful learning and understand content better (Chen et al., 2022). Surprise could be experienced when learners encounter new information (D'Mello & Grasser, 2011), hence they may pay more attention to processing the surprising content, improving their learning outcomes (Muis et al., 2018). Surprisingly, we found that frustration positively predicted perceived learning. When frustration was elicited from a difficult task, regulation of the frustration and student persistence could lead to effective task-completion and greater positive emotions like interest and happiness (Tomas et al., 2018). Furthermore, experiencing frustration may be a precursor to happiness if there is a sense of achievement from task mastery (King et al., 2017). Frustration during data science learning could have been resolved, predicting perceived learning.

Contrastingly, after the consultation with expert in the first cycle, students reported intense negative emotions, whereas they reported more interest, excitement, surprise, and happiness after the expert consultation in the second cycle. This could be due to the presentation of progress in the presence of a large community, which could have led to public speaking anxiety in the first cycle (Raja, 2017). Frustration (Fang et al., 2017) could also stem from an innate fear of not performing up to standards or not performing as well as others (Ryan & Deci, 2017). Differently, in the second cycle, consultations took place without the presence of other groups. Group members informally shared their progress with experts, making them feel less stressed and more supported. Also, in the first cycle, feedback (which may be perceived as negative) was received in front of the community, which might arouse negative feelings and threaten students' self-esteem (Briñol et al., 2018). In the second cycle, instead of feeling criticized, groups might feel like experts were helping them overcome obstacles.

Theoretically, our findings contributed to how to provide feedback in data science learning. Reassurance should be given before feedback, and we should ensure students feel safe sharing and refining ideas. Practically, educators should pay attention to increasing interest, surprise, happiness, and manage appropriate levels of frustration that could be resolved. To do so, teachers can design relatable data science content.

Despite our contributions, one limitation is that our analyses were based on self-reported emotions and perceived learning, which could have been influenced by external personal factors. Perceived learning may not be an accurate measurement of actual data science knowledge. Factors such as participants' personalities, data science backgrounds, and engagement were not considered in the regression. Future research should consider these factors and consider using technology to collect real-time emotions, to develop a better understanding of emotions and data science learning.

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References

Briñol, P., Petty, R. E., Stavraki, M., Lamprinakos, G., Wagner, B., & Díaz, D. (2018). Affective and cognitive validation of thoughts: An appraisal perspective on anger, disgust, surprise, and awe. *Journal of Personality and Social Psychology, 114*(5), 693–718. https://doi.org/10.1037/pspa0000118

Chen, X., Huang, Z., & Lin, W. (2022). The effect of emotion regulation on happiness and resilience of university students: The chain mediating role of learning motivation and target positioning. *Frontiers in Psychology, 13*, 1029655–1029655. https://doi.org/10.3389/fpsyg.2022.1029655

D'Mello, S., & Graesser, A. (2011). The half-life of cognitive-affective states during complex learning. *Cognition and Emotion, 25*(7), 1299–1308. https://doi.org/10.1080/02699931.2011.613668

English, L. D. (2014). Promoting statistical literacy through data modelling in the early school years. In E. Chernoff & B. Sriraman (Eds.), *Probabilistic thinking: Presenting plural perspectives* (pp. 441–458). Springer. https://doi.org/10.1007/978-94-007-7155-0_23

Fang, H., He, B., Fu, H., & Meng, L. (2017). Being eager to prove oneself: U-shaped relationship between competence frustration and intrinsic motivation in another activity. *Frontiers in Psychology, 8*, 2123–2123. https://doi.org/10.3389/fpsyg.2017.02123

Finzer, W. (2013). The data science education dilemma. *Technology Innovations in Statistics Education, 7*(2), 1-9. https://doi.org/10.5070/T572013891

Hazzan, O., & Mike, K. (2023). The birth of a new discipline: Data science education. In *Guide to teaching data science: An interdisciplinary approach*. Springer. https://doi.org/10.1007/978-3-031-24758-3_4

Heinemann, B., Opel, S., Budde, L., Schulte, C., Frischemeier, D., Biehler, R., … & Wassong, T. (2018, November). Drafting a data science curriculum for secondary schools. In *Proceedings of the 18th Koli Calling International Conference on Computing Education Research* (pp. 1-5). https://doi.org/10.1145/3279720.3279737

King, D., Ritchie, S. M., Sandhu, M., Henderson, S., & Boland, B. (2017). Temporality of emotion: Antecedent and successive variants of frustration when learning chemistry. *Science Education (Salem, Mass.), 101*(4), 639–672. https://doi.org/10.1002/sce.21277

Muis, K. R., Chevrier, M., & Singh, C. A. (2018). The role of epistemic emotions in personal epistemology and self-regulated learning. *Educational Psychologist, 53*(3), 165–184. https://doi.org/10.1080/00461520.2017.1421465

Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*(4), 315–341. https://doi.org/10.1007/s10648-006-9029-9

Pekrun, R., Marsh, H. W., Elliot, A. J., Stockinger, K., Perry, R. P., Vogl, E., Goetz, T., van Tilburg, W. A. P., Lüdtke, O., & Vispoel, W. P. (2023). A three-dimensional taxonomy of achievement emotions. *Journal of Personality and Social Psychology, 124*(1), 145–178. https://doi.org/10.1037/pspp0000448

Pekrun, R., & Stephens, E. J. (2012). Academic emotions. In K. R. Harris, S. Graham, T. Urdan, S. Graham, J. M. Royer, & M. Zeidner (Eds.), *APA educational psychology handbook, Vol. 2. Individual differences and cultural and contextual factors* (pp. 3–31). American Psychological Association. https://doi.org/10.1037/13274-001

Raja, F. (2017). Anxiety level in students of public speaking: Causes and remedies. *Journal of Education and Educational Development, 4*(1), 94-110.

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness.* Guilford Publications.

Scherer, K. R. (2009). The dynamic architecture of emotion: Evidence for the component process model. *Cognition and Emotion, 23*(7), 1307–1351. https://doi.org/10.1080/02699930902928969

Thompson, J., & Arastoopour Irgens, G. (2022). Data detectives: A data science program for middle grade learners. *Journal of Statistics and Data Science Education*, *30*(1), 29-38. https://doi.org/10.1080/26939169.2022.2034489

Tomas, L., King, D. T., Henderson, S., Rigano, D., & Sandhu, M. (2018). The resolution of frustration in middle school science classes: The role of the classroom teacher. In S. M. Ritchie & K. G. Tobin (Eds.), *Eventful learning: Learner emotions*. (pp. 133–156). Brill. https://doi.org/10.1163/9789004377912_007

van den Berg, G., & Coetzee, L. R. (2014). Academic self-concept and motivation as predictors of academic achievement. *International Journal of Educational Sciences, 6*(3), 469–478. https://doi.org/10.1080/09751122.2014.11890158

Volet, S., Seghezzi, C., & Ritchie, S. (2019). Positive emotions in student-led collaborative science activities: Relating types and sources of emotions to engagement in learning. *Studies in Higher Education (Dorchester-on-Thames), 44*(10), 1734–1746. https://doi.org/10.1080/03075079.2019.1665314

Wortha, F., Azevedo, R., Taub, M., & Narciss, S. (2019). Multiple negative emotions during learning with digital learning environments – Evidence on their detrimental effect on learning from two methodological approaches. *Frontiers in Psychology, 10*, 2678–2678. https://doi.org/10.3389/fpsyg.2019.02678

YouCubed. (2022, December 28). Data big ideas - YouCubed. https://www.youcubed.org/data-big-ideas/

Zhu, G., Scardamalia, M., Moreno, M., Martins, M., Nazeem, R., & Lai, Z. (2022). Discourse moves and emotion in knowledge building discourse and metadiscourse. *Frontiers in Education, 7,* Article 900440. https://doi.org/10.3389/feduc.2022.900440