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A case study of solving a complex genetics problem to develop generative AI literacy in health science

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With the emergence of generative artificial intelligence (GenAI) and GenAI-enabled tools, teachers have a responsibility to educate learners about ethical and responsible AI use while presenting opportunities for effective use to support student learning (TEQSA, 2024). Most importantly, students need to develop GenAI literacy skills such as prompt engineering and to critically evaluate the GenAI outputs in support of their learning and as future professionals (Giray, 2023).

This case study from a second-year genetics course evaluated student perceptions of GenAI tools. Students received education on GenAI literacy and applied these skills to a prescribed genetics problem-solving assessment task. Quantitative data was collected using 5-point Likert scale surveys before and after completion of the scaffolded task. Additionally, student assessment performance marks were evaluated.

Students reported increased understanding of prompt engineering and greater confidence at engaging with GenAI tools. Student assessment performance was not impacted through the availability of GenAI, indicating that the assessment integrity or purpose was not compromised. However, there was a correlation between assessment performance and assessor evaluation of student prompting and output analysis.

Health science graduates will encounter careers influenced by GenAI enabled tools (Salari et al., 2025). Therefore, students require education and opportunity to develop GenAI literacy skills whilst at university. This case study outlines a strategy for teachers to provide AI literacy in health science courses while maintaining assessment integrity and purpose.

Keywords: AI literacy, assessment design, generative artificial intelligence, genetics, prompt engineering

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Introduction

The rapid advancement of generative artificial intelligence (GenAI) has transformed higher education, with impacts on teaching and professional practice for healthcare and health sciences (Adarkwah et al., 2025; Busch et al., 2025). As GenAI tools become increasingly sophisticated and accessible, higher education institutions need to harness the educational potential to ensure students develop GenAI literacy skills, while maintaining the integrity and validity of assessment practices (TEQSA, 2024).

Future health science graduates will inevitably encounter AI-enabled tools and research applications in their careers (Salari et al., 2025). However, many curricula currently lack structured approaches to developing students' GenAI literacy, particularly beyond foundational AI disciplines such as data science, computer science and engineering (Ng et al., 2021; Southworth et al., 2023). A recent systematic review found generally low to moderate AI literacy rates among healthcare professionals, with many students lacking sufficient understanding and feeling unprepared to apply AI in practice (Kimiafar et al., 2023).

GenAI literacy encompasses more than basic tool familiarity. It requires sophisticated skills in prompt engineering, critical evaluation of AI outputs, and understanding of the ethical implications of its use (Frehywot & Vovides, 2024; Giray, 2023; Long & Magerko, 2020). Students must learn to leverage these tools effectively while maintaining academic integrity and developing independent critical thinking capabilities (Cotton et al., 2024). The Australasian Academic Integrity Network has emphasised that students must "develop AI literacy skills" to critically evaluate AI outputs and properly acknowledge any AI assistance to avoid misconduct (AAIN, 2023). However, there is also a growing call for higher education institutions not to simply communicate permissible uses of GenAI to students as a form of academic integrity enforcement, but rather to restructure assessment design to facilitate meaningful use of these tools (Corbin et al., 2025).

Despite recognition of these needs, limited empirical evidence exists regarding effective pedagogical strategies for integrating GenAI literacy into health science curricula, and current evidence for AI's educational benefits has been characterised as "poor”, with calls for more rigorous studies (Feigerlova et al., 2025).

The aim of this case study is to develop an assessment that fosters GenAI literacy skills and examine student perceptions and performance outcomes when using GenAI in problem-solving-based assessments. This case study provides insights for health science educators seeking to balance GenAI integration with educational integrity in their assessment practices.

Methods

Course structure

A second-year undergraduate genetics course designed predominantly for the Bachelor of Laboratory Medicine and Bachelor of Biomedical Science programs was selected for this study. Delivered over 13 weeks, the course combines pre-recorded lectures with face-to-face seminars, tutorials and laboratory practicals. The existing assessment plan supported a structural redesign to allow GenAI integration. The assessments consist of a problem-solving assessment (25%), practical component (35%), and a final interactive oral assessment (40%). The AI-literacy development task was embedded within the problem-solving assessment, a common assessment format in health science curricula. The problem-solving assessment had four equal equivalent versions randomly assigned to students with one specific question dedicated for the use of GenAI. The versions of the assessment had been used in previous offerings of the course, without the incorporated GenAI use.

AI-literacy scaffolding

Students were provided with a 1-hour face-to-face workshop in teaching week 5 which introduced the basis of GenAI platforms, the principle of prompt engineering, and the process of output evaluation. The workshop included both didactic delivery on the capabilities and limitations of GenAI, and active engagement for how students could utilise GenAI in the problem-solving assessment. Students could ask questions and interact with GenAI with guidance. A recording of the session was provided in the learning management system (LMS). The problem-solving assessment, submitted at the end of week 6, consisted of 8 questions regarding a complex inheritance genetic problem. Students solved the first 7 problems manually. The eighth problem directed students to use their AI literacy skills to guide Microsoft CoPilot through the problem (Appendix 1). Students provided the GenAI transcript with evidence of output analysis. Marks for the eighth problem were attributed to the solution of the problem, students' AI prompting, and their analysis of the AI output (Appendix 2). CoPilot was the recommended tool as access is provided and supported by the institution. This choice ensures fairness and equity, however, students were permitted to use any tool available to them.

Participants and data collection

Data was collected from the 54 undergraduate students who completed the course in 2024. Student demographics were obtained from the university's enrolment data (Appendix 3). De-identified assessment grades, course grades and historical grades were obtained, with permission from the course coordinator, for quantitative analysis of student performance. Survey data was collected through two optional, paper-based, anonymous five-point Likert scale surveys (Appendix 4). Surveys were pilot-tested among the teaching team and ethics committee and adjusted as necessary. The "pre-survey" was provided in-class during teaching week 2. The "post-survey" was provided in-class during teaching week 10. Response rates were 96.6% and 81.5% respectively. This reduction is attributed to students choosing not to complete the surveys and reduced attendance late in the semester. To reduce response bias, the surveys were distributed and collected by a third-party academic who had no influence or involvement in marking the problem-solving assessment task.

Data analysis

GraphPad Prism (Version 10.2.3) was used to analyse the data. The five-point scale questions were analysed with non-parametric Mann-Whitney tests, with a p-value of <0.05 considered significant. To examine the relationship between student AI literacy skills and ability to solve the problem, we computed the Pearson correlation coefficient (r) which was interpreted according to conventional thresholds (Akoglu, 2018). The analysis of student performance in the problem-solving assessment in 2024 was assessed using a non-parametric Kruskal-Wallis test, with p-value of <0.05 considered significant. Comparison analysis with past versions of the assessment were analysed by non-parametric Mann-Whitney tests with a p-value of <0.05 considered significant.

Ethics statement

This study received human ethics with a waiver of consent approved from the University of South Australia Human Research Ethics Committee (#207479).

Results

Student cohort

The cohort was predominantly female (77%) and Australian domestic students (64%), and included students from three different undergraduate programs predominantly the Bachelor of Laboratory Medicine. These demographics are consistent with previous cohorts. We did not undertake subgroup analyses as these would have yielded very small numbers, limiting the reliability of any conclusions and risking over-interpretation.

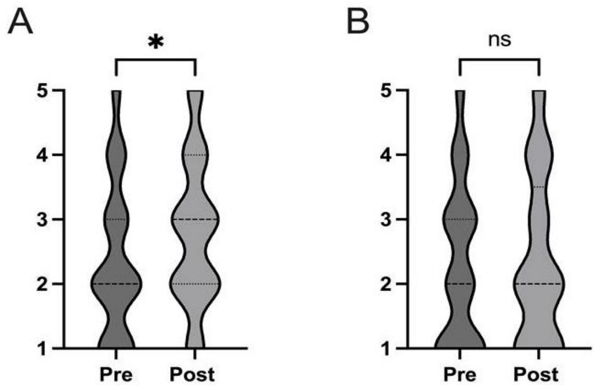
Survey data

Written surveys were provided to students at two points in the semester: before the workshop on the use of GenAI, and after students had completed the assessment. There was a significant increase in the number of students who reported using GenAI for their studies

(Figure 1A), and the mean frequency of use shifted from monthly to weekly. Students did not report an increase in use outside of their university studies (Figure 1B).

Figure 1: Mean Likert-style survey responses to the pre- and post-surveys

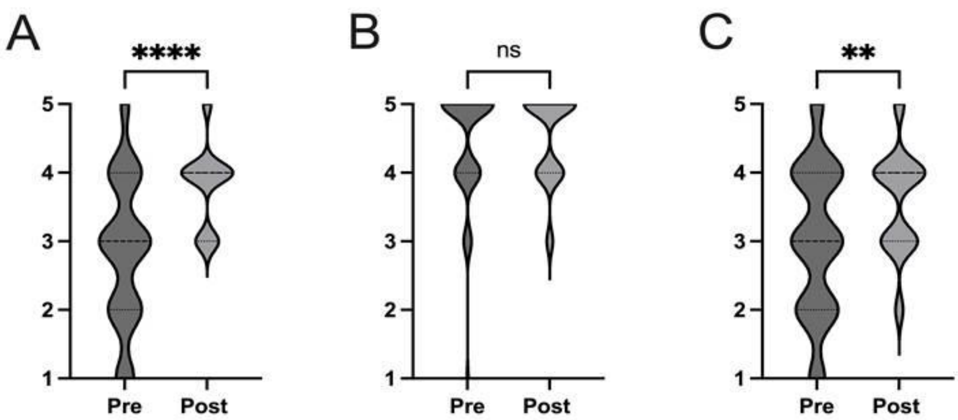
A numerical score was assigned to each response: 1-never; 2-rarely (once a month or less); 3-sometimes (once a week); 4-often (several times a week); and 5-always (daily). The survey statements included A: How often do you use GenAI in your tertiary studies? B: How often do you use GenAI outside of your tertiary studies? Mann-Whitney U test. * p < 0.05.



Student self-rating in the post-survey shows an increase in student understanding of prompt engineering (Figure 2A) and their confidence in using GenAI for academic purposes (Figure 2C). There was no change in their recognition of the importance of reviewing the accuracy of the information provided by GenAI; students recognise the importance of this at both timepoints (Figure 2B).

Figure 2: Mean Likert-style survey responses to the pre- and post-surveys

A numerical score was assigned to each response: 1-strongly disagree; 2-disagree; 3-neutral; 4-agree; and 5-strongly agree. The survey statements included A: I have a good understanding of prompt engineering for GenAI. B: It is important for individuals to review the accuracy of the information provided by GenAI. C: I am confident in using GenAI tools for academic purposes. ** p < 0.01, **** p < 0.0001.



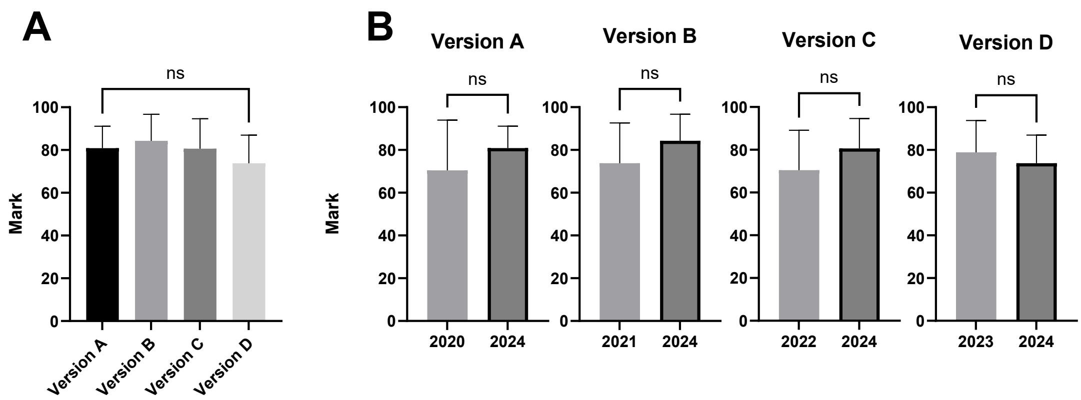
GenAI literacy skills and performance relationship

Analysis of the GenAI-assisted question revealed strong positive correlations between students' GenAI literacy skills and problem-solving success. The student performance in the

AI specific question was marked against criteria in the rubric (Appendix 2) for the solution of the genetics problem, prompting the GenAI tool and analysis of the GenAI outputs. Effective prompting showed a strong correlation with the correct solution ($r = 0.58$, $p < 0.0001$), while students' ability to critique GenAI responses demonstrated an even stronger relationship with success at solving the problem ($r = 0.62$, $p < 0.0001$). Overall assessment performance remained consistent across the assessment versions (Figure 3A) and with previous cohorts (Figure 3B). The deliberate integration of GenAI into the assessment did not appear to affect overall assessment performance, as evidenced by consistent grading outcomes compared to previous iterations. This suggests that the use of GenAI did not compromise assessment integrity. However, consistency in performance alone does not confirm that GenAI inherently supports or maintains academic integrity; further research would be needed to establish any relationship between integration of GenAI and academic integrity.

Figure 3: Comparison of assessment versions and historical performance

A: Median mark out of 100 with standard error for the problem-solving assignment versions in 2024.
B: Historical performance in assessment median mark out of 100 with standard error comparison between previous cohorts and in 2024 with the requirement to use GenAI for the final question.



Discussion

The question is no longer whether health science students should engage with GenAI tools, but how effectively they can be prepared to do so responsibly (Salari et al., 2025). Therefore, students require adequate opportunity to develop GenAI literacy skills such as prompt engineering, and critical evaluation of AI outputs (Frehywot & Vovides, 2024).

This case study demonstrates that strategic integration of GenAI literacy into disciplinary assessments enhances student perceived confidence and skills. Through development and inclusion of GenAI tools in the course students reported an increase in use of GenAI tools for academic purposes following the task. This suggests that targeted instruction in prompt engineering and output evaluation can effectively enhance students' willingness to engage with these technologies. This aligns with recent calls for development of AI literacy education by the Australasian Academic Integrity Network (AAIN, 2023).

The increase in AI use for academic but not personal applications suggests that students developed AI capabilities for the discipline-specific context rather than more broadly. This pattern aligns with authentic assessment models which emphasise that learning is most effective when assessments simulate the real-world contexts (Gulikers et al., 2004). This finding could suggest that teaching AI literacy within disciplinary-specific assessment tasks may be more effective than teaching them as generic technical competencies.

However, the differential adoption between academic and personal contexts could reflect factors such as differing motivation levels across contexts or previous fear of allegations of academic misconduct now reduced through increased confidence engaging with AI-tools for academic work. Students may be reporting on deliberate engagement with AI-enabled tools and overlook incidental interactions. Further research examining disciplinary contextualised AI use in assessment practice is needed to explore these patterns.

Importantly, the overall assessment performance remained consistent with previous cohorts, indicating no advantage or disadvantage occurred when incorporating the GenAI-assisted task. The correlation between students' effective prompting and critique of GenAI outputs and their success on the GenAI-assisted question underscores the pedagogical value of teaching students to interact critically with AI tools. This finding supports the notion that GenAI literacy is not merely about tool usage but requires higher order thinking skills, including synthesis, knowledge of content and context, along with critical analysis (Cotton et al., 2024; Giray, 2023).

The inclusion of the AI-assisted assessment task impacted on students' understanding of prompt engineering and confidence in using GenAI tools, highlighting the effectiveness of short, targeted interventions. Students already recognised the importance of verifying GenAI outputs which, encouragingly, suggests they may already possess an awareness of AI's limitations. This finding reinforces the need for curricula to move beyond basic awareness and toward deeper engagement with the nuances of AI-generated content, including bias, accuracy, and transparency (Busch et al., 2025; Tolentino et al., 2024).

This study demonstrates a structural rather than merely instructional approach to AI integration. Instead of adding AI guidelines to existing assessments, we redesigned the assessment for meaningful AI collaboration. From a curriculum design perspective, embedding GenAI literacy within discipline-specific assessments, as demonstrated in this study, offers a promising model for integrating digital competencies without detracting from core learning outcomes. Requiring students to apply GenAI critically, rather than rely on it for simple answers, preserved the integrity of the assessment. This approach aligns with TEQSA's (2024) recommendations for responsible AI integration in higher education.

Nevertheless, this pilot study has limitations that should be considered when interpreting the data. The relatively small sample size (n=54) and single-institution context may limit generalisability. Complex problem-solving questions that require application of discipline-specific knowledge are common practice in science education and, likely, other disciplines. At the time of this study, these genetic interaction types of problems are resistant to completion by GenAI alone. Vulnerability will need to be regularly reviewed; however, we hope these results prompt other educators to consider AI capabilities and recognise elements which cannot be completed solely by GenAI. Lastly, we did not assess students' AI-literacy skills which may have existed prior to the case study. We do recognise that, at the time of this study, other courses within their program did not intentionally offer development in AI-literacy.

These limitations suggest several directions for future research. Qualitative methods such as interviews or focus groups are needed to understand the motivations, attitudes and contextual factors that shape student engagement with GenAI. Examining demographic subgroups would enable exploration of how factors such as prior performance, discipline or technology experience mediate engagement and outcomes. Longitudinal studies could help assess whether GenAI literacy skills are durable and transferable to clinical or professional contexts. Finally, replication across multiple institutions and larger, more diverse cohorts would strengthen the generalisability of these findings.

Conclusion

In conclusion, this case study contributes and extends the growing body of evidence supporting GenAI literacy in health science education by investigating how to prepare students for responsible and effective AI use within their discipline. We recommend embedding AI literacy skills in discipline-specific assessments to ensure meaningful application of AI skills. Assessment should be redesigned to incorporate authentic, targeted learning interventions focusing on AI collaboration to develop literacy skills. Critical analysis of AI output is effective in building student efficacy with using AI ethically in their studies. Lastly, to maintain academic rigour, educators should aim to design scaffolded tasks that integrate AI as a tool rather than a shortcut.

This case study illustrated how GenAI can be integrated into assessments, showing that students can develop meaningful skills through structured support. It provides a practical framework for educators navigating the evolving landscape of AI in higher education.

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Disclosure of the use of AI-assisted technologies during writing

The authors used generative AI tools for the purpose of editing throughout the article. The authors take full responsibility for the content.

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Appendix 1: Problem-solving assessment instructions

Can AI perform genetic analysis?

Well done! You've used your knowledge and understanding of genetic interactions and statistics to answer the previous questions. But can Generative AI also solve complex genetic problems?

The task: Using Microsoft CoPilot you need to use prompts to direct the discussion and solve the problem. We suggest pasting the scenario information into CoPilot and then adding questions that will provide the information you need to solve the problem. Use as many prompts as necessary to generate the answer you wish to submit.

- You will need to provide transcripts of your "conversation/s" with CoPilot. To do this either highlight all the content and copy to a document or take screenshot pictures and paste to a document. Export function will only save the last output, not previous parts of the conversation and there is no save or history feature as with other AI tools.
- You need to analyse the CoPilot output for accuracy by identifying any responses that are inaccurate, not applicable to the scenario or that are semi-accurate with errors. If you agree with the outputs and do not believe there are errors, this is ok but make a statement as to why you agree with all the conversation output.
- Secondly, provide the evidence to support or reject the answer as presented by CoPilot by generating the solution on paper.

Appendix 2: Problem-solving assessment rubric

Criteria			**Marks**
Solution of the problem (10 marks)	10-9	Solution is accurate and addresses all aspects of the problem. Solution was achieved through CoPilot and written evidence to support all elements of the question.	
	8-7	Solution is accurate and addresses most aspects of the problem. Solution was achieved through CoPilot and written evidence to support most elements of the question.	
	6-5	Solution is incomplete or has minor errors. The written support is accurate and addresses the aspects of the question.	
	4-3	Solution is incomplete or has major errors. The written support is inaccurate or does not address all aspects of the question.	
	2-1	Solution is incorrect and not supported with a written support.	
Prompting in CoPilot (3 marks)	3	Effectively uses CoPilot with sufficient prompting to produce a comprehensive output	
	2	Minimal prompting and the CoPilot output is basic	
	1	No further prompting and the CoPilot output is insufficient for solving the problem	
Analysis of the output (4 marks)	4	Correctly identified all inaccurate information in the CoPilot output.	
	3	Correctly identified most inaccurate information in the CoPilot output	
	2	Identified some key accurate/inaccurate information in the CoPilot output	
	1	No evidence of analysis of CoPilot output	
Transcript of CoPilot conversation (3 marks)	3	Complete transcript was provided	
	2	An incomplete transcript was provided	
	1	No transcript was provided	

Appendix 3: Student demographics

Gender	
Male	12
Female	41
International?	
Yes	19
No	34
Program	
B. Biomed. Sci.	11
B. Lab. Med.	39
B. Pharm. Sci.	3
GPA (out of 7)	5.25 +/- 1.01

Appendix 4: Survey questions

1. How often do you use GenAI … Tick the option that applies to you

	…in your tertiary studies	…outside of your tertiary studies
Never		
Rarely		
Sometimes		
Often		
Always		

If you do currently use GenAI, which platform/s do you currently access?

2. Complete the following table based on your current use of GenAI:

GenAI application	Never	Rarely	Sometimes	Often	Always
Learning/revising new concepts					
Writing (English) assistance					
Drafting essays					
Generating ideas/brainstorming					
Data analysis					
Proof-reading and editing					
Other (please specify):					

3. Generative AI tools did improve my learning experience.

Strongly disagree　Disagree　Neutral　Agree　Strongly agree

4. I have a good understanding of prompt engineering for GenAI.

Strongly disagree　Disagree　Neutral　Agree　Strongly agree

(Prompt engineering is the skill of creating specific instructions or questions to get useful answers from GenAI tools like ChatGPT).

5. It is important for individuals to review the accuracy of the information provided by GenAI.

   Strongly disagree Disagree Neutral Agree Strongly agree

6. I am confident in using genAI tools for academic purposes

   Strongly disagree Disagree Neutral Agree Strongly agree

7. I believe genAI tools will be useful in my future career.

   Strongly disagree Disagree Neutral Agree Strongly agree