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Using GenAI for Objective Structured Clinical Examination (OSCE) Preparation: A Retrospective Study in Australia and Malaysia

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Abstract

This paper explored students' use of Generative Artificial Intelligence (GenAI) for Objective Structured Clinical Examinations (OSCE) preparation using a retrospective cohort study conducted over two years (2023–2024) across Australia and Malaysia. Results analysed OSCE grades and written self-reflections from students. The Unified Theory of Acceptance and Use of Technology (UTAUT) model was applied as a lens to interpret qualitative data using summative content analysis. Of 997 students, 163 (16.3%) stated they did use GenAI to prepare for OSCEs. Across both campuses, there was no significant difference in mean OSCE grades between GenAI users (79.9%, SD = 15.3) and non-GenAI users (79.6%, SD = 17.4; p = .6); however, non-GenAI users performed significantly better (p < .05) in four of the seven communication rubric criteria. Themes around mistrust or perceived inaccuracy of GenAI data for clinical application deterred use in non-users. From our results, the use of GenAI did not demonstrate additional benefits for overall OSCE preparation, suggesting the potential need for more pedagogically aligned applications of GenAI tools to maximise their utility for clinical assessment preparation.

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Practitioner Notes

1. The use of GenAI in OSCE preparation did not yield significant improvements in overall performance and was associated with reduced performance in assessed communication skills.
2. Students primarily utilised GenAI to generate practice scenarios.
3. Perceived limitations in GenAI's clinical accuracy and alignment with trusted resources discouraged broader student adoption.
4. Evidence of reduced performance in communication criteria, despite students perceiving GenAI as helpful, underscores the need to improve AI literacy and integrate educator guidance.
5. Cultural differences in learning strategies mean GenAI support should be tailored. In this study, Malaysian students leaned toward leveraging GenAI for practical and language-related support.

Keywords

Generative Artificial Intelligence; Objective Structured Clinical Examinations; The Unified Theory of Acceptance and Use of Technology;

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Introduction

Objective Structured Clinical Exams (OSCEs) are comprehensive clinical assessments used to assess the competency of students in many healthcare professions through real world simulations (Epstein, 2007). OSCEs are essential for assessing a student's ability to apply clinical knowledge and show readiness for practice (Abdulnour et al., 2022). Presently, health profession education (HPE) students use more traditional study techniques such as self-tests (Baatar et al., 2017; Zheng et al., 2022), learning from pre-recorded lecture videos (Bridges, Stefaniak, & Baaki, 2018), practicing with friends or using digital tools (Blamoun, Hakemi, & Armstead, 2021; Duvivier et al., 2012; Lim et al., 2023). Generative Artificial Intelligence (GenAI) now offers another preparation strategy for OSCEs, but little is known about how it is used, and whether its use leads to academic success or harms learning.

GenAI analyses data such as text or images to create new content, and has become increasingly popular in health education for its ability to tailor learning materials to students' needs (Almansour & Alfhaid, 2024; Nguyen et al., 2024). Artificial Intelligence (AI) literacy is also becoming increasingly important for HPE students and healthcare professionals as the prospective use of GenAI as a tool for the diagnosis, treatment, and care of patients becomes more profound (Alowais et al., 2023). Understanding how to utilise and interpret the outputs of GenAI may become critical in optimising patient care (Rana et al., 2025). HPE students must be able to not only understand these outputs, but also the limitations and ethical implications of GenAI in the context of optimising patient care (Naik et al., 2022). As GenAI continues to evolve, HPE students will need to be aware of the advancements of the technology to be able to collaborate with GenAI systems effectively to mitigate the risks of bias and error (Abdelwanis et al., 2024). The widespread integration of GenAI across disciplines positions AI literacy as a leading learning objective in contemporary higher education (Walter, 2024). Importantly, higher education research highlights true AI literacy is not just technical know-how but it also involves critical evaluation, ethical judgement, and human-centred application (Fitzgerald, et al., 2025). Equally important, student trust in GenAI, shaped by reliability, and its capacity for personalised learning, contrasts with distrust arising from concerns about unreliability, potential misuse, and misalignment with academic goals (Wang, Li, Cheung, & Wong, 2025). Some health profession students expressed mistrust toward GenAI, attributing it to perceived limitations in its knowledge and accuracy, suggesting that doubts arise when the system's assessments are viewed as lacking sufficient understanding or precision (McLaughlin, Ponte, & Lyons, 2025).

> **Research Question 1.** Does using GenAI for OSCE preparation have an impact on OSCE grades?
>
> **Research Question 2.** What factors were associated with the use or non-use of GenAI for OSCE preparation?

This paper explored the use of GenAI for OSCE preparation using objective OSCE grades as well as student written reflections to provide educators with a more comprehensive view of how GenAI might be used to prepare for clinical assessments. As our course is taught in two countries, we utilised this opportunity to conduct our study in two student populations across our two campuses (Australia and Malaysia).

Some studies have shown that HPE students have been using GenAI platforms to prepare for OSCEs by practising case-based scenarios (Holderried et al., 2024; Pereira et al., 2023). The impact of GenAI on academic performance has not been widely explored, nor the understanding of how GenAI supports the preparation for OSCEs. Exploring these aspects of learning addresses not only the use of GenAI in practicing for OSCEs, but also the rationale behind the integration of GenAI in HPE and whether it aligns educational and ethical standards (Naik et al., 2022).

Literature

Generative Artificial Intelligence and OSCE preparation

Recent developments in AI have contributed to enhancing OSCE preparation processes by creating of tailored OSCE scenarios, delivering instant feedback, and providing students with unlimited opportunities to practice. Most of these tools are local innovations and/or have evaluated GenAI impact using perception data or research administered tools (Lee et al., 2025; Chastain et al, 2025; Pereira et al., 2025). A more comprehensive evaluation of freely accessible, student-selected GenAI tools using real OSCE test data is still required to fully understand their impact. Perception data reveals use of GenAI tools in OSCE preparation has been noted to be generally well-received, with 58.5% of students reporting them as beneficial, with highlighted challenges, including a perceived a lack of humanisation and occasional inaccuracies (Rehman et al., 2025). Emerging research indicates that when students engage with AI-generated preparatory tools, or use AI to create their own, they develop greater self-efficacy and increased confidence in their ability to take and successfully pass an OSCE (Chastain et al, 2025).

GenAI Acceptance and UTAUT

In 2025, the proportion of students using GenAI tools to prepare for assessments has jumped from 53% last year to 88%, compared to a drop from 47 to 12% of those who have not used GenAI for their assessments (Freeman, 2025). A recent report found that students primarily use Claude™ to create and improve educational content across disciplines including designing practice questions (Anthropic Education, 2025). The Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) provides a framework to understand how individuals adopt new technologies, including GenAI. UTAUT identifies four key constructs influencing technology use: performance expectancy (belief that the technology improves performance), effort expectancy (ease of use), social influence (pressure or encouragement from others), and facilitating conditions (support available for its use). These constructs, along with individual and contextual elements, shape users' willingness to adopt technology. Studies have demonstrated the model's relevance in educational contexts, showing that perceived performance benefits, peer and educator influence, and institutional support significantly drive students' adoption of GenAI (Ivanov et al., 2024; Jang, 2024; Kavitha & Joshith, 2024; Li et al., 2024).

Method

Study Design

A retrospective cohort study conducted over two years (2023-2024) across two campuses in Australia and Malaysia. This project was approved by the institute’s Human Research Ethics

Committee (Project ID: approval 32749). The primary aim of this study was to elicit whether using GenAI for OSCE preparation had an impact on OSCE grades. The secondary aim was to investigate what factors were associated with the use of GenAI for OSCE preparation. Our primary outcome was the difference in OSCE grades between students who did use GenAI for OSCE preparation and those who did not. Secondary outcomes were reasons students stated for using or not using GenAI for OSCE preparation.

Participants

Undergraduate pharmacy students from all four year levels of a pharmacy course (Degree being a four year course) at a major tertiary institution across two campuses (Australia and Malaysia) were included if they completed a written reflection after their OSCE. Each year level in the Australian campus has approximately 200-300 students whilst the Malaysia campus ranges from 100-150 students per year level. Both campuses have less student enrolments for lower year levels. The OSCE is a yearly mandatory assessment for all students at both campuses, and all students in the cohort who completed the OSCE has been included in the study.

Context: OSCE Curriculum Overview

In the degree program, a summative OSCE is completed annually for all year levels and comprises 3-4 stations each 8-10 minutes long. Stations are run consecutively. Each station is marked with an analytical (clinical) checklist with binary measures (Yes/No) and a communication rubric with a global rating scale from 1-4. The communication rubric has seven criteria: 1) Verbal cohesion and pace; 2) Terminology suits audience needs; 3) Structure and logical flow; 4) Empathy and respect; 5) Active listening; 6) Clear instructions and justifications; 7) Confirms effectiveness of communication from receiver. Each station has a simulated patient/doctor in the room who role plays the scenario with the student. Each station is based on a clinical scenario that is representative of practice e.g. a pregnant lady who asks for tinea treatment.

Data collection

The study retrospectively analysed collected responses from one written self-reflection which was mandatory and part of the OSCE assessment. The reflection did not contribute any marks towards their OSCE but needed to be completed within 24 hours of completing the OSCE to pass the assessment. The reflection had no word limit but needed to be completed within 30mins. The reflection included a self-reflection on how they thought they performed in the OSCE but also asked the students to answer two additional questions: 1) “Did you use GenAI tools to prepare for your OSCEs? Please discuss why or why not; and 2) If you did use GenAI tools to prepare for your OSCEs, please discuss how you used these tools.These two questions were used in the analysis of this study. The research team did not generate or analyse GenAI-produced OSCE scenarios as part of this study.

Data analysis

To examine the relationship of GenAI use to OSCE grades, students were classified as “non-GenAI users” if they did not use GenAI to prepare for the OSCEs, and “GenAI users” if they did, based on whether they stated they used GenAI in the written reflection. This self-reported use was then analysed against OSCE grades using inferential statistical tests selected to align with the level of measurement, group structure, and distributional characteristics of the data. Independent-samples t-tests were used because they are appropriate for comparing mean values

of continuous outcomes between two independent groups, GenAI users and non-GenAI users, with each student contributing a single observation to one group only. Non-parametric alternatives, specifically the Wilcoxon rank-sum test, were applied when distributional assumptions were not met, to provide robust group comparisons without reliance on parametric assumptions. Fisher's exact tests were used for categorical comparisons to ensure valid inference when sample sizes were limited. Statistical analyses were performed in R using the base package (R Core Team, 2024),

The qualitative data from written reflections were analysed abductively (Thompson, 2022) using deductive coding and inductive coding. For deductive coding, data was mapped against the four key constructs of UTAUT (Venkatesh et al., 2003) using summative content analysis (Kleinheksel et al., 2020). To obtain inductive themes, the data was analysed using the framework analysis (Ritchie & Spencer, 1994) to elicit the prime reasons for not using or using GenAI to prepare for OSCEs. Inductive themes were constructed independently of the UTAUT framework and were not able to be forced across every UTAUT construct. Inductive themes were constructed independently of the UTAUT framework and did not map across all UTAUT constructs. This approach was methodologically appropriate, as inductive analysis prioritises participants' meanings and experiences and allows themes to emerge from the data without imposing preconceived theoretical assumptions or analytic categories (Liu, 2016).

The following definitions of the UTAUT constructs were genuinely applicable and were applied: *Performance expectancy* was defined as the belief that using GenAI would enhance students' performance and productivity in OSCE preparation. *Effort expectancy* referred to the belief that GenAI would reduce the perceived effort associated with OSCE preparation. *Social influence* was defined as the extent to which students were influenced by peers, instructors, or external platforms, such as social media, in deciding to use GenAI. *Facilitating conditions* referred to the availability of resources and technical support, including reliable clinical content, to effectively use GenAI for OSCE preparation (Venkatesh et al., 2003).

Prior to coding, the four team members involved in coding the reflections (JC, DL, TP, AL) conducted a team reflexivity exercise, where they discussed UTAUT and any biases related to their experience of GenAI in assessment preparation. None of the team members noted any sway for or against GenAI use for assessment preparation. This was an iterative process until all four team members agreed on the name and/or allocation of the codes. Coding was done in stages, firstly a subset of the data together (20%) was coded by two of the four team members (JC and TP) discussed and re-coded results until an intercoder reliability of Cohen's kappa 0.80 was achieved, then another 20% was coded and the process was repeated. The final 60% of data was coded by one researcher (JC). Co-occurrences identified between inductive themes from the framework analysis and deductive themes from the summative content analysis were visualised by Gephi Software (Bastian, 2009).

Results

Using GenAI for OSCE preparation and its impact on OSCE grades

Overall, 997 student reflections, across 4 year levels and 2 campuses (718 from Australia and 279 from Malaysia), were analysed; of these students, 163 (16.3%) stated they did use GenAI to prepare for OSCEs. Of 163 students, 28.8% were from second year, 54.6% from third year and 16.6% from fourth (final) year. Of 163 students, 38.7% were from the Malaysian campus, the rest from the Australian campus. Across both campuses, those who reported using GenAI in OSCE preparation had a mean OSCE grade of 79.9% (SD = 15.3) (Figure 1), and those who did not use GenAI had a mean grade of 79.6% (SD = 17.4), with a two sample t-test showing no significant difference between the two groups t(129.64) = 0.21, p = .83, 95% CI [−2.89, 3.58]. Among Australian students only, those who reported using GenAI in preparation for OSCE had a mean grade of 79.0% (SD = 12.7) performing similarly to those that did not use GenAI to prepare with a mean grade of 79.4% (SD = 14.7), t(53.65) = −0.16, p = .87, 95% CI [−4.24, 3.60]. Among Malaysian students, those who reported using GenAI in preparation had a mean OSCE grade of 80.7% (SD = 17.3) compared to 80.3% (SD = 23.8) in those that did not use GenAI to prepare; again, both GenAI users and non-GenAI users performed similarly (*p* = .19) (Wilcoxon test). There were no significant differences in GenAI use across year levels, and while international students at the Australian campus performed worse than domestic students among non-GenAI users, they performed better among GenAI users, though these differences were not statistically significant (p = .38 for domestic subgroup comparison).

Figure 1

Average OSCE overall grade (%) comparison based on AI Usage

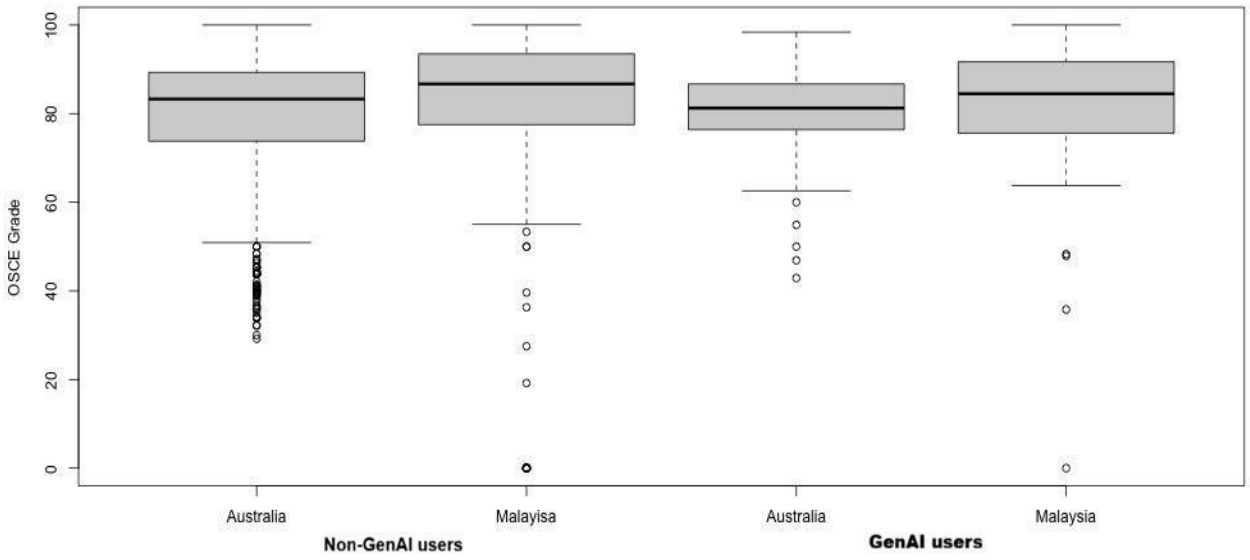
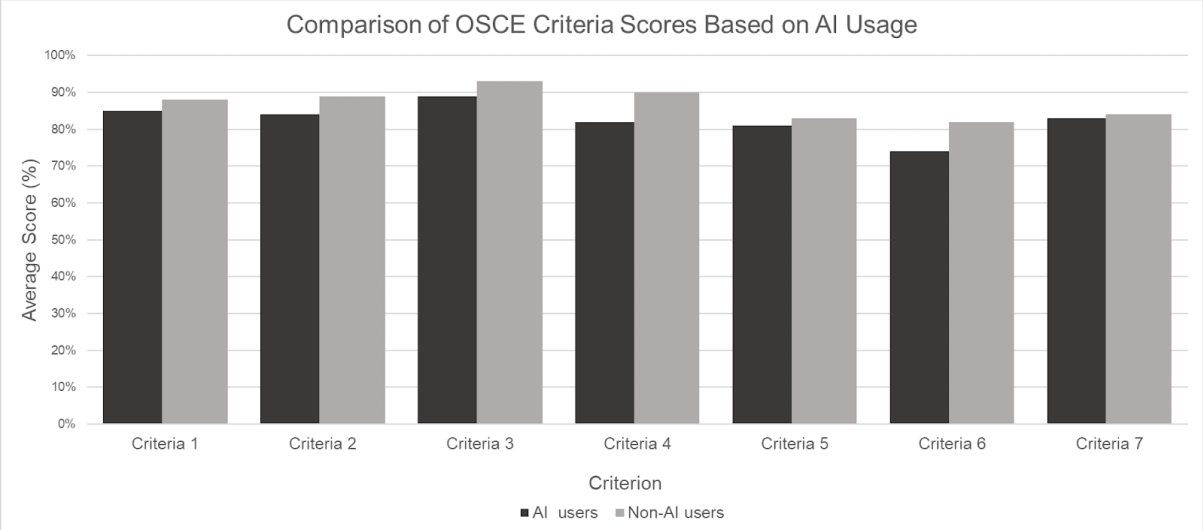


Figure 2

Comparison of OSCE Communication Criteria Scores Based on GenAI Usage



Criteria 1) Verbal cohesion and pace; Criteria 2) Terminology suits audience needs; Criteria 3) Structure and logical flow; Criteria 4) Empathy and respect; Criteria 5) Active listening; Criteria 6) Clear instructions and justifications; Criteria 7) Confirms effectiveness of communication from receiver.

When looking at communication rubric criteria 1-7. There were significant differences in Criteria 2, 3, 4, and 6, where non-AI users performed better. Criteria 2: $t(116.03) = -2.61$, $p = .010$; Criterion 3: $t(116.34) = -2.20$, $p = .030$; Criterion 4: $t(115.03) = -4.15$, $p < .001$; Criteria 6: $t(116.60) = -2.85$, $p = .005$ (Figure 2).

Reasons for using and not using GenAI for OSCE preparation

Six themes were constructed from the reflections regarding why students used or did not use GenAI for OSCE preparation. They were categorised into two distinct groups: those who used GenAI (Themes 1-3) and those who did not (Themes 4-6).

Theme 1: GenAI can support efficient OSCE case creation (Australia 20%; Malaysia 30.2%), revealed that students valued the flexibility and efficiency of GenAI and its ability to create many novel and diverse practice scenarios when they were ready to practice. "I used ChatGPT to help me create patient cases…. ChatGPT can help make the case more complete with symptoms, past medical history, vital signs, and lab results. It did help me save some time when I was creating cases to practice with friends." Student P4M27

Theme 2: GenAI can help support oral communication (Australia 10.0%; Malaysia 25.4%), highlighted how students utilised GenAI to rephrase medical jargon into simpler terms, refine their questions, and overcome language barriers when engaging with GenAI to get the right information. “I utilised artificial intelligence (AI) to simplify complex medical terminology, which greatly aided my preparation for the OSCEs. For instance, when I found it challenging to explain "pyelonephritis" to a "patient," AI taught me to describe it more accessible as "inflammation of the kidney due to bacterial infection." This approach was helpful for explaining other medical terms as well. Additionally, I used AI to generate potential questions a "patient" might ask, which allowed me to practice formulating responses independently,” (Student P3P135). GenAI was able to help

students with their history taking questions, “You could ask AI, what type of questions would be appropriate regarding a specific condition/ailment. I did this for [nicotine replacement therapy] and it provided an insight into the type of questions I should consider asking.” (Student P3P30). This was a feature used by many non-native English-speaking students. “Because I'm not a native English speaker, I use AI to help me check grammar.” (Student P3P217).

Theme 3: Using GenAI to simulate patient interaction for increased practice (Australia 4.0%, Malaysia 4.8%), showed that students used GenAI to mimic realistic conversations with patients and clinicians, enhancing their confidence and preparation before speaking to another peer or colleague. This is like theme 1, but theme 1 supported students generating cases they could practice with GenAI or their peers, whereas theme 3 discussed students using GenAI to practice clinical questioning using on the spot prompts rather than a full case. “I used the voice feature of ChatGPT to simulate patient interactions. This was particularly useful because it allowed me to practice my communication skills in a controlled environment. The AI could act as different patients with varying conditions, which helped me adapt my approach to each scenario. This kind of practice was invaluable for building my confidence and fluency in handling diverse medical conversations.” (Student P3P293). Moreover, GenAI was seen to have a much more rapid output of feedback and could play various roles, “I used AI to practice talking to virtual patients who had different pharmacy questions. This helped me get better at talking to people, making decisions, and feeling more confident in different situations. The AI gave me instant feedback, which allowed me to improve my responses and apply what I learned. It was a great addition to my study routine and made me more ready for the OSCEs and future work in pharmacy.” (Student P3P185). In contrast, students who did not use GenAI for OSCE preparation expressed concern related to the reliability of GenAI output.

Theme 4: It is more reliable to follow our given trusted resources instead of GenAI (Australia 25.0%; Malaysia 19.0%), identified that some students distrusted GenAI as it pulled information from all sources around the world, and was generally unable to screen or access reliable clinical guidelines and resources like our local therapeutic guidelines which generally requires subscription access, “I used AI to create community cases, however, I think the content is not too relevant to our syllabus, hence I recommend using our own knowledge to create cases based on our university content given by our lecturers.” (Student P3M74)., “No, I didn't use ChatGPT for making notes as ChatGPT doesn't have access to the standard clinical resources, I can't trust whether the answer ChatGPT gives is correct and up to date.” (Student P4P140).

Theme 5: Not ready to use it now but considering using AI for future OSCE preparation, (Australia 17.0%, Malaysia 11.1%), reflected students’ willingness to use GenAI for OSCE preparation but noting hesitancy with using it now due to fear of academic integrity issues. “I did not use AI for OSCE preparation, but now that I know I am allowed to do that, I may do it next time with an AI chatbot. This may be helpful for me if I cannot find a friend who is free to practise with me.” Student P3M1. Theme 6: A perception that GenAI should not be used for clinical purposes (Australia 24.0%; Malaysia 9.5%) , showed that while some students trusted GenAI for non-clinical applications, they did not think it would be appropriate to use it for clinical applications, “I'm not sure how you can use AI, as the practice for OSCE is more for real people with pharmacy questions which you can find the answers in the proper resources.” (P3P271); “Didn't use it. Assume it wouldn't be too helpful with OSCE based questions, as communication is a major part of the marking. ChatGPT may be able to help with making practice OSCE cases or helping with

phrases or communication strategies." (Student P4P109); "I tried out artificial intelligence in creating art or music just for fun to see what the AI is capable of. The tools are somewhat similar in the sense that they're advanced and able to produce an outcome to the prompts." (Student P2M100); "I have used it to conduct research on some assessment, but I reworded it into my own sentence. In that regards I find AI to be very helpful." (Student P2P70).

Co-occurrence of inductive themes

Table 1

Coded instances across UTAUT constructs for Gen-AI users vs non-GenAI users

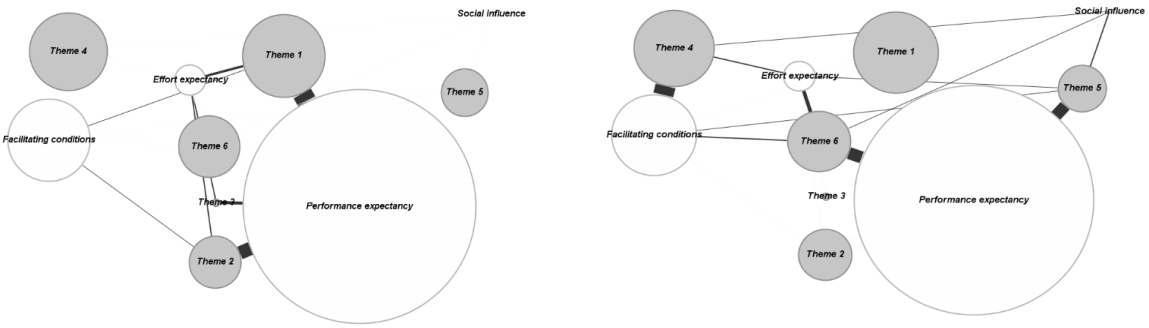
	GenAI users (n=72)		Non-GenAI users (n=91)	
Performance expectancy (belief that the system enhances student performance)	86.1%	"Yes, AI helps to improve my language and communication way, and how to talk empathetically" (Student P2M75)	45.1%	""I used Artificial Intelligence seldom and used for making plans, such as a travel plan. In the coming future, I am unlikely to trust ChatGPT for 100% and, even if I use it to assist my work, I would assist to double check and highlight the main points by myself. The suggestions and conclusions provided will be general fundamental overview." (Student P4P132)
Effort expectancy (belief in effort reduction)	11.1%	"I used it to make cases for me and my friends to practice. I find it very helpful as we dont have to make cases ourselves." (Student P3M73)	9.9%	"Actually I didn't use it to prepare for the OSCEs, because I believe only the things I really spend time on make impression on me." (Student P3P232)
Social influence (effect of external perceptions)	0.0%	N/A	4.4%	"I never try other tool to practice, I have many friends who have same opinions with me, we all don't really like simulated experience, so we chose to gather practice each other and gave the feedback." (Student P2P140)
Facilitating conditions (effect of ecosystem and tool itself - system capabilities)	2.8%	"I tried to use AI to create additional OSCE case and practice with them. However it does not very helpful as it requires a whole database of pharmacy knowledge which is too specific. I would only recommend it if Monash can design one for your own." (Student P3P308)	40.7%	"I chose not to rely on artificial intelligence in preparing for OSCEs because I consider it unreliable. Instead, I prefer to refer to trusted resources for obtaining standard and appropriate treatment information." (Student P3M3)

Table 1 shows the percentage distribution of coded instances across UTAUT constructs for Gen-AI users (n=72) and non-GenAI users (n=91) subgroups with performance expectancy being the highest code for GenAI users and social influence being the lowest (0%). Percentages in Table 1 reflect the proportion of participants in whom each theme was identified, with each theme counted once per participant even if mentioned multiple times within an individual response.

Analysis of the association between the inductive themes and the characteristics UTAUT are visualised in the co-occurrence plots in Figure 3. In Figure 3A (GenAI Users), Themes 1-3 all have thick connecting edges to Performance Expectancy. In contrast, Figure 3B (Non-GenAI Users) shows Theme 4 has a close association with the Facilitating Conditions characteristic of the UTAUT, whereas Themes 5 and 6 display strong connections to Performance expectancy. Each node represents an inductive theme (grey) and UTAUT characteristic (white), sized proportionally to the number of students contributing to that theme amongst the cohort. Connecting edges indicate co-occurrence, with thicker edges representing stronger co-occurrence.

Figure 3

Co-occurrence networks of inductive themes 1-6 mapped to UTAUT constructs of GenAI Users (left) and Non-GenAI Users (right).



Discussion

Overall, the main findings revealed no significant difference in mean OSCE grades between students who used GenAI for preparation and those who did not, although GenAI non-users performed better on four out of seven communication criteria. Studies in the literature have showed mixed results of GenAI's impact on students' performance in HPE, with some reporting improved exam outcomes (Hsu, 2023; Roganović, 2024) while others found better results through traditional methods (Saravia-Rojas et al., 2024; Shin et al., 2024). This study found that GenAI was useful for creating OSCE case materials which could lead to enhanced performance through repeated practice. This expectation is rooted in the belief that GenAI can provide personalised practice materials, thereby deepening understanding and facilitating the application of knowledge in practical contexts (Binhammad et al., 2024). However, several comments in Theme 4

highlighted students' concerns about the accuracy and reliability of GenAI outputs for HPE. Therefore, HPE students should develop the skills to identify and address potential inaccuracies or biases in GenAI-generated content (Bernardi et al., 2023; Rajabi et al., 2023).

Interestingly, our analysis with UTAUT found that creating simulations (Theme 1) was not linked with performance expectancy in non-GenAI users, perhaps suggesting that many students currently view the conversational nature of GenAI as unhelpful unlike Romero-Rodríguez et al. (2023), who found that performance expectancy played a significant role in shaping the intention to use GenAI. Theme 3 suggests that GenAI users did try to incorporate a conversational aspect into practice such as using the microphone to simulate conversation. Also surprisingly, there were no social influences impacting on positive uses (Themes 1,2,3) in GenAI users but the facilitating conditions had a strong link with mistrust in non-GenAI users (Figure 3). Possibly the provision of more trusted, educator-designed GenAI tools in combination with more adaptive and intentional approaches to GenAI use could improve the trust in GenAI (Abdulnour, et al. 2025). Current GenAI tools may not convey the emotion inherent in human interaction, which may explain the drop in some communication rubric scores in the AI users (Figure 2).

Healthcare educators have raised concerns GenAI may not effectively model clinical reasoning or replicate authentic patient interactions (Chan & Zary, 2019), potentially hindering the development of critical thinking skills and introducing inaccuracies that could compromise patient safety (Walsh, 2020). Wang et al. (2025) showed that trust plays a key role in shaping how students choose to use GenAI, and Zhang et al. (2025) similarly noted that higher trust can lead students to depend more heavily on AI in ways that may weaken skills like communication. Thus, trust dynamics directly shape not only how students use GenAI but also the quality of communication practice, helping to explain why communication performance was poorer among GenAI users despite perceived usefulness.

While many comments from students highlighted the perceived effort-saving benefits of GenAI and its use for non-clinical purposes (theme 6), students appeared hesitant to use it for educational purposes. The was a small link in GenAI users between effort expectancy and themes 1 and 6 (Figure 3) may suggest that students do not yet know how to use GenAI as well as they do for non-clinical applications. Other studies in HPE have found the effort expectancy has allowed students to focus on comprehension and deeper learning rather than extensive searches (Jallad et al., 2024; Roganović, 2024; Saravia-Rojas et al., 2024). Menon & Shilpa (2023), also found that GenAI's ease of use and time-saving capabilities make it highly appealing to students by simplifying tasks and enhancing productivity.

Even though GenAI-users noted that GenAI supported improvement of clinical communication skills (theme 2), performance was statistically worse for AI-users in communication criteria 2) Terminology suits audience needs; 3) Structure and logical flow; 4) Empathy and respect; and 6) Clear instructions and justifications. One possibility is that students who have weaker communication or weaker students academically may be more likely to use GenAI for assessment preparation or may also not be using GenAI effectively to improve communication and clinical knowledge. Strengthening AI literacy is essential for equipping learners with the skills to engage confidently with evolving technologies and interpret AI-generated health information responsibly (Ang, 2025).

Evidence of reduced performance in communication criteria, despite students perceiving GenAI as helpful, underscores the need to improve AI literacy and provide educator guidance for responsible and effective use. Communication performance serves not only as an outcome but as an indicator of students' ability to evaluate, adapt, and humanise GenAI outputs. Without adequate AI literacy, learners may struggle to use AI tools effectively or critically and ethically interpret AI-generated insights (Nazaretsky et al., 2025). Addressing these challenges requires supporting students in recognising bias, plagiarism, and outdated information, with educators playing a pivotal role in guiding ethical and productive AI-supported learning (Lee et al., 2024). This aligns with Lyu et al. (2025), who emphasised educators' responsibility in fostering critical engagement and promoting balanced integration of AI alongside traditional approaches. These findings highlight the importance of strengthening students' AI literacy and providing structured educator guidance to support responsible, ethical, and effective use of GenAI in clinical learning contexts.

There have also been challenges to use GenAI in professional communication in intercultural contexts where there can be natural language processing constraints, with experts recommending a hybrid approach of using human educators for personalised guidance and cultural insights, and rely on AI generated content to develop their professional content knowledge (Dai, 2025). When investigating other cultural differences between Malaysian and Australian differences, our results showed Malaysian students leaned toward leveraging GenAI for practical and language-related support (using GenAI more for case creation and communication support), while Australian students showed greater scepticism about its clinical reliability. An older study has indicated that Malaysians students may adopt more surface learning, structured and teacher-directed approaches, valuing efficiency and clear guidance, whereas Australian students tend toward independent, constructivist learning strategies emphasising critical thinking and resource validation (Yin, 2005), which could explain why Malaysian students embraced for generating cases and simplifying jargon, but more updated comparisons are needed.

OSCE practice in resource limited settings are also known to be challenging (Sobh, 2025), and may perhaps explain why Malaysian students also utilised GenAI for case creation. These differences may reflect broader educational and cultural factors. Malaysian students often experience more structured, teacher-directed learning environments (Esmaril et al., 2024), which may encourage reliance on tools that provide clear guidance or simplify linguistic complexity. In contrast, Australian students are often stereotyped as engaging in more independent and critical learning approaches, despite the empirical evidence for this being limited (Tomlins, 2025), which may heighten their scepticism about the accuracy of GenAI for clinical content. Together, differences in educational culture, learning resources, prior OSCE exposure, and communication confidence may help explain variations in students' reliance on and trust in GenAI, suggesting that GenAI-supported learning strategies should be tailored to students' linguistic, cultural, and educational contexts, particularly for language support and case preparation.

The study has a broad population of students across many year levels and across two countries. The nature of self-reporting AI use can lead to underreporting, especially when students feel uncertain about admitting their reliance on AI tools like ChatGPT for academic purposes, even though it was made clear to students that the reflection was to support learning and educator feedback and would not contribute to assessment marks. We did not collect how students were initially introduced to GenAI and which specific tools they used. We do not know whether it was

personal discovery, peer influence, or recommendations from educators that prompted them to start using these tools. We tried to explore this under social influence in our coding but nothing specific arose. This raises questions about what drives students to adopt GenAI technologies in their study practices, and how those initial influences shape their ongoing use. Understanding what influences their decision to start using GenAI tools could provide insight into the factors that shape both the motives and the extent of reliance on these technologies in educational settings.

Practical Implications

As GenAI becomes more popular and if AI hesitancy declines, future research could replicate this study to see if students are able to use GenAI effectively by evaluating impact using workplace-based assessment data. One of the challenges facing the use of GenAI in healthcare education is the need for high-quality data to train GenAI models. As healthcare data is often complex, confidential, and subject to strict privacy regulations, it is essential that researchers and educators work closely with medical professionals, data scientists, and regulatory bodies to ensure that the data used to train AI models is both accurate and ethically obtained (Dave & Patel, 2023).

In this study, the use of GenAI was not shown to significantly improve OSCE performance, and indeed hindered communication performance in some areas. Our study resonates with the recent study by Bastani et al. (2024) who found GenAI to be detrimental to performance. The research team did not generate, trial, or evaluate GenAI-produced OSCE outputs, as this was outside the scope of the study, which focused on students' self-reported GenAI use and its association with OSCE performance. Further research could consider investigating GenAI user outputs to understand use and non-use of GenAI and why it has impacted on students' performance, as well as testing well-designed GenAI tools for OSCE preparation, steered by teachers with pedagogical skill and intent.

Theoretical Implications

Whilst we used UTAUT to code across both countries, we acknowledged that the UTAUT model has been examined only minimally in developing countries (Bayaga & du Plessis, 2024) and that cultural and geographical factors may influence its applicability (Xue et al., 2024). We also found that UTAUT did not fully capture issues of trust, privacy, and security. We suggest that a combined theoretical approach may be necessary to unpack findings, particularly when exploring cross-cultural contexts or settings where clinical accuracy is essential. Additionally, incorporating actual user behaviour and perceptions of AI-generated output introduces further complexity for UTAUT coding.

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analysis; writing – review and editing. **Karunaratne:** writing – review and editing, **Exintaris:** writing – review and editing. **Yuriev:** formal analysis; writing – review and editing. **Lim:** Conceptualisation; methodology; writing – original draft; formal analysis; data collection; writing – review and editing.

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