Generative AI as a "placement buddy": Supporting pre-service teachers in work-integrated learning, self-management and crisis resolution

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This study explored the integration of generative artificial intelligence (GenAI) in supporting pre-service teachers (PSTs) during their work-integrated learning placements, focusing on its role in lesson planning, teaching and WIL crisis resolution. Using the unified theory of acceptance and use of technology framework, the study investigated how AI literacy, self-efficacy and social influences affect PSTs' acceptance and use of GenAI tools. Data collected from surveys and focus-group interviews with 126 PSTs reveals that GenAI enhances PSTs' efficiency, improves stress management and provides timely support in managing professional relationships. Results highlight differences in perceptions of GenAI across demographic groups, teaching subjects and school contexts. The findings emphasise raising awareness of GenAI's potential in supporting PSTs, as well as the need for discipline-specific AI training in initial teacher education programmes to foster confident, ethical and effective application in placements.

Implications for practice or policy:

- Initial teacher education programmes should incorporate AI literacy and prompt engineering training, in combination with other educational technology tools and in alignment with specific disciplinary subjects.
- Schools and mentor teachers need training and preparation to support PSTs in integrating GenAI into work-integrated learning.
- Educational policy should address the disparities in access to GenAI tools, ensuring equitable opportunities for all PSTs.

Keywords: generative artificial intelligence (GenAI), work-integrated learning (WIL), AI literacy, initial teacher education (ITE), pre-service teachers (PSTs), unified theory of acceptance and use of technology (UTAUT) framework, case study

Introduction

Pre-service teachers (PSTs) have repeatedly reported suffering from a range of emotional and professional challenges during their work-integrated learning (WIL), challenges that can significantly impact their overall well-being and effectiveness in school placements (Jackson, 2015; Wenham et al., 2020). Effectiveness during placements is frequently tested by the complex dynamics of WIL, which are characterised by constant high-stakes evaluation by mentor teachers and other stakeholders (Onen & Ulusoy, 2015). PSTs often experience anxiety due to conflicts between their own teaching preferences and the expectations of their mentor teachers or the school context (LaPalme et al., 2022; Trent, 2023). This can contribute to a sense of inauthenticity and impostor syndrome, exacerbating stress levels and affecting the quality of their teaching practice. This emotional strain is compounded by "praxis shock" (Ballantyne, 2007, p. 181), a disorientation that occurs when PSTs transition from theoretical initial teacher education (ITE) programmes to the realities of classroom teaching (Edwards & Nutall, 2015; Madonna, 2024). Though grounding ITE programmes in practical experiences (Ballantyne & Retell, 2020) and uplifting the quality and consistency of support from mentor teachers for PSTs (Hasson, 2018) have been found to help align PSTs' expectations with the realities of teaching, they are not easily sustained approaches. Mentor teachers often struggle to balance their dual roles as both coaches and assessors, which can lead to ambiguous or conditional support that may undermine the PSTs' confidence and progress (Jaspers et al., 2014; Meyer, 2013; Moosa, 2018; Peiser et al., 2022; Tillema et al., 2011).

Recent developments in educational technology have highlighted generative artificial intelligence (GenAI) as a potentially transformative tool for addressing challenges in education-specific WIL. Studies like those by Zhang et al. (2023) and Doroudi (2023) demonstrate GenAI's capacity to provide personalised feedback, facilitate reflective practice and offer adaptive learning resources, thereby enhancing the formative experiences of PSTs (Grossman & McDonald, 2008; Mishra et al., 2023; Trent, 2023). However, the adoption of GenAI in educational settings has sparked significant debates about its benefits and risks. A systematic review by Zawacki-Richter et al. (2019) found that while many studies laud the potential benefits of AI, there is a notable absence of educators' voices and a lack of focus on ethical and theoretical considerations in the AI discourse. Educators and PSTs often exhibit "algorithm aversion" (Xu et al., 2023, p. 215), a scepticism towards AI-driven solutions, fearing inaccuracies and biases that could undermine educational content's reliability and ethical standards (Burton et al., 2017; Logg & Matz, 2022). This aversion is influenced by concerns that AI may depersonalise education, leading to a loss of the human connection deemed essential to learning (Al-Zahrani, 2024; Pokrivcakova, 2023; Xiao et al., 2024). The perception of GenAI as a "socioscientific controversy" (Borgerding & Dagistan, 2018, p. 288) by PSTs underscores the need for a balanced integration of AI that aligns with educational values and mitigates ethical concerns (Karahan, 2023). Addressing these issues, Adams et al. (2023) have advocated adhering to principles of transparency, fairness, non-maleficence and privacy in AI deployment, whereas Mulvihill and Martin (2024) have suggested that educational practices around digital citizenship and ethical AI use can foster responsible engagement.

One of the pivotal benefits of GenAI lies in its ability to bolster PSTs' self-efficacy (SE; Huang et al., 2024; Yao & Wang, 2024), which is a belief in their ability to succeed (Bandura, 1982) in their roles as educators. Higher SE among PSTs typically correlates with a greater openness to integrating innovative technologies like GenAI, thereby increasing teaching effectiveness (Samarescu et al., 2024; Sanusi et al., 2024). However, the actual effectiveness and efficiency of teaching with GenAI hinges on how well PSTs understand and leverage these technologies. AI literacy is beyond operational competence; it involves acquiring a deep understanding of how AI uses can be aligned with pedagogical goals and ethical standards (Yao & Wang, 2024). For instance, AI can automate the grading of assignments or the tracking of student progress, which in turn allows teachers to allocate more resources to interact directly with students, thus enhancing the quality of education delivered through enhanced efficiencies.

Current ITE programmes often fall short in preparing PSTs for the nuanced use of AI in educational settings (Ayanwale et al., 2024; Ding et al., 2024). There is a pressing need for curricula that deeply integrate AI training with pedagogical strategies towards improved PST SE, so that teachers may be more proactive in their use of AI to support diverse learning needs in classrooms (Sperling et al., 2024; Uzumcu & Acilmis, 2024). By enhancing PSTs' understanding of AI through targeted training, educators can better equip them to harness AI's capabilities effectively, thus improving not only student motivation and academic performance but also their own teaching competence and workload efficiency (Chiu et al., 2023).

Although GenAI holds significant promise for supporting PSTs on school placements, literature reveals substantial gaps in how these technologies are integrated into ITE. There is a noted deficiency in comprehensive preparation that aligns AI tools with WIL goals, such as preparing PSTs for complex classroom environments and professional communication. To address these gaps, this paper outlines an innovative use of GenAI in combination with other educational technologies in a placement preparatory course within ITE programmes, designed to equip PSTs with the skills and confidence necessary to navigate their upcoming placements effectively. In doing so, the study sought to unveil the complex interplay of resistance, literacy, social influences and contextual factors when leveraging GenAI to support PSTs, by asking:

- To what extent do PSTs consider GenAI as a viable resource for planning and conducting WIL?
- In what ways can GenAI assist PSTs in preparing for WIL?
- How can GenAI support PSTs in resolving uncertainties and crises encountered during WIL?

Theoretical framework

This study utilises the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) as a guiding framework to analyse PSTs' engagement with GenAI, both in their preparatory courses and during WIL. UTAUT is well-suited to this context as an integrative and predictive model for explaining technology acceptance and use behaviour (UB) among educators (Al-Qeisi et al., 2015; Buabeng-Andoh & Baah, 2020), including the adoption of AI (Ibrahim et al., 2024). Given the complexities identified in the literature, the UTAUT model provides a comprehensive structure to explore the multiple dimensions influencing PSTs' acceptance and use of AI technologies through the constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC). PE and EE are particularly relevant, considering that PSTs' willingness to adopt AI is linked to their belief that AI can enhance their teaching performance and is easy to use (Kaufmann, 2021; Pokrivcakova, 2023). SI aligns with evidence suggesting that perceptions shaped by influential figures in education significantly affect PSTs' attitudes towards AI (Sanusi et al., 2024). FC refers to the availability of organisational and technical infrastructure that supports the use of technology. Additionally, UTAUT's emphasis on behavioural intention (BI) and UB enables a nuanced exploration of both the intentions behind AI adoption and PSTs' use patterns, which assists in addressing the observed gap between stated intentions and actual use of AI technologies (Bagozzi, 2007).

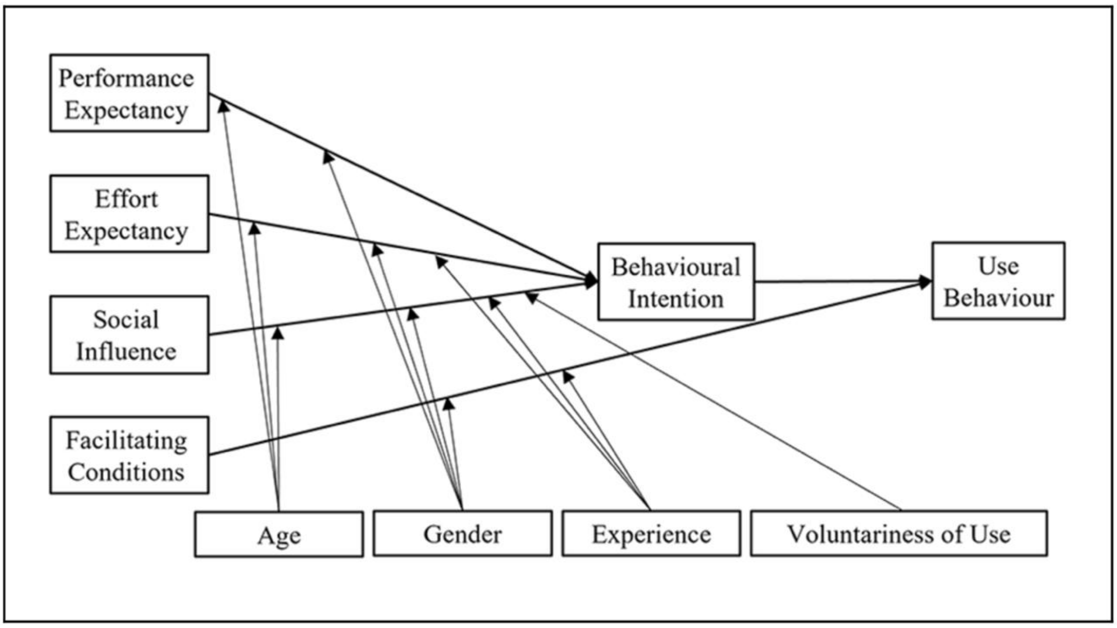

Figure 1. UTAUT framework, adopted from Venkatesh et al., 2003, p. 447

Although UTAUT offers a robust framework – explaining up to 70% of the variance in users' intentions to use technology (Venkatesh et al., 2003) – its limitations often necessitate adaptation (Barrane et al., 2019), as was the case for this study. The critique that UTAUT oversimplifies the link between intention and actual use (Blut et al., 2021; Jevsikova et al., 2021) aligns with findings that indicate a complex interplay between PSTs' confidence, anxiety and actual engagement with AI tools (Uzumcu & Acilmis, 2024). Consequently, this study extended the UTAUT framework by incorporating constructs from the affective domain – such as SE – to better capture psychological and emotional factors influencing PSTs' engagement with AI. This approach facilitated a more holistic investigation of the multifaceted challenges and drivers of AI adoption, ensuring that the study's findings are contextually relevant and reflective of the realities faced by PSTs in their placements.

Methods

This research was conducted under the ethical guidelines established by the University of Adelaide and approved as a low-risk project by the university's Human Research Ethics Committee, with steps taken to ensure that subjects were not disadvantaged or harmed during the study. The study employed a mixed-methods approach to collect data from an interventional case study in an ITE course with a large and diverse cohort of PSTs, to investigate the direct impact of an intervention within its natural context, capturing detailed insights about the processes and outcomes involved. This method is valuable when studying complex educational phenomena (Yin, 2018), as it enables the examination of how specific strategies – like the integration of GenAI – affect participants' learning and performance, within the course and later in their school placements (Merriam & Tisdell, 2016). Interventional case studies can enable the combination of qualitative and quantitative data to enhance data reliability and validity, supporting their generalisability within comparable contexts (Flyvbjerg, 2006). They can uncover understandings of how interventions function, including expected and unexpected effects (Stake, 2006), and help to identify the conditions under which these interventions are most effective (Baxter & Jack, 2008).

Course context

This case study involved 151 PSTs enrolled in the final year of their ITE programmes at the University of Adelaide. These PSTs specialised in various teaching subjects and were required to undertake a 5-week WIL component, teaching in secondary school classrooms. The WIL placements were the only graded (summative) assessment in this course. To prepare for WIL, PSTs participated in a placement preparation course comprising six 3-hour face-to-face seminars, supported by online asynchronous resources. The course's intended learning outcomes aimed to familiarise PSTs with placement goals and evaluation criteria. It also equipped them with key skills such as lesson planning, teaching strategies, classroom management and managing professional relationships. The course materials included:

- pre-recorded lectures with transcripts
- course readings and videos
- guest speakers
- digital H5P interactive elements (e.g., branching scenarios, interactive videos, image hotspots, drag-and-drop, flashcards)
- digital collaborative Miro board for reflective discussions
- instructions for utilising ChatGPT (versions 3.5, 4o mini and 4o) for exercises in prompt writing.

During face-to-face seminars, PSTs engaged with presentations that developed knowledge accrued during lecture recordings, participated in reflective discussions, and engaged in interactive exercises.

A key innovation in the course was the targeted training on AI literacy, where PSTs used ChatGPT with consistent signed-in accounts to develop prompt writing skills. This process involved creating precise, contextually appropriate prompts to generate meaningful outputs, while understanding the capabilities, tendencies and limitations of the GenAI model. In-seminar exercises required PSTs to create prompts for classroom scenarios such as differentiated questions for mixed-ability classes, problem-solving examples for mathematics, or the management of professional relationships with mentor teachers. To maximise the pedagogical appropriateness of AI-generated content, PSTs evaluated AI responses against the Australian Professional Standards for Teachers (Australian Institute for Teaching and School Leadership, 2022) and participated in peer-review exercises to critique and refine prompts.

The course also featured five branched scenarios – interactive narratives presenting various WIL situations via H5P – allowing PSTs to make decisions at key points, leading to different outcomes based on their choices. PSTs independently completed branched scenarios in face-to-face seminars, making brief notes on their choices and motivations. They then queried GenAI for recommendations on responding to decision points, iteratively exploring the implications of each choice. PSTs reflected on GenAI's recommendations with peers and connected these discussions to the broader class. WIL began soon after the seminars concluded.

Data collection methods

This study utilised a mixed-methods triangulated approach, comprising a survey, focus-group interviews and placement outcome data. It should be noted that this study draws from self-reported data across a diverse cohort of PSTs from various ITE programmes at the University of Adelaide. The findings are inherently limited by self-report bias and the single site of the study, which may not fully capture experiences in other contexts. Nonetheless, the robust mixed-methods approach enhances the validity and contextualises the findings.

Survey

Participants were invited to complete a digital survey at the end of their placements. The survey collected demographic data and quantitative responses to 22 questions. The questions targeted UTAUT constructs and SE in relation to using GenAI for WIL purposes. Responses were collected on a 7-point Likert scale.

Table 1
Survey questions

Survey question	UTAUT construct
SQ1: To what extent did using AI improve the quality of your lesson planning during placement?	PE
SQ2: To what extent did using AI enhance the efficiency of producing your lesson planning during placement?	PE
SQ3: To what extent did using AI improve the quality of your teaching materials during placement?	PE
SQ4: To what extent did using AI improve the efficiency of producing your teaching materials during placement?	PE
SQ5: To what extent did AI provide useful advice on resolving conflicts with mentor teachers during placement?	PE
SQ6: To what extent did using AI enhance the range and quality of classroom management techniques you used during placement?	PE
SQ7: To what extent did AI suggest effective strategies for resolving conflicts with students after unsuccessful lessons?	PE
SQ8: To what extent did AI improve the quality of your email communications during placement?	PE
SQ9: To what extent did AI enhance the efficiency of producing your email communications during placement?	PE
SQ10: How easy was it to use AI for email communications during placement?	EE
SQ11: How easy was it to use AI to produce lesson plans during placement?	EE
SQ12: How easy was it to use AI to produce teaching materials during placement?	EE
SQ13: How easy was it to use AI to suggest conflict resolution strategies during placement?	EE
SQ14: How easy was it to use AI to suggest classroom management strategies during placement?	EE
SQ15: To what extent did your peer pre-service teachers recommend the use of AI for placement?	SI
SQ16: To what extent did your mentor teacher recommend using AI for placement?	SI
SQ17: To what extent did your university lecturers recommend using AI for placement?	SI
SQ18: To what extent was your educational institution supportive in providing training and support for using AI tools?	SI
SQ19: To what extent did the opinions of your educational institution influence your decision to use AI during placements?	SI
SQ20: To what extent were you familiar with AI tools before placement?	FC
SQ21: To what extent did your experience with AI before placement impact your use of its use during placements?	FC

SQ22: To what extent do you feel confident about using AI for teaching after these placements and related courses?	SE

Focus-group interviews
Participants for the focus-group interviews were selected through purposive sampling to gather deeper insights for the research objectives. We ensured diversity in terms of cultural and academic backgrounds, teaching subjects and school placements. This approach enriched the data by capturing a wide range of experiences (Creswell & Poth, 2018; Palinkas et al., 2015). Two focus-group sessions were conducted after the placement, each comprising seven participants. Semi-structured interviews were guided by UTAUT-aligned questions (see Appendix) to explore GenAI use in teaching, practical challenges and ethical concerns. Participants were encouraged to ask additional questions based on the conversation's context. Interviews followed a protocol of de-identification and balanced moderation (Ho, 2006), lasting between 45 and 70 minutes. Data was analysed using reflexive thematic analysis (Braun & Clarke, 2019).

Placement outcome data
Upon WIL completion, PSTs received individual reports from their mentor teachers. These reports provided a binary pass/fail grade along with qualitative feedback. De-identified data from these reports was used, alongside the school's Index of Community Socio-Educational Advantage (ICSEA) value, which measures socio-educational factors such as parental education, occupation and geographical location.

Results

A total of 126 PSTs volunteered to participate in the research, each responding to the surveys, consenting to take part in the focus-group interviews and consenting for their placement report data to be harvested. Quantitative data from the surveys was analysed using descriptive and inferential statistical methods to identify patterns between participants' demographic details and their PE, EE, FC, SI and SE in relation to using GenAI in WIL. Qualitative data from the focus-group interviews was parsed using thematic analysis to identify relevant recurring experiences and perceptions. These findings were also mapped against ICSEA data.

Survey findings

In survey results, PSTs reported overall positive perceptions of the PE and EE of GenAI during WIL but revealed significant differences across teaching subject variables.

Gender
Kruskal-Wallis H-test analysis reveals that there are statistically significant differences between genders in their responses to most questions about GenAI usage during WIL. Female participants reported higher scores to the questions, indicating a more positive impression of the extent to which GenAI has assisted them in WIL, with a higher median response to 12 of the 22 questions.

Age
Spearman correlation coefficients between age (grouped into 5-year ranges) and survey responses suggest a weak inverse relationship with age. The strongest inverse coefficient resulted for SQ22 (-0.155). The strongest direct coefficient resulted for SQ21 (0.093). This suggests that younger participants recorded the greatest SE in using GenAI for WIL, while older participants felt that they learned most about using AI. The average of the questions' correlation coefficients (-0.02) indicates a very weak relationship between age and the questions relating to GenAI use in WIL.

Teaching subject
Results from Kruskal-Wallis H-tests indicate significant differences between the responses to survey questions given by participants across different teaching subjects. Almost all the survey questions showed p values below 0.05 when juxtaposed to teaching subject, indicating strong disparities in how PSTs from various disciplines perceive the use of GenAI for WIL. This is confirmed by a multivariate analysis of variance, which reports a highly significant F value of 0.0397 for the teaching subject effect in Wilks'

lambda, and p values less than 0.0001 for Pillai's trace and Hotelling-Lawley trace. The average regression analysis R-squared result across the survey questions is 0.682, indicating that 68.2% of the variability in GenAI's perceived usefulness for WIL is explained by the teaching subject variable. Adjusted for the number of predictors in the data, R-squared is 0.663. This confirms that participants from different teaching subjects significantly differ in their responses to how GenAI tools are used and perceived in their respective fields.

Table 2
Responses to survey questions by teaching subject

Teaching subject	Median	Mean	Regression analysis coefficient compared to baseline
Science	7.0	6.80	+2.91 ($p < 0.0001$)
Geography	7.0	6.48	+2.74 ($p < 0.0001$)
Mathematics	6.5	5.98	+2.26 ($p = 0.002$)
Music	6.5	5.63	+1.49 ($p = 0.001$)
History	5.0	4.81	+1.31 ($p = 0.001$)
Languages	4.0	4.18	+0.18 ($p = 0.665$)[a]
English	4.0	4.06	+0.14 ($p = 0.719$)[b]
Computer Science	4.0	3.95	

[a,b] Not statistically significant.

Both the mean and median responses to all survey questions for all teaching subjects are above the midpoint of the Likert scale (3.5), revealing that participants' views on GenAI for WIL were positive overall. Participants teaching Science, Geography and Mathematics perceived a significantly greater benefit from GenAI compared to participants teaching Computer Science, the baseline group. The significant influence of teaching subject applies to all UTAUT constructs, as well as SE. This suggests that subject-specific characteristics loom large in determining the extent to which GenAI tools are effective for school placements.

Questions relating to GenAI's effectiveness in suggesting classroom management strategies registered an average response of 5.19, similarly to questions pertaining to conflict resolution strategies (5.20), indicating moderate perception of PE. These scores are slightly lower than those registered by questions pertaining to lesson planning (5.24) and creating teaching materials (5.26). The extent to which GenAI can assist with email communication registered a markedly higher average score (5.40). Overall, for questions determining PE, responses averaged 5.26, indicating positive views well above the Likert midpoint. The average score for the responses related to how easy GenAI was to use is 5.38, revealing a clearly positive EE. Questions examining SI also registered a positive average score of 5.33. The lowest-scoring question, averaging 4.73, was SQ20, relating to FC. The question relating to SE (SQ22) registered the highest average score at 5.73. The disparity between FC and SE is meaningful, as it suggests a significant degree of learning across the placement preparation courses and placement in relation to using GenAI for WIL, notwithstanding equivocal support for its use in schools. The average ICSEA value for the schools in the data set is 992.33 (slightly below the national average benchmark of 1000). Results indicate a moderate positive correlation ($p = 0.334$, $p < 0.001$) between ICSEA value and AI-related survey responses.

Among the 126 participants, four failed their placement; all others passed. Neither the number nor the distribution of the failed placements is statistically significant.

Focus-group interview findings

The thematic analysis of focus-group interview responses identified key phrases, words and concepts that appeared frequently across the transcript and recorded them as codes. Examples of initial codes included "confidence boost", "stress reduction", "learning curve", "lack of support", "privacy concerns", "ethical considerations" and "contextual limitations". Similar codes were further grouped together to form broader themes. For example, codes related to "time-saving", "stress reduction" and "work-life balance" were clustered under a theme related to "well-being and stress management".

Well-being and stress management

Most participants found that GenAI reduced their stress by saving time on recurring tasks, making them feel more confident in managing their workload. Some participants reported initial stress and frustration when learning to use GenAI, particularly when support was lacking or when the tools did not work as expected:

> After struggling for a while trying to figure it out on my own, I found myself asking AI for advice a lot about how to deal with social situations. This was reassuring, as I often felt that I couldn't ask the mentor teacher because they don't always have time or show interest […] plus I didn't want to risk making a bad impression. (PST2)

> I was honestly a bit stressed about not wanting to rely on a machine too much. I wanted to develop my own skills […] but I used it to generate ideas when it's overwhelming. (PST7)

> I used AI to bypass my frustration [laugh] when I had to write professional sounding emails. Somehow reading AI-drafted emails it knocked some sense into me, like therapy [laugh]. (PST14)

Learning curve

Many participants initially struggled with understanding how to use GenAI tools effectively, especially when there was inconsistent support or training. Despite early challenges, participants generally found that their proficiency with GenAI improved, making the tools more useful and less burdensome:

> AI can be mind-blowing, but knowing how to integrate it into daily teaching processes was a different story. It didn't come quickly for me. (PST3)

> [A] bit of a learning curve, and not all the prompts I put in got good results. But when I managed to get ChatGPT to kinda "understand" [air quote gesture] me and reach a level of accuracy, it started saving me time, and frustration too. (PTS4)

PE

Participants frequently mentioned that GenAI was effective in lesson planning, creating tailored teaching materials, generating quiz questions or activities, advising on conflict resolution and reminding of important information while on placement. A few participants found that GenAI was less effective in classroom management or in contexts where a more nuanced understanding of the classroom dynamics was required, while others suggested the effectiveness developed with practice and/or calculated timing:

> The AI was fantastic! It helped me generate really good quiz questions and activity ideas for my Science classes. It even recommended some free online tools to help with the activities […] my students often loved it. (PST9)

> I had the same mentor teacher twice: he was friendly and attentive at first but then tended to do other work while observing my class and did not give me any feedback, even when I asked. I thought I offended him, but when I asked ChatGPT, it convinced me he was likely just busy. The university liaison seemed think the same. (PST14)

> In classroom management, AI didn't really help. It felt like those situations required a more human touch in real time. To manage student behaviours in the classroom, I usually looked for reflections using AI after the fact. It's impossible to do it in real time. (PST8)

> If I was unsure of the potential consequences, or whether a strategy was likely to succeed, I would ask AI and it would tell me. It's like having a placement buddy! (PST1)

Ethical considerations

Participants expressed concerns about the use of student data in GenAI tools, with some opting not to use certain features due to uncertainty about data security. There were also mixed concerns about fairness, particularly regarding the unequal access to and training for using GenAI tools among students, which could exacerbate existing inequalities:

> Privacy can be a problem, I think. I noticed some AI tools asked for specific student data for better responses, and I wasn't prepared to enter that. (PST12)

> Privacy wasn't a concern for me; we were already taught plenty about not entering confidential or student data into any AI model. I think most of us are smart enough. (PST6)

> [AI] comes with Internet access, so it will continue to be around. It would have been unfair if students like us were not trained or allowed to use these tools before placement or finding jobs […] we need all the help we can get to compete. (PST9)

SI and FC

The level of support from mentor teachers and institutions significantly influenced how comfortably participants could integrate GenAI into their teaching. Participants noted differences in GenAI tool availability and support based on the school's ICSEA value, with higher-ICSEA schools offering more resources and infrastructure for effective GenAI use. An interesting sentiment was noted in which some participants recommended self-learning or a more adaptive approach to using GenAI:

> By far [this course] had the best innovation with AI in my opinion. Others seem so cautious and negative about students using AI to cheat etc. Here our well-being is a higher priority, isn't it? (PST9)

> At my school with high-ICSEA, I noticed lots of awareness and familiarity with AI tools. My mentor teacher and other staff seemed more open to me using it; we even exchanges notes. (PST11)

> I didn't feel much support from my school; they told me to be wary of AI […] it wasn't prohibited but I didn't feel comfortable using it […] at least not openly. (PTS4)

The thematic analysis of the focus-group interviews reveals that PSTs held that GenAI held significant promise for enhanced stress-management and professional effectiveness during WIL. However, as predicted through the UTAUT framework, the perceived effectiveness of AI was often contingent on context, FC and SI. Ethical considerations, particularly around privacy and fairness, also emerged as important factors.

Discussion

The examination of the extent to which PSTs consider GenAI to be a viable resource for conducting effective WIL reveals a nuanced landscape. The findings show PSTs' generally positive perceptions towards GenAI, largely citing its ability to provide personalised feedback, facilitate reflective practice and streamline the preparation process. This resonates with the literature that highlights GenAI's potential to enhance SE (Yao & Wang, 2024) and teaching effectiveness (Huang et al., 2024). Such alignment suggests that when GenAI tools are positioned by university educators as useful professional aids, they are more readily embraced by PSTs, confirming the relevance of SI and FC as critical UTAUT constructs in this context. The study also reveals strong relationships between PE and EE, showing that GenAI's utility is closely tied to its ability to easily improve job performance, thereby supporting UTAUT's premise that these factors cohere with BI and UB.

The results reveal significant differences across teaching subjects in terms of perceptions of GenAI's usefulness, echoing and adding to findings from another study in the field (Qu et al., 2024). PSTs specialising in Science, Geography and Mathematics reported the highest benefits from GenAI, citing its ability to assist with structured, procedural tasks such as lesson planning and test generation. This suggests an epistemological alignment between these disciplines and GenAI's capabilities, where predictable, rule-based knowledge creation ostensibly fits with the mechanisms of GenAI tools. Conversely, PSTs from disciplines such as English and Languages expressed more reservations, suggesting that GenAI tools often lack the contextual sensitivity required for effective teaching in these areas.

Interestingly, PSTs specialising in Computer Science exhibited an outlier pattern. Despite having high SE and high AI literacy, they reported lower PE compared to other subjects. This may be due to GenAI's ability to undermine core Computer Science teaching processes, as it can readily generate code: a key learning outcome of the subject. The tension between GenAI's capabilities and the pedagogical goals of Computer Science highlights the risk of GenAI being perceived as a threat rather than a tool in disciplines where content-creation overlaps heavily with GenAI's strengths. These findings suggest that GenAI literacy training in ITE programmes should not be a one-size-fits-all, but rather cover both core principles and discipline-specific characteristics and requirements, providing tailored examples of how it can be applied in various teaching contexts.

Another important finding suggests GenAI's potential capacity to act as a critical resource in high-stakes situations by providing real-time, non-judgmental support and advice. In instances where mentor teachers failed to provide timely or constructive feedback, GenAI often filled a critical gap, alleviating some stress and allowing PSTs to take more informed decisions by acting as a "placement buddy" (PST1). The ability of GenAI to offer quick, reliable solutions and suggestions was enhanced by the 6-week model training and prompt-engineering embedded in the placement preparatory courses. This in turn assisted PSTs in addressing immediate classroom challenges and professional relationships, enhancing their crisis-management skills – a key component of their professional development. This adaptive support instils work habits conducive to SE, resilience and adaptability, crucial for career longevity. Overall, the findings demonstrate that GenAI could effectively reduce PSTs' praxis shock during WIL by bridging the gap between theoretical knowledge and practical application. This study not only reaffirms the potential of GenAI to transform educational experiences but also spotlights the need for structured AI training within ITE curricula to optimise these benefits.

It is noteworthy, however, that while GenAI can offer immediate solutions and feedback, many PSTs still value the guidance that experienced educators (e.g., mentor teachers, university liaisons, lecturers) provide, which they perceive as vital for their authentic professional development. This sentiment aligns with broader educational concerns about AI's depersonalisation of learning and the ethical implications of algorithmic biases. The value that PSTs placed on human mentorship stresses its continued importance in WIL environments. In turn, it also highlights the need for ITE programmes to not only enhance AI literacy in a way that balances technical competence with ethical standards but also integrate AI tools in a manner that complements and supports, rather than replaces, human elements of mentorship. This way, deliberately integrating GenAI tools into ITE programmes can enrich the training ecosystem to better equip PSTs to handle the complexities of modern classrooms.

Differential access to GenAI tools based on institutional support, as highlighted in both the survey results and qualitative findings, reveals significant disparities in the FC and the SI affecting PSTs. Survey data indicate that PSTs at higher-ICSEA schools have better access to AI resources. This disparity is vividly echoed in the qualitative insights where a participant from a high-ICSEA school observed common familiarity and access to AI tools among mentor teachers and other staff. In contrast, another participant from a low-ICSEA school expressed an apprehension that it may have been wrong to use AI. This demonstrates the uneven playing field faced by PSTs, which may affect their confidence and willingness to integrate AI into their practice. It is advisable, therefore, for ITE programmes and educational policymakers to implement strategies that increase the availability of AI tools across various educational settings. Equitable access to AI tools, complemented by comprehensive training and a supportive and balanced learning environment, can mitigate the disparities noted in this study. Institutional policies should aim for more uniformity in AI resource distribution and foster professional development to encourage schools to approach AI tools as beneficial adjuncts to teaching processes, rather than replacements, shortcuts or taboos.

Finally, as PST performance during WIL placements was the only graded (summative) assessment in the placement preparatory course used in this study, we educators were afforded a privileged opportunity to flexibly integrate GenAI into the course's learning outcomes, teaching and capability development. Performance-based WIL assessment design is largely impervious to academic integrity risks that GenAI commonly poses to educators in conventional merit courses. Here we openly encouraged PSTs, with contextualised introduction and scaffolded guidance, to experiment with GenAI and to reflect on the impact of such uses during the course and while on placement. This explicit educational approach has revealed that many students are eager to learn new skills genuinely and use technological aids to better manage the complexities and stresses of their placements, rather than for shortcuts or dishonesty. The interesting remark by PST9 – "Other [courses] seem so cautious and negative about students using AI to cheat, here our well-being is a higher priority" – coupled with other comments around privacy and safety concerns, reflects a more nuanced understanding of AI's role in real-world productivity from students than they are often given credit for. This course may serve as a case study illustrating how prevailing fears over academic integrity with the introduction of GenAI in education may have led to practices that not only hinder the authentic integration of AI but also potentially weaken students' learning effectiveness, autonomy and authenticity. In contrast, our approach highlights the benefits of embracing AI thoughtfully and innovatively in WIL.

Conclusion

The conclusions drawn from this study suggest that although GenAI holds substantial promise for enhancing WIL for PSTs, its integration into ITE programmes must be approached with careful consideration. For educators looking to utilise these insights, it is crucial to recognise that the scalability and effectiveness of GenAI tools can vary significantly based on several factors, including disciplinary needs, the facilitating conditions of the placement school and the existing AI literacy of both students and staff. Educators aiming to adopt GenAI in their teaching practices should consider targeted pilot programmes that allow for gradual integration and tailoring to the specific needs of different disciplines and to the contextual nuances of each field. Most importantly, integrating GenAI as a pedagogically complementary tool can enrich the educational experience, providing PSTs with additional support while preserving the mentor-student relationship that is critical for professional growth and development.

The study also highlights the importance of infrastructure and support in the effective use of GenAI. Institutions should invest in robust technological assets and training programmes to ensure that both educators and PSTs are equipped to use these tools effectively. Equitable access to GenAI resources should be a priority, ensuring that all PSTs, regardless of the ICSEA values of the schools in which they are placed, have similar opportunities to benefit from these technologies.

Looking forward, key areas for future research include exploring the long-term impacts of GenAI integration on teaching effectiveness and student outcomes. There is a need for comprehensive studies that evaluate how GenAI tools influence the teaching trajectories and career success of PSTs post-graduation. Additionally, further research should investigate the ethical implications of AI in education, particularly how data privacy and bias can be managed to mitigate negative impacts on students. As GenAI technologies continue to evolve, the voices of both educators and PSTs will be essential to refine and adapt AI tools to better meet the educational demands of the future.

Author contributions

Author 1: Conceptualisation, Data curation, Investigation, Formal analysis, Writing – original draft, Writing – review and editing; **Author 2**: Conceptualisation, Data curation, Investigation, Formal analysis, Writing – review and editing.

Data availability statement

The data from this research is stored in secure institutional repositories and can be accessed upon approved request. Access will be granted under the conditions outlined by the University of Adelaide's data governance policies to ensure confidentiality and appropriate use.

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Appendix

Focus-group semi-structured questions	UTAUT construct
Can you describe your overall experience using AI tools during your placement?	PE, EE, SI, FC
In which specific areas (e.g., lesson planning, classroom management, student engagement) did AI tools seem most effective to you? Why?	PE
Were there any situations where you found AI tools less useful or even counterproductive? If so, can you share examples?	PE
How easy or difficult was it to learn and integrate AI tools into your daily teaching tasks? What factors influenced this?	EE, FC, SI
Did using AI during your placement increase or decrease your confidence in your teaching abilities? In what ways?	SE
How well supported did you feel by your educational institution, university course coordinators, tutors and mentor teachings in using AI tools? What kind of support or training made or would have made a difference?	FC, SI
What ethical considerations or concerns do you think should be addressed when integrating AI tools in education?	PE, EE, SI
Was your well-being and stress management impacted by your use of AI? In what ways?	SE