

Supporting at-risk students in CS1 courses at scale

Alexandra Vassar^a; Jake Renzella^b; Andrew Cain^c; Julien Ugon^d
University of New South Wales, Sydney^{a,b}, Deakin University^{c,d}
Corresponding Author Email: a.vassar@unsw.edu.au

ABSTRACT

CONTEXT

Computing students often begin their university journey in large CS1 computing courses, where it is crucial that we foster a positive and supportive space for all students. With challenging course curriculum, and a diverse range of student backgrounds, we need to support the span of students from those that are highly competent and potentially ready to enter CS2, down to novices struggling to acclimatise to university life. It is this scale and diversity of the student cohort that can often pose challenges in providing effective support. Our CS1 course accommodates around 3,000 students annually, with a significant number of students identified as at-risk of failure each term.

PURPOSE OR GOAL

Unfortunately, reaching out to these students individually to provide interventions has become impractical due to the time and resource constraints. In the past, we would email at-risk students offering extensions, one-on-one support, or assistance in establishing special considerations or Equitable Learning Plans. However, we noticed a decline in student engagement and responses to these intervention emails, potentially due to email fatigue from irrelevant institutional correspondence. It became important to be able to reach out to these students at scale and ensure they were getting the appropriate support that they need.

APPROACH OR METHODOLOGY/METHODS

Using PowerAutomate, we designed a prototype to provide informal, bespoke intervention messages. We were able to evaluate our hypothesis that students would engage further with a more informal method of correspondence. Data was collected based on response rates of students to the initial message, and then any follow up messages throughout the course.

ACTUAL OR ANTICIPATED OUTCOMES

Anticipated results, based on the prototype, suggest that we saw a response rate of more than double, from 27% to 51% - helping to increase our reach impact when supporting a larger number of diverse students through this program. By incorporating this system into an LMS, we anticipate will produce an even more marked increase in student response rates.

CONCLUSIONS/RECOMMENDATIONS/SUMMARY

This project describes our experiences in approximately doubling the response rate of our intervention outreach activities from 27% to 51% using our prototype, and then details how we plan to integrate the outreach system into a learning management system to automatically deliver the intervention at scale. By implementing this integrated outreach system, we aim to provide better support to at-risk students in CS1 courses and create a more inclusive learning environment.

KEYWORDS

CS1, Student Wellbeing, Inclusivity

Introduction

There is increasing evidence that Australian university students are at a higher risk for psychological distress and mental health disorders (Akullian et al., 2020a; Baik et al., 2019; Browne et al., 2017; Larcombe et al., 2016; Stallman, 2010). Stallman (Stallman, 2010) found an elevated level of psychological distress in 84% of participating university students (from a sample size of 6500 students at two major Australian universities), whereas only 29% of the general population report elevated stress to the same level. Similar trends have been observed in the United States (Eisenberg et al., 2013) and the United Kingdom (Hubble & Bolton, 2020), where significant mental health issues have also been identified among tertiary students. Prolonged levels of such psychological distress can lead to heavy impacts on academic and social participation in university and impairments to attention, information processing, general motivation, lower self-efficacy, and impulse control (Baik et al., 2019). As students continue to deal with mental health challenges, their ability to persevere through difficulties diminishes, leading to a higher likelihood of dropping out from their courses, a common occurrence in the first-year experience, where a prevalent reason cited by students for seriously considering deferring or withdrawing from their studies is related to their wellbeing (Baik et al., 2015). Some research also indicates that computer science students are particularly vulnerable to mental illness in comparison to the rest of the general population (Passos et al., 2022). It is thus critical that student wellbeing become a crucial consideration when designing and implementing introductory computing (CS1) courses, which serve as students' first introduction to computer science.

These statistics clearly show the dire need for interventions even before the response to emergency teaching because of the COVID-19 pandemic. However, in the last few years, with the disruptions to education caused by the global COVID-19 pandemic, and the subsequent isolation of students, the response of universities to the growing crisis has led to a further decline in mental health and wellbeing (Siegel et al., 2022). Students have felt that their sense of belonging has been negatively affected, which has impacted their overall engagement with courses (Mooney et al., 2021) where the sex of respondents to surveys was considered, female students largely reported more negative impact than their male counterparts (Siegel et al., 2022). Thus, student wellbeing has become a growing concern in CS1 courses, with students prone to feelings of anxiety and depression (Akullian et al., 2020b). In the last year in Australia, the prevalence of anxiety among university students was reported to be 32% (high) to 39% (very high) (Lynette Vernon et al., 2022), with an overall percentage of 71% of students reporting elevated psychological levels. Recognizing the potential challenges and stressors that students may encounter in this foundational stage, it is important for educators to prioritize their wellbeing. CS1 courses can foster student wellbeing by promoting a supportive and inclusive learning environment, offering resources for mental health support, and encouraging a healthy balance in their studies. This helps to set up a positive foundation for their future studies in computer science and establish a good sense of belonging at the very start of their computing journey.

Background

CS1 courses are usually based in the foundational understanding of computer science, which often involves learning how to program. Learning and teaching programming is challenging, with students required to undertake deep learning approaches to succeed. As such, introductory computing courses often have high attrition and failure rates (Quille & Bergin, 2019). Students entering the University Introductory Programming course come from varied backgrounds and abilities, which also introduces challenges when designing support mechanisms. Additionally, the introductory programming course is often students' first taste of university life, and most students are unfamiliar with or unaware of the support services available.

Our introductory computing course (CS1) attracts many students each term, with approximately 3,000 students enrolling each calendar year. As students begin their university journey via the first course of introductory programming, one of our priorities is to foster a positive and supportive space for students to learn. A challenge in supporting students in the course is its breadth and

scale. In such large courses, the number of at-risk students is significant, and reaching out to these individual students has become prohibitive due to the scale, time and effort required.

There are nine teaching weeks in the course, not including a mid-term flexibility week which allows students a chance to revise and catch up on course content. Our CS1 course is designed to introduce students to the fundamental concepts and principles of programming. The course covers programming fundamentals, algorithms, data structures, debugging exercises, and problem-solving techniques. It aims to develop student's programming skills and enhance their logical and analytical thinking abilities. The weekly breakdown of topics covered include:

- **Week 1:** Introduction to computing platforms, variables, constants, data types
- **Week 2:** Control flow, custom data types
- **Week 3:** Functions, static arrays
- **Week 4:** 2D arrays, strings
- **Week 5:** Pointers
- **Week 7:** Dynamic arrays, manual memory, Linked lists
- **Week 8:** Linked lists (extended)

It is worth to note that Week 6 is a mid-term break, with no content being covered, and Week 9 brings concepts together with revision. Students are assessed primarily via two major assignments, and an invigilated examination at the end of term.

To support students, we employ a variety of teaching strategies primarily including:

- **Weekly lectures:** Primary delivery of course content
- **Weekly tutorials:** 3-hour active classes with activities, presentations, team-exercises run by an academic tutor in a student-tutor ration of about 20:1.
- **Help/Revision sessions:** Optional drop-in-drop-out revision sessions run each week, where students can receive assistance with bugs or understanding.

Globally, and in our CS1 offering, the curriculum of introductory computing courses is known for its challenging nature. Despite our efforts to provide a comprehensive and supportive learning environment, we continually observe a consistent failure rate of around 23% each course offering.

The CS1 course is only available for computing majors in specific course offerings. In others, the course is available as an elective for non-computing students. Regardless, each student enrolled in the CS1 course experiences the same curriculum with the same amount of support. This variety in the background and student experience poses a significant challenge in ensuring our course caters to the range of students who may study it.

When exploring individual student progress, we notice many students start to show signs of risk (of completion or failure) by around week 3. This relatively early signpost allows us to identify, contact, and provide additional support to these students. By identifying the underlying causes and implementing appropriate strategies, we can enhance the learning experience for students and improve their chances of success in the course, and subsequent computer science courses.

Strategies to support at-risk students

We take a proactive approach to supporting at-risk students to enhance their chances of academic success and wellbeing. By identifying students who may be at risk of falling behind or facing challenges, we can implement timely interventions and provide targeted support. This section outlines our existing tools and strategies for identifying and reaching out to at-risk students, emphasizing the importance of early intervention and ongoing communication.

Identifying at-risk students

To identify students who may be facing difficulties in their academic journey, we consider multiple indicators. In Week 1 of each term, we pay close attention to students who have previously failed the CS1 course and are retaking it to advance in their studies. These students are categorized as "Past Fails/Repeat students" and are considered at-risk. Additionally, students who enter the program with a low Weighted Average Mark (WAM) and those with an impacted academic standing are also identified as at-risk individuals. In later weeks, to further enhance our identification process, we involve our tutors who play a crucial role in identifying at-risk students. During weeks three and five of each academic term, tutors have the responsibility of nominating students whom they believe may be at risk. They consider various factors such as attendance records, performance in weekly activity lab tasks, and any other relevant indicators based on their professional judgment. This manual identification process conducted by tutors helps us identify students who may require additional support and interventions to ensure their academic success.

In this educational setting, students participate in scheduled lab sessions with their assigned tutor on a fortnightly basis. These sessions provide a valuable opportunity for students to engage with their tutors and discuss their progress. Following these conversations, the tutors assign a traffic light rating to each student, indicating the extent to which they are falling behind, and the level of effort required to catch up. This rating system serves as an important tool in determining the appropriate interventions to offer and the urgency with which additional support needs to be provided. Students who receive a red or orange rating are promptly contacted to assess their specific needs and discuss potential interventions. Those categorized as red, indicating a significant lag in their progress, are offered personalized one-on-one support to address their academic challenges effectively. This proactive approach ensures that students in the most critical situations receive the necessary attention and resources to regain their academic footing.

We have a range of existing outreach tools and interventions in place to provide support to students who may require additional assistance. One such tool is Special Considerations, which allows students facing extenuating circumstances to request adjustments to their assessments or deadlines. The Equitable Learning Plan (ELP) is another intervention available for students who may need support in putting in place interventions for health issues that are continuing. This helps such students to have a more equal access to education with the necessary ongoing adjustments to their work.

Revision sessions are conducted to help students review and consolidate their understanding of key concepts, those are the most common interventions offered in Weeks 3 and 5 those students that are classified in the "Orange" category of the traffic light system. This means they get first preference to nominate a revision session which will go over the previous fortnight of content with a range of sample problems that the students can get support in solving. Small extensions may be granted to students who need a bit of extra time to complete their assignments, and weekly problem sets. Additionally, extra tutorials are offered to support students who need further clarification or guidance. These students are referred to tutorials that are already scheduled and running, and they may elect to attend any number of extra tutorials or laboratory spaces that week, provided there is physical capacity to accommodate them. Lastly, miscellaneous support is available to address any other specific needs or challenges students may encounter. Through these varied interventions, we aim to provide comprehensive support to students and ensure they have the resources and assistance necessary to succeed academically.

Prior work

Many Learning Management Systems offer rule-based automatic intervention systems that can be run at specific times in the term. A challenge with these systems is that they rarely offer the possibility to take the individual context of the students into account. In our experience it can happen that a student has responded to a prior intervention and is in the process of following a catch-up plan set up with their teaching team and still triggers the rule set up for a later intervention, resulting in the student receiving a message that does not apply to them. Further,

these systems rely on all student-related data be encompassed in a single platform, which is often not the case in computing courses.

Prototyping a new intervention

Previously, we utilised our at-risk identification metrics and used email as the main point of contact with our students. Due to the scale of the course, students would get reached out to over email twice a term. In the first week, we proactively email repeat students and those with a low Weighted Average Mark (WAM), reminding them of the available resources and support systems. During the third/fourth week, we reach out to students identified as at-risk, acknowledging their potential struggles, and providing information about support services, tutoring options, study groups, and other resources. However, one problem we have encountered is that a low percentage (around 20%) of students reply to emails, which hinders effective communication and support. We have developed an automated intervention communication system to address the low response rate of at-risk CS1 students. This innovative approach replaces the traditional cold emails sent to at-risk students with personalised intervention messages generated using Microsoft Power Automate and delivered through Microsoft Teams (Figure 1). By utilising this informal chat platform for student outreach, we aimed to establish a more personal and meaningful connection, dispelling the notion of generic mass emails. Part of our approach using the informal chat system is consciously keeping the language casual and chatty to ensure students feel at ease. We aim to avoid intimidating tones implying they have done something wrong or fallen too far behind. Instead, we focus on simply checking in with them in a friendly manner, fostering a more approachable and supportive environment. This approach has encouraged open communication and building positive relationships with students. The outcomes have been promising, with a significant increase in student engagement.

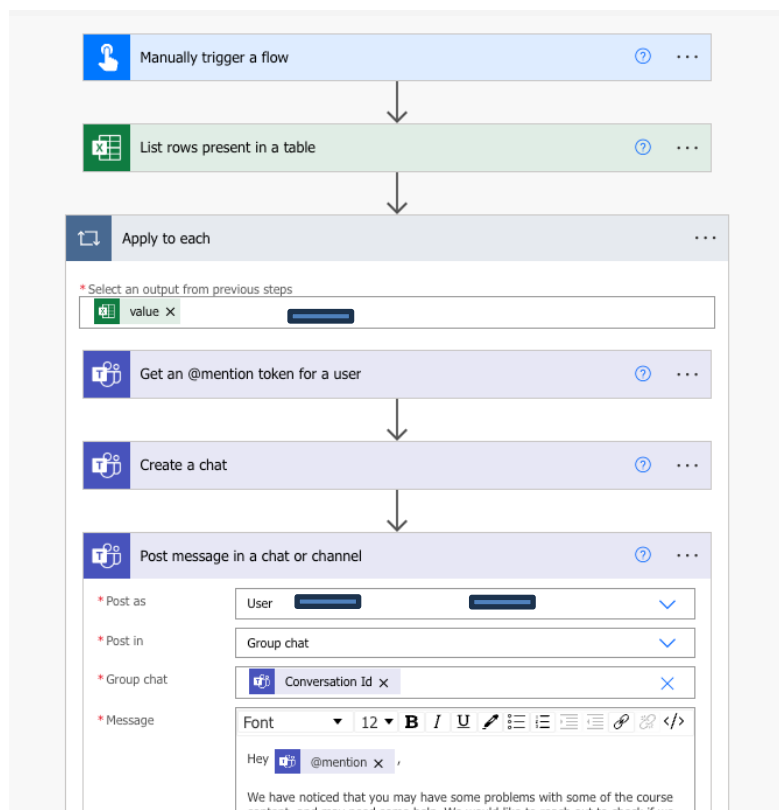


Figure 1: Example of a Power Automate flow for reaching out

Method

Participants

The participants in this study comprise students enrolled in first-year introductory computing courses at our institution. The total number of students overall is $n = 5587$ (Table 1). These courses represent the initial step in their academic journey, marking the beginning of their degree program. The introductory computing course is a fundamental and mandatory component of their curriculum, serving as a prerequisite for advancing further in their studies.

Table 1: Number of students in each term of the program

Year/Term	2021 T2	2021 T3	2022 T1	2022 T2	2022 T3	2023 T1	2023 T2
No of students	657	640	912	768	627	1081	902

It is important to note that the teaching staff remained consistent throughout all these terms, ensuring continuity in the delivery of the course material. Additionally, the course content and materials remained unchanged across these terms, providing a stable foundation for evaluating the students' progress and performance. These factors contribute to a coherent and consistent study group, allowing for meaningful analysis of the participants' experiences and outcomes in the first-year introductory computing courses.

Data collection and analysis

Data for this study were collected through a systematic and proactive approach to support students in their first-year introductory computing courses. On a fortnightly basis, students who were identified as falling behind were contacted (See Section: Identifying at-risk students). In the initial week, particular attention was given to those students who had previously failed the course, aiming to provide early assistance. Interventions offered to these students included revision sessions, extra lab opportunities, and small extensions, tailored to address their specific needs and challenges.

During the first three terms, communication with students was conducted via email. Receiving such insignificant response rates, the communication shifted to a less formal mode of communication with Teams messages. Notably, the context of initial data collection was marked by the tail end of the COVID pandemic, a period during which students were transitioning back to in-person classroom settings. In analysing the data, responses were carefully evaluated; replies were recorded only if they contributed significantly to the conversation. Superficial responses like simple thank-you messages were not included in the final dataset. This approach ensured that the data analysis focused on meaningful interactions, providing valuable insights into the effectiveness of the interventions and the students' responses during this crucial period of educational transition.

Results

Through systematic analysis of historical at-risk intervention email responses, we have observed the response rate increase from approximately 22% when contacted via email to an average of 47% (Figure 2). The positive feedback from students has been overwhelmingly encouraging. For example, one student in a 2022 term expressed gratitude for the outreach and their improved coping with the subject, while another student in the 2023 term's cohort appreciated the offered extensions and support, commenting that they appreciate "that they feel they will be supported through their term". The prototype has provided valuable insights into interventions' effectiveness and fostered a more positive overall environment. Additionally, the direct line of communication with lecturers has increased student follow-up messages, enabling immediate support implementation and a greater chance of success in future terms.

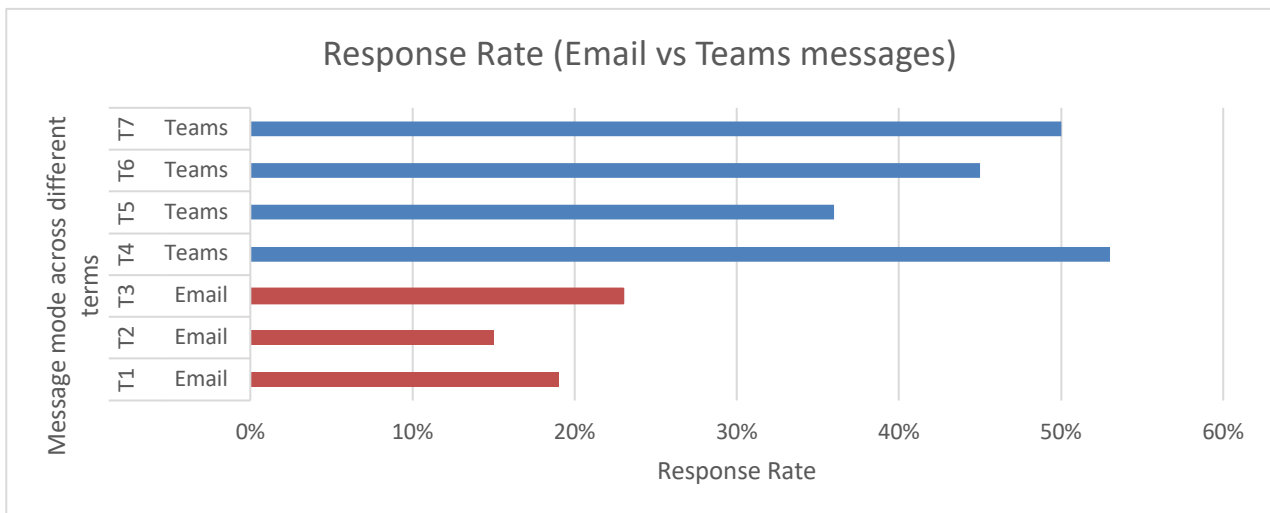


Figure 2: Response rate in Email vs Teams message format

Anecdotal evidence also suggests a decrease in failure rates, with the failure rate decreasing from 22% in a term of 2022 to 18% in the subsequent terms since implementing the ongoing intervention (Table 2). However, to draw more conclusive results, further analysis is required, focusing on the specific students whom we reached out to and tailored interventions according to their needs.

The email intervention took place at the tail end of the COVID-19 online education period, with some students returning to in-person teaching, when exams were non-invigilated and conducted online, leading to significant concerns about academic integrity during that time.

Table 2: Overall Course Failure Rates across terms

Term	Overall Course Failure Rate
2021 T1 (online non-invigilated exam)	15.3%
2022 T2 (online non-invigilated exam)	9%
2022 T3 (online non-invigilated exam)	10.5%
2022 T4 (in person invigilated exam)*	22%
2023 T5-T7 (in person invigilated exam)	18.3%

Limitations

This paper presents our experiences in identifying at risk students and transitioning from formal email communications to informal chat messages. While initial evaluations indicate that the response rate from at risk students has almost doubled, several limitations impact the generalisability of our findings. Although there are indications from student communications that our responses have helped students get back on track to passing the course, we have yet to formally measure this correlation. Further rigorous investigation is needed to ascertain the extent to which our responses positively influence students' course performance.

Additionally, we did not conduct a direct comparison between email and Teams responses within the same cohorts. This was due to our continuous refinement of the prototype to optimise the response rate, making it challenging to assess them simultaneously. Future research could adopt

a concurrent email/Teams message strategy to determine which communication method yields a higher response rate.

Addressing these limitations in future studies will enhance the overall understanding and effectiveness of our intervention approach.

Conclusion and Recommendations

Integrating intervention mechanisms into the learning management system provides the opportunity to automate aspects of the identification and communication to at-risk students but can also be expanded to provide a mechanism to promote engagement and encourage participation from all students within the cohort.

Features in other Learning Management Systems, such as BrightSpace's Intelligent Agents, allow the identification of personalised interventions for students. These typically use email to contact students but may benefit from other more direct means of communication. Ideally, these features should make it easy to set up communication plans that provide students with personalised progress updates at regular intervals, targeted at providing students with actionable advice on how best to progress with their studies. Incorporating aspects such as personal learning goals, current progress, and engagement would help to keep students connected with their studies. While these tools are suitable, our platform is system-agnostic, allowing us to take a holistic approach to at-risk outreach, with minimal technical effort.

The prototype has provided us with a cost-effective way to test the hypothesis and validate its effectiveness before committing to the development and integration of such a solution into a learning management system. By conducting tests and refining the prototype, we have gained valuable insights into its functionality and potential impact on the learning environment. This approach allows us to make informed decisions and ensure the successful implementation of the solution in the future, saving both time and resources.

Future Work

In the future, we seek to expand this project to support student progress through adaptations to a feedback and assessment tool we are developing. This tool promotes frequent formative feedback that typically involves weekly task submissions. This provides us with more touch points than traditional assessment approaches, providing more data to help inform intervention strategies. Currently, we observe that staff export data from this tool to help inform their decisions on the messages to send to students. Automating this process will help us better connect with students, as demonstrated in this paper. We plan to implement a framework that will allow course teams to implement an intervention and communication strategy to help engage students in their courses. This will include the ability to define things like periodic checkpoints (e.g. weekly) in which a series of conditions can be checked and trigger a message to students, as well as checkpoints corresponding to specific events (e.g. submission of an assignment). This will enable course teams to classify and target groups of students, such as struggling students but also provide the capacity to create a range of classifications such as disengaged students, those well behind, students on target for success, and students who are working well ahead. Providing customised messages to incentivise each of these groups aims to ensure students receive more personalised messages and encouragement through their studies.

In creating such a system, we anticipate the need to identify and automate the collection of data points around access to instructions, content, submission, student aspirations, and details from feedback received. These data points, together with details associated with specifics of the required tasks, will help form the classifications. The data points will include not only the current status of the students, but also their past context, including their response to prior interventions. The system should then be able to perform a range of actions for each classification within a given intervention. The collection of a wide range of data, combined with sophisticated machine learning tools, will give us the possibility to maximise the effect of our intervention strategies.

Connecting these in with more modern communication tools, such as teams messaging, will help ensure that these interventions are more likely to be received and actioned by students.

References

- Akullian, J., Blank, A., Bricker, L., DuHadway, L., & Murphy, C. (2020a). Supporting mental health in computer science students and professionals. *SIGCSE 2020 - Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, 958–959. <https://doi.org/10.1145/3328778.3366980>
- Akullian, J., Blank, A., Bricker, L., DuHadway, L., & Murphy, C. (2020b). Supporting Mental Health in Computer Science Students and Professionals. *Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, 958–959.
- Baik, C., Larcombe, W., & Brooker, A. (2019). How universities can enhance student mental wellbeing: the student perspective. *Higher Education Research and Development*, 38(4), 674–687. <https://doi.org/10.1080/07294360.2019.1576596>
- Baik, C., Naylor, R., & Arkoudis, S. (2015). The First Year Experience in Australian Universities: Findings from Two Decades, 1994-2014. *Melbourne Centre for the Study of Higher Education*.
- Browne, V., Munro, J., & Cass, J. (2017). The Mental Health of Australian University Students. *Journal of the Australian and New Zealand Student Services Association: Number, 50*, 51.
- Eisenberg, D., Hunt, J., & Speer, N. (2013). Mental health in american colleges and universities: Variation across student subgroups and across campuses. *Journal of Nervous and Mental Disease*, 201(1), 60–67. <https://doi.org/10.1097/NMD.0b013e31827ab077>
- Hubble, S., & Bolton, P. (2020). Support for students with mental health issues in higher education in England. *UK Parliament Briefing Paper*.
- Larcombe, W., Finch, S., Sore, R., Murray, C. M., Kentish, S., Mulder, R. A., Lee-Stecum, P., Baik, C., Tokatlidis, O., & Williams, D. A. (2016). Prevalence and socio-demographic correlates of psychological distress among students at an Australian university. *Studies in Higher Education*, 41(6), 1074–1091. <https://doi.org/10.1080/03075079.2014.966072>
- Lynette Vernon, Dr Kathryn Modecki, & Dr Kylie Austin. (2022). *Understanding Wellbeing Challenges for University Students During Crisis Disruption*.
- Mooney, C., Dublin, C., & Becker, B. A. (2021). *Investigating the Impact of the COVID-19 Pandemic on Computing Students' Sense of Belonging*. 12(2), 612–618.
- Passos, M. S. L., Murphy, C., Mawr College Bryn Mawr, B., Rita Zhen Chen, U., Gonçalves Santana, M., & Soares Passos, G. (2022). *Association of Positive and Negative Feelings with Anxiety and Depression Symptoms among Computer Science Students during the COVID-19 Pandemic*.
- Quille, K., & Bergin, S. (2019). CS1: how will they do? How can we help? A decade of research and practice. *Computer Science Education*, 29(2–3), 254–282. <https://doi.org/10.1080/08993408.2019.1612679>
- Siegel, A. A., Zarb, M., Anderson, E., Crane, B., Gao, A., Latulipe, C., Lovellette, E., McNeill, F., & Meharg, D. (2022). The Impact of COVID-19 on the CS Student Learning Experience How the Pandemic has Shaped the Educational Landscape. *Annual Conference on Innovation and Technology in Computer Science Education, ITiCSE*, 165–190. <https://doi.org/10.1145/3571785.3574126>
- Stallman, H. M. (2010). Psychological distress in university students: A comparison with general population data. *Australian Psychologist*, 45(4), 249–257. <https://doi.org/10.1080/00050067.2010.482109>

Copyright statement

Copyright © 2023 Names of authors: Alexandra Vassar, Jake Renzella, Andrew Cain and Julien Ugon. The authors assign to the Australasian Association for Engineering Education (AAEE) and educational non-profit institutions a non-exclusive licence to use this document for personal use and in courses of instruction provided that the article is used in full and this copyright statement is reproduced. The authors also grant a non-exclusive licence to AAEE to publish this document in full on the World Wide Web (prime sites and mirrors), on Memory Sticks, and in printed form within the AAEE 2023 proceedings. Any other usage is prohibited without the express permission of the authors.