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Blending with AI: The role of student characteristics in blended learning personalisation

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Blended learning personalisation tailors experiences to individual student needs, leveraging technology to create flexible and inclusive learning environments. Achieving this requires understanding student characteristics that comprise personal backgrounds, attitudes, preferences and prior knowledge and how these inform the student–teacher–technology–curriculum relationship. Artificial intelligence (AI) presents further opportunities for blended learning personalisation in contemporary higher education, highlighting the need to understand student perspectives on AI's potential role. This mixed methods study investigated which student characteristics are associated with preferences for different personalisation approaches, including how students perceive AI's role in blended learning environments. We surveyed 113 students at an Australian research-focused university, followed by semi-structured interviews with a subset of 20 participants. Our results suggest that student characteristics vary in significance, being significant in shaping feedback and supporting learning, but not in how learning materials are personalised. We provide recommendations for further research and practice on AI implementation and blended learning personalisation.

Implications for practice or policy:

- Course designers could enhance personalisation interventions by focusing on feedback rather than alternative learning materials.
- Policymakers should design AI implementation policies as context sensitive rather than uniform.
- Educators implementing student-facing AI tools should provide clear guidance on appropriate use to address concerns about overreliance and academic integrity.
- Programme leaders should review learning experiences across year levels, given the variation in student perceptions of course quality.

Keywords: personalised learning, blended learning, artificial intelligence, student engagement, higher education, mixed methods

Introduction

The integration of digital technologies into higher education has been accompanied by persistent claims about the transformative potential of *personalised learning* (Alamri et al., 2021; Bernacki et al., 2021). While adapting instruction to individual needs is not new, the term has become associated with technological solutions that often reflect institutional imperatives as much as learning theory and pedagogical evidence (Fariani et al., 2023; Tsai et al., 2019; van der Stap et al., 2024). Blended learning, which combines face-to-face and online elements, has also become the primary context in which personalisation claims are made and tested (Halverson & Graham, 2019; Smith & Hill, 2019). Despite widespread adoption of blended learning in higher education (Alammary et al., 2014; Anthony et al., 2022), fundamental questions remain about which aspects of learning should be personalised, for whom and based on what evidence.

Recent systematic reviews have examined institutional approaches to blended learning, identifying that frameworks often emphasise technological infrastructure, faculty training, and policy development, with less attention to how student characteristics might inform personalisation approaches (Anthony et al., 2022; McCarthy & Palmer, 2023). While these frameworks describe what institutions should implement at a macro level, evidence remains limited about the different needs and preferences of students within blended environments. The rapid emergence of large language models and generative artificial intelligence (AI) tools has renewed enthusiasm for automated personalisation while simultaneously raising questions about student trust, pedagogical appropriateness and the role of educators (Bhutoria, 2022; Chan, 2023; Zawacki-Richter et al., 2019). This gap between institutional frameworks and student perspectives creates uncertainty about blended learning design that is both technologically feasible and pedagogically valued by learners.

This study investigated student perspectives on personalisation in blended learning environments, with particular attention to the emerging role of AI tools used to support teaching and learning in higher education. Rather than evaluating a specific adaptive learning system or institutional framework, we examined which student characteristics (if any) are associated with preferences for different types of learning personalisation, and how students perceive AI in supporting their learning. By incorporating the student voice, we provide bottom-up empirical evidence to complement institutional frameworks, contributing to more responsive blended learning design.

Key concepts

We operationalise the definitions of key terms that have been variably interpreted in literature:

Personalised learning refers to educational approaches that adapt aspects of the learning experience (content, pace, pedagogy, assessment or feedback) based on individual learner characteristics (Walkington & Bernacki, 2020), distinguishing it from general student-centred pedagogy. Personalisation exists on a continuum and may not be exclusively technology mediated, though digital systems increasingly enable personalisation at scale (Tsai et al., 2019). Personalisation approaches can reflect institutional interests rather than empirically validated pedagogical benefits (Guzmán-Valenzuela et al., 2021), motivating our focus on what students value.

Blended learning can refer to a range of approaches and philosophies, often leading to confusion as to what is meant under such a broad definition. For the purposes of this paper, we adopted Torrisi-Steele and Drew’s (2013, p. 372) definition of blended learning as “the use of technology with face-to-face teaching”. In doing so, we aligned with Dziuban et al.’s (2018, p. 12) critique that much "blended learning" is actually "blended teaching" emphasising delivery logistics rather than student experience. Our interest lies in how blended environments support meaningful personalisation responding to diverse learner needs.

Student characteristics encompass demographic factors (age, language background, enrolment status) and dispositional traits (motivation, confidence, help-seeking behaviours) that may influence learner engagement, preferences and outcomes (Kintu et al., 2017; Tempelaar et al., 2021). Rather than assuming these characteristics should drive learning design, we investigated whether students perceive them as relevant to their learning needs.

Learning preferences are operationalised as students’ stated inclinations towards instructional formats (videos, lectures, practicals), feedback types (written, oral, rubric) and delivery modes (face-to-face or online). We distinguish these measured preferences from learning styles, which lack empirical support (Kirschner, 2017; Pashler et al., 2008), treating them as context dependent and potentially malleable rather than fixed traits (Bernacki et al., 2021).

Blended learning personalisation

Blended learning can support personalisation by combining structured teaching with flexible delivery, enabling students to engage at their own pace and in preferred formats (Alamri et al., 2021; Halverson & Graham, 2019). However, personalised learning often functions as a reactive educational approach, relying on adaptive systems that collect student data through digital platforms (Bernacki et al., 2021). Most research on these systems has evaluated effectiveness through outcomes or engagement metrics rather than investigating what students value or desire from personalisation efforts (Walkington & Bernacki, 2020). Institutional frameworks frequently emphasise these technological solutions over understanding student characteristics that could proactively inform design (McCarthy & Palmer, 2023). In the context of emerging AI tools, this reactive orientation raises further questions about what diverse student cohorts need from personalised learning. This study investigated which student characteristics inform personalisation preferences in blended learning, providing evidence for proactive educational design.

Student characteristics and personalisation

Student characteristics play a critical role in shaping how learners engage with curriculum, technology and teachers (Borup et al., 2020). While demographics and learning analytics are frequently used to track and predict behaviours (Wong & Li, 2020), dispositional factors associated with student characteristics act as facilitators of engagement and may help provide a more holistic picture of learner needs (Figure 1).

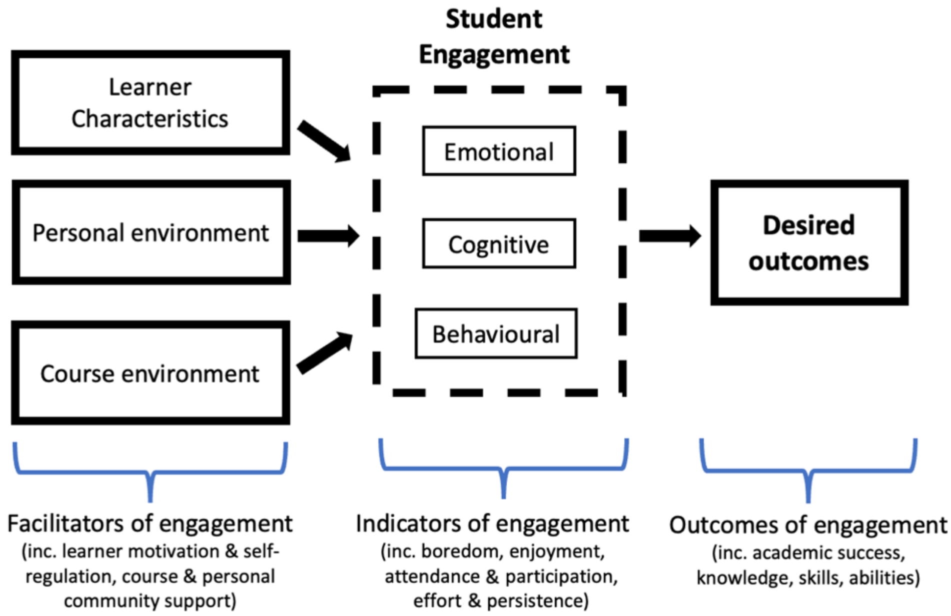

Figure 1. General model of student engagement adapted from Borup et al. (2020, p. 811)

Borup et al.'s (2020) academic communities of engagement framework conceptualises student engagement as emerging from the interaction between learner characteristics and three types of community support: academic, social and personal. In their framework, learner characteristics function not as fixed predictors but as contextual factors that shape support needs. The framework emphasises a need for community building in online and blended learning to account for interactions that might normally occur in a face-to-face setting. This perspective aligns with Halverson and Graham's (2019) model of engagement, who noted that learner characteristics and learning experience were strong facilitators of engagement rather than independent variables. Together, these frameworks demonstrate the importance of student characteristics in learning personalisation, yet questions remain about which specific characteristics inform which personalisation preferences in blended environments.

AI and learning personalisation

AI has the potential to reshape learning personalisation through scalable, data-driven interventions. In this study, the term AI refers specifically to student-facing tools such as large language models and generative AI applications, rather than teacher-facing systems such as learning analytics platforms supported by machine learning. ChatGPT, for example, is claimed to support personalised learning by generating adaptive explanations, providing on-demand support and recommendations based on individual needs (Naznin et al., 2025). However, effective AI-enabled personalisation requires specific pedagogical guidance. AI tools perform best when teachers provide clear learning objectives and quality criteria, scaffolding students' interactions rather than allowing autonomous use (Chan, 2023). While AI can facilitate certain aspects of instruction, it cannot replace the relational and contextual insights provided by educators. We treated student AI acceptance as a component of the student-technology relationship within our conceptual framework, functioning as a student characteristic that may shape how learners engage with AI-enabled personalisation, rather than as a standalone outcome. Student acceptance, ethical considerations and concerns about overreliance remain challenges (Fariani et al., 2023; Luan et al., 2020). Understanding how students perceive AI's role in personalised learning is therefore essential for responsible implementation (Choung et al., 2023).

Purpose of this study

This study investigated how student characteristics inform personalised approaches to blended learning and explored the way students perceive AI technologies as potential support within this process. Guided by a conceptual framework (Figure 2) that maps the relationships between student, teacher, technology and curriculum (comprising content, pacing, assessment and learning activities), we adopted a mixed methods approach involving surveys and interviews with students from a research-intensive Australian university.

Our research was guided by the following research questions (RQs):

- RQ1: Which student characteristics are associated with preferences for different personalisation approaches in blended learning environments?
- RQ2: What do students want from blended learning personalisation and how do they perceive AI's potential role?

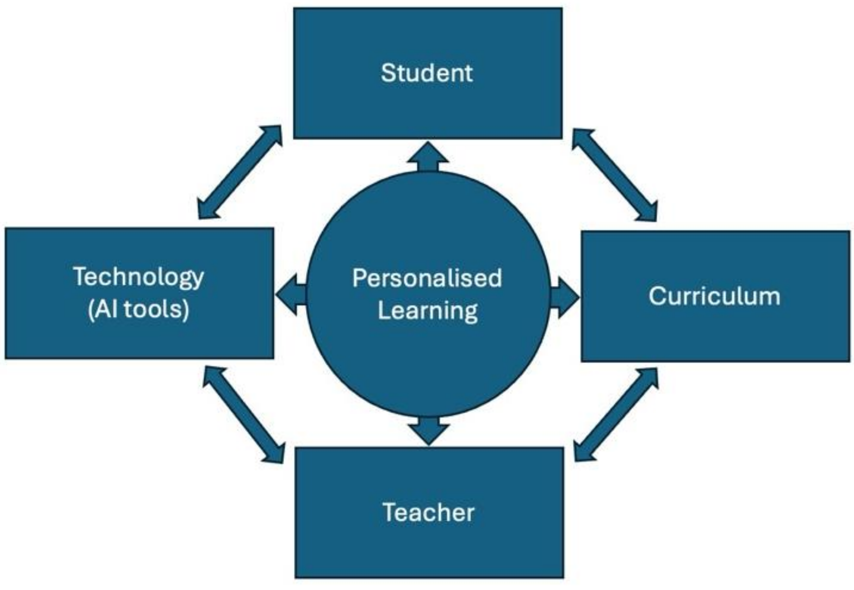

Figure 2. Conceptual framework for blended learning personalisation

Methods

Theoretical background of the study

This study adopted a critical realist paradigm, examining both measurable patterns in student characteristics (ontological realism) and the subjectively constructed meanings students assign to personalisation and AI (epistemological constructivism). This lens enabled investigation of structural relationships while honouring diverse learner experiences (Al-Huneidi & Schreurs, 2012; Zachariadis et al., 2013).

The conceptual framework (Figure 2) integrated three theoretical perspectives: social constructivism, which positions learning as socially mediated knowledge construction through interaction with teachers, peers, technology and curriculum (Alamri et al., 2021; Borup et al., 2020); self-determination theory, which informs measurement of motivation, autonomy and engagement (Alamri et al., 2020); and the technology acceptance model, which examines how perceived usefulness and ease of use shape technology adoption (Davis, 1989). These theoretical lenses guided variable selection, survey development and analysis.

This explanatory sequential mixed methods design (Creswell & Plano Clark, 2017) was quantitatively led, with a survey establishing patterns in how student characteristics relate to personalisation preferences and qualitative interviews providing elaboration and explanatory depth. Data analysis followed conceptual framework relationships (student-curriculum, student-technology and student-teacher), with quantitative analysis testing associations and qualitative analysis employing deductive thematic coding (Braun & Clarke, 2006) guided by the conceptual framework while remaining open to emergent themes. Integration of the two strands occurred through interpretation in the discussion rather than during analysis, as qualitative findings are used to contextualise and elaborate the quantitative patterns rather than test them.

Data collection

Ethical approval was granted for student data collection at the end of the second teaching semester in 2023. Data were collected using a combination of an online survey and semi-structured interviews. The survey items were designed to gather student views on personalised learning and technology interventions, with a focus on AI as a support mechanism.

Participants (n = 113) included undergraduate (79.6%) and postgraduate (20.4%) students who had completed a minimum of four university courses, studying in the fields of education, computer science or health science. These students were recruited through course announcements within the university learning management system (Canvas). At the end of the survey, participants were asked if they would undertake an online interview to provide additional feedback and a subset of students (n = 20) agreed to this. Interviewees reflected the demographic composition of the survey sample, including undergraduate and postgraduate students across education, computer science and health science.

Survey instrument

The student survey was developed following best practices for educational questionnaire development (Artino et al., 2014). Survey items were designed following a comprehensive literature review of relevant scholarship addressing blended and technology enhanced learning (Dunn & Kennedy, 2019; Kintu et al., 2017; Tempelaar et al., 2021). Items were developed to align with the conceptual framework (Figure 2), addressing four conceptual domains. These were student demographics (background characteristics), learning dispositions (informed by self-determination theory), technology support and AI perceptions (informed by the technology acceptance model) and curriculum structure preferences (informed by social constructivism).

Student demographic items (10 items) captured background characteristics including gender, age, Aboriginal or Torres Strait Islander status, parental university attendance, household income, year level, language spoken at home, domestic or international student status, enrolment type and learning disability status. These demographic categories were selected based on research indicating their potential relationship to learning preferences and technology acceptance (Kintu et al., 2017; Tempelaar et al., 2021).

Learning disposition items (16 items, 5-point Likert scale) reflected motivation, engagement, confidence, self-regulation, help-seeking, collaboration, and learning preferences. These dimensions were drawn from established engagement frameworks (Halverson & Graham, 2019; Martin & Borup, 2022).

Technology support and AI perception items (12 items) included binary items assessing AI tool use, 5-point Likert items measuring comfort with AI and perceived quality and open-ended items evaluating use and acceptance. Items were informed by the technology acceptance model constructs (Davis, 1989) and AI education research (Chan, 2023; Choung et al., 2023).

Curriculum structure preference items (6 items) were informed by learning models that support personalisation (Alamri et al., 2021). Items assessed preferred methods for learning new material (categorical, multiple selection), preferred feedback types (categorical, multiple selection), satisfaction with course materials and resources (5-point Likert), preference for face-to-face versus online learning (binary) and need for content aligned with personal interests (binary).

We validated the instrument by independently assessing domain coverage, item clarity and construct alignment based on our expertise in educational technology and higher education pedagogy. Internal consistency reliability was assessed using Cronbach's alpha for the learning dispositions items (16 items, $\alpha = 0.80$) and technology support and AI perception items (6 items, $\alpha = 0.80$). Both exceeded the conventional threshold ($\alpha = 0.70$) for exploratory research (Boateng et al., 2018), as appropriate for an instrument under early-stage development. Cronbach's alpha was not calculated for curriculum structure items, as these comprised heterogeneous formats assessing conceptually distinct preferences rather than a single latent construct. The final survey comprised 44 items organised according to the conceptual framework themes (Table 1).

Table 1
Survey instrument themes

Theme	No. of items	Scale(s) used
Student demographics	10	Categorical, yes/no
Learning disposition	16	Categorical, yes/no, 5-point Likert
Technology support	12	Yes/no, 5-point Likert, open ended
Curriculum structure	6	Categorical, yes/no, 5-point Likert

Semi-structured interviews

Student participants were asked 18 interview questions. These were designed to build on the items and themes developed in the surveys and informed by research addressing blended learning personalisation (Alamri et al., 2020). Example questions included “What is the biggest factor that impacts your ability to learn?”; “Does the teacher involvement influence your effort?”; “Does the use of technology to aid learning interactivity influence your effort?” and “Would you be comfortable if AI was used for this type of personalisation?”. All interviews were undertaken online using Zoom and recorded to assist with transcription.

Data analysis

Survey data were prepared for statistical analysis by removing open-ended questions and incomplete responses. Analysis was undertaken using SPSS (version 28.0.1.0), evaluating student demographics against survey items associated with disposition, technology and curriculum. The Pearson chi-square test of independence was used to evaluate categorical data associated with curriculum structure. An independent samples *t* test was used to compare means and determine significance between demographics and theme data consisting of only two groups, while a one-way analysis of variance with a Tukey post-hoc test was used to compare means and determine significance of demographics and theme data consisting of multiple groups. Statistical significance was defined as $p < .05$ in all cases. Open-ended survey questions were analysed in Qualtrics Text iQ to determine common themes.

This study was exploratory and intended to be hypothesis generating rather than confirmatory. We tested multiple associations across student characteristics and learning environments to identify patterns warranting further investigation. Given the number of tests conducted, the Type I error risk of false positives was elevated. We acknowledge this limitation but report unadjusted *p* values for transparency. All statistically significant findings reported here should be interpreted as candidate associations requiring replication. Some demographic categories had very small samples (e.g., $n = 3$ for non-binary students, $n = 9$ for students with learning disabilities, $n = 7$ for fourth-year students). Chi-square tests involving these subgroups have limited reliability due to low expected cell frequencies; results are reported for completeness but should be interpreted as preliminary patterns requiring replication with larger samples rather than robust findings.

Student interviews were coded deductively (Braun & Clarke, 2006). Initial codes derived from the conceptual framework comprised course_structure, feedback_value, course_satisfaction (student-curriculum); AI_use, AI_concerns, tech_comfort (student-technology); and teacher_role, interaction_value, teacher_enthusiasm (student-teacher). Emergent codes comprised peer_engagement, learner_motivation, and cost_benefit. Analysis was carried out using NVivo (version 1.7.1). Interviewees were allocated pseudonyms consisting of a first letter to represent student and a number (i.e., S1, S2).

Results

Descriptive statistics

Descriptive statistics were run for student demographics to determine frequencies (Table 2). Demographics comprised personal background, year level and type of enrolment. Gender was used as a demographical descriptor in this study to refer to a person's psychological sense of their gender, rather than a binary construct (American Psychological Association, 2015).

Table 2
Frequency distribution of students

Demographics	Category	Frequency	Percent
Student gender	Female	70	61.9%
	Male	40	35.4%
	Non-binary or third gender	3	2.7%
Student age	18–24	90	79.6%
	25–34	15	13.3%
	35+	8	7.1%
Aboriginal or Torres Strait Islander	Aboriginal	0	0%
	Torres Strait Islander	0	0%
	Both Aboriginal and Torres Strait Islander	0	0%
	Neither	113	100%
Parents' university	One parent	31	26%

Demographics	Category	Frequency	Percent
	Both parents	48	40%
	Neither parent	40	34%
Household income	Less than $100,000	37	44%
	$100,000–$150,000	29	35%
	$150,000–$200,000	13	15%
	$200,000–$250,000	2	2%
	$250,000–$300,000	1	1%
	More than $300,000	2	2%
Year level	First year	48	42.5%
	Second year	16	14.2%
	Third year	19	16.8%
	Fourth year	7	6.2%
	Postgraduate	23	20.4%
Language at home	English	50	44.2%
	Other than English	63	55.8%
Student status	Domestic	68	60.2%
	International	45	39.8%
Enrolment type	Full-time	105	92.9%
	Part-time	8	7.1%
Learning disability	Yes	9	8.0%
	No	104	92.0%

Note. Household income reflects n = 84 valid responses; 29 participants declined to answer this question.

Which student characteristics are associated with preferences for different personalisation approaches in blended learning environments? (RQ1)

The data were analysed according to the conceptual model with themes aligned to the relationships of student-curriculum and student-technology. Survey results (Table 3) suggest associations between student demographics and preferences for learning materials and feedback. For learning materials, age and audio resources were notably connected, indicating that 90.3% of students do not favour audio resources. Among the small subgroup of students reporting a learning disability (n = 9), tutorials were unanimously preferred. Given the sample size, this is best interpreted as an illustrative descriptive observation rather than a robust group-level pattern. For comparison, students without learning disabilities also demonstrated a substantial preference (60.6%) for tutorials.

Regarding preferred feedback types, 62.8% of students aged 18–24 preferred rubrics, whereas none of the students aged 35 and older favoured this feedback type. Gender data revealed that only 15% of students preferred class rankings, and male students (59.5%) were more likely to prefer test results compared to female students (38%). All three non-binary or third gender students preferred feedback via test results; however, this sample is too small to support inference. Students who spoke only English preferred written feedback (69.8%) and rubric templates (68.3%), while second-language students favoured a combination of written and oral feedback (66.7%). Enrolment status reflected the language results, showing significance only for written feedback and rubric templates. Year level suggested a non-linear association with written feedback preference (p = .025). Third-year students most strongly preferred written feedback (77.8%), while postgraduate students least preferred it (33.3%).

Table 3 presents chi-square tests of independence examining preference response distribution across demographic categories. Significant result (p < .05) indicates differing preference patterns across demographic groups.

Table 3
Chi-square test of independence for relationships related to student demographics and dispositions related to curriculum structure

Relationship	Category	Yes	No	df	Value	Sig. (2-sided)
Age * Prefer audio resources	18–24	5 (6.3%)	75 (93.7%)	2	8.37	.015
	25–34	2 (13.3%)	13 (86.7%)			
	35+	3 (37.5%)	5 (62.5%)			
	Total	10 (9.7%)	93 (90.3%)			
Learning disability * Prefer tutorials	Learning disability	9 (100%)	0 (0%)	1	5.53	.019
	No learning disability	57 (60.6%)	37 (39.4%)			
	Total	66 (64%)	37 (36%)			
Age * Prefer rubric template	18–24	49 (62.8%)	29 (37.2%)	2	12.54	.002
	25–34	6 (42.9%)	8 (57.1%)			
	35+	0 (0%)	8 (100%)			
	Total	55 (55%)	45 (45%)			
Gender * Prefer test results	Male	22 (59.5%)	15 (40.5%)	2	7.44	.024
	Female	23 (38.3%)	37 (61.7%)			
	Non-binary or third gender	3 (100%)	0 (0%)			
	Total	48 (48%)	52 (52%)			
Gender * Prefer class rankings	Male	6 (16.2%)	31 (83.8%)	2	6.85	.033
	Female	7 (11.7%)	53 (88.3%)			
	Non-binary or third gender	2 (66.7%)	1 (33.3%)			
	Total	15 (15%)	85 (85%)			
Language * Prefer written feedback	English only	30 (69.8%)	13 (30.2%)	1	7.55	.006
	Other than English	24 (42.1%)	33 (57.9%)			
	Total	54 (54%)	46 (46%)			
Language * Prefer written and oral feedback	English only	15 (34.9%)	28 (65.1%)	1	9.94	.002
	Other than English	38 (66.7%)	19 (33.3%)			
	Total	53 (53%)	47 (47%)			
Language * Prefer rubric templates	English only	29 (67.4%)	14 (32.6%)	1	4.72	.030
	Other than English	26 (45.6%)	31 (54.4%)			
	Total	55 (55%)	45 (45%)			
Enrolment status * Prefer written feedback	Domestic enrolment	38 (63.3%)	22 (36.7%)	1	5.26	.022
	International enrolment	16 (40%)	24 (60%)			
	Total	54 (54%)	46 (46%)			
Enrolment status * Prefer rubric templates	Domestic enrolment	41 (68.3%)	19 (31.7%)	1	10.77	.001
	International enrolment	14 (35%)	26 (65%)			
	Total	55 (55%)	45 (45%)			
Year * Prefer written feedback	First year	25 (62.5%)	15 (37.5%)	4	11.11	.025
	Second year	5 (35.7%)	9 (64.3%)			
	Third year	14 (77.8%)	4 (22.2%)			
	Fourth year	3 (42.9%)	4 (57.1%)			
	Postgraduate	7 (33.3%)	14 (66.7%)			
	Total	54 (54%)	46 (46%)			

Note. Pearson's chi-square test with significance set at $p < .05$.

Demographic relationships with learning dispositions and technology support (Table 4 and Table 5) indicate exploratory associations with language, enrolment status, learning disability, age and year level. English-only speakers showed higher enjoyment of their current studies ($p = .004$), but lower belief in AI feedback quality (p = .041). Enrolment status showed several relationships; enjoyment of current study (p < .001) and use of AI for feedback (p = .041) reflected the results observed for language. International students were more likely to seek help (p = .044) and desire one-on-one teaching (p = .003), whereas domestic students found studies more career-relevant (p = .040). Additionally, students with learning disabilities showed lower learning confidence (p = .030).

Table 4
Independent samples t test for significant differences between student demographics and dispositions related to learning and technology support

Disposition	Category	*M*	*SD*	*t*	*df*	Sig. (2-sided)
Enjoy current study	English only	4.22	0.69	2.98	104.94	.004
	Other than English	3.71	1.11			
AI feedback	English only	2.41	1.02	-2.07	91	.041
	Other than English	2.92	1.28			
Enjoy current study	Domestic enrolment	4.21	0.71	3.45	65.32	<.001
	International enrolment	3.53	1.18			
Actively seeks help	Domestic enrolment	3.58	1.05	-2.04	110	.044
	International enrolment	3.98	0.94			
Relevant to career	Domestic enrolment	4.42	0.72	2.08	110	.040
	International enrolment	4.09	0.95			
One-on-one teaching	Domestic enrolment	2.85	1.02	-3.04	98	.003
	International enrolment	3.53	1.18			
AI feedback	Domestic enrolment	2.50	1.16	-2.09	69.82	.041
	International enrolment	3.03	1.20			
Confident learner	Learning disability	3.78	0.83	-2.20	110	.030
	No learning disability	4.27	0.63			

Note. Independent samples t test for significance set at p < .05.

Among the exploratory associations identified, students aged 25–34 reported higher AI comfort than those 35+ (p = .002). Students aged 25–34 (p = .008) as well as those aged 18–34 (p = .002) expressed greater confidence in AI's potential to improve teaching quality compared to students 35+. First-year students (p = .007) and postgraduate students (p = .022) were more likely to enjoy learning new things than third-year students. First-year students were also more likely to enjoy their current studies compared to both third-year (p = .007) and postgraduate students (p = .004). First-year students also showed higher satisfaction with course materials (p = .006) and resources than third-year (p = .043), fourth-year (p = .015) and postgraduate students (p = .020). Although fourth-year students had the lowest representation (n = 7), the survey data suggest they were more likely to agree that AI feedback quality matches teacher feedback compared to first-year (p = .006), second-year (p = .004) and postgraduate students (p = .045).

Table 5
Means, standard deviations and one-way analyses of variance for significant differences between student demographics and dispositions related to learning and technology support

Disposition	Category	*M*	*SD*	*F*	*df*	Sig. (2-sided)	Tukey post-hoc Category	Sig.
AI comfort	18–24	3.55	1.00	6.19	2	.003	25–34 > 35+	.002
	25–34	4.27	0.79					
	35+	2.57	1.27					
AI quality teaching	18–24	3.81	0.88	2.82	2	.003	18–24 > 35+	.002
	25–34	3.91	0.94				25–34 > 35+	.008
	35+	2.57	1.13					
Enjoy learning	1st year	4.73	0.45	4.16	4	.004	1st year > 3rd year	.007
	2nd year	4.53	0.52				PG > 3rd year	.022
	3rd year	4.26	0.65					

Disposition	Category	*M*	*SD*	*F*	*df*	Sig. (2-sided)	Tukey post-hoc Category	Sig.
	4th year	4.29	0.49					
	PG	4.74	0.45					
Enjoy study	1st year	4.29	0.71	4.49	4	.002	1st year > 3rd year	.023
	2nd year	4.07	1.16				1st year > PG	.004
	3rd year	3.53	0.84					
	4th year	4.00	0.58					
	PG	3.43	1.24					
Course resources	1st year	4.03	0.77	4.68	4	.007	1st year > 3rd year	.043
	2nd year	3.50	0.76				1st year > 4th year	.015
	3rd year	3.22	1.00				1st year > PG	.020
	4th year	2.71	1.38					
	PG	3.19	1.33					
Course material	1st year	4.22	0.62	4.14	4	.004	1st year > PG	.006
	2nd year	3.64	0.84					
	3rd year	3.61	0.70					
	4th year	3.71	0.76					
	PG	3.48	1.08					
AI feedback	1st year	2.51	1.05	3.91	4	.006	4th year > 1st year	.006
	2nd year	2.17	1.03				4th year > 2nd year	.004
	3rd year	2.88	0.89				4th year > PG	.045
	4th year	4.14	1.07					
	PG	2.74	1.49					

Note. PG = postgraduate. One-way analyses of variance significance set at $p < .05$.

What do students want from blended learning personalisation and how do they perceive AI's potential role? (RQ2)

Qualitative survey feedback and semi-structured interviews were used to inform our understanding of student motivation and engagement. The interview data were analysed according to the conceptual model with themes aligned to the relationships of student-curriculum, student-technology and student-teacher. Overall, students agreed that face-to-face was a better learning experience than online learning (72.6%). However, interview feedback suggests that there is nuance associated with this approach. While many students share a preference for in-person learning, attendance was tempered by feelings associated with relevance, difficulty and time in terms of cost and benefit to the individual:

> Classes ended up being online and I think they could have been face-to-face. And I think the face-to-face would have been better, so we've got more of that human interaction. (S2)

> If the teaching material is old and not a new technique, I will lose my motivation. And if it is too confusing or difficult to understand, I gradually reduce my effort. (S9)

When ranking the importance of teacher roles, students identified the roles in the following order of importance: knowledge facilitator and subject matter expert were considered most important, followed by designer of learning and assessor of learning. The role of researcher was ranked as least important. Students were acutely aware of the time cost involved in learning activities. The availability of video recordings was a strong contributor to decision-making when it came to attendance, assessment policy was also a key factor in determining the value of in-person attendance:

> I don't go to the lectures. I find it takes me about an hour to get in, if it's only for like an hour, then there's two hours of travel. (S8)

Although only two demographic categories (age and learning disability) showed statistical significance concerning preferred learning materials, there was a clear overall preference. Survey data suggest that students favour practical activities or workshops (74.5%), tutorials (64.7%) and videos (61.8%) for learning new material (Figure 3). In the survey, *video* referred to pre-recorded video content including recorded lectures and demonstrations, *lectures* referred to live lecture presentations delivered face-to-face or synchronously online and audio referred to audio-only recordings. Students could select multiple preferences, with interactive formats (practical activities, tutorials) being most preferred and passive audio-only content least preferred.

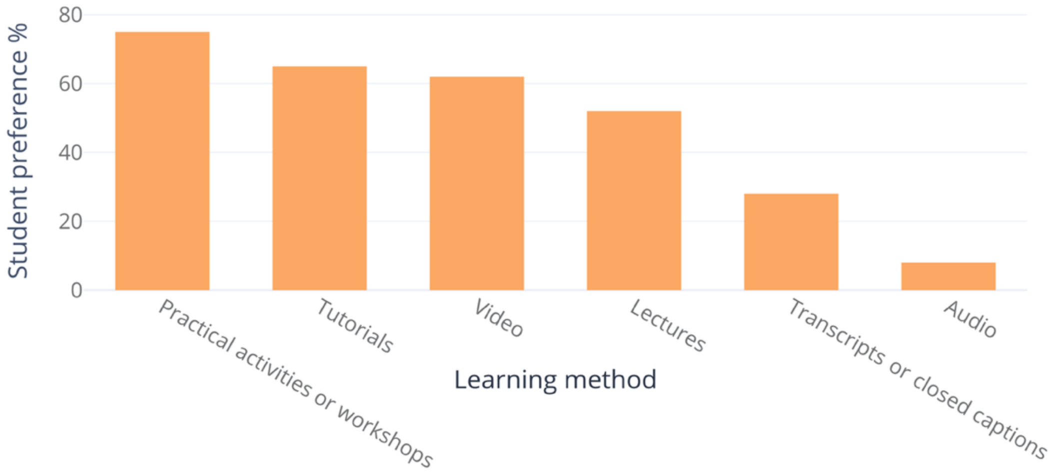

Figure 3. Preferred method of learning new material

When asked more broadly about the need for content aligned with their personal interests, 66.3% of students indicated that this was not a requirement. This sentiment was echoed in the interviews, where students expressed a strong preference for interactive learning activities and connection with teachers:

> Most of the time it's not useful if you only go through all the lectures. Yeah, I feel workshops are more useful, much more useful for me. (S15)

While transcripts were not a preferred method of learning new material for many students, these were highlighted by two student interviewees as important for those with learning difficulties:

> The issue with video lectures for me specifically is that I kind of have an audio processing disorder. So, if there aren't captions, or if there isn't a written transcript that I can follow along with, it's really difficult for me to sit through a one-hour lecture and absorb the information. (S4)

Many students (60.6%) agreed that AI tools could enhance the quality of teaching, and 70.3% believed that AI tools could improve the quality of their learning. However, only 24.4% of students felt that AI could provide feedback on par with teacher feedback. The importance of humanness emerged as a strong theme in the student interviews, with students expressing a need for validation and individual understanding:

> Maybe you spend, you know, many hours writing something. And to think that no human being is going to even read it after you're done would be pretty yeah, that would be pretty upsetting. (S2)

> You know, like the traditional ways, like teacher-student interactions and understandings, they can't really be replaced by the technology. Because the technology don't know the people. (S13)

When asked about the best use of AI in teaching and learning (Table 6), the top three student responses were personalisation (26.4%), research (18.7%) and automation tools (17.6%).

Table 6
Student (n = 91) perspectives on the best use of AI in teaching and learning

Student AI best use	Percent
Personalisation	26.4%
Research	18.7%
Automation	17.6%
Summary tool	16.5%
Feedback	11.0%
Accessibility	9.9%

In determining the types of AI currently utilised by students, ChatGPT was the most popular, with 46.8% of respondents indicating they have used this generative AI tool (Table 7). The common use case suggests a desire for learning personalisation and enhanced understanding:

> It's just that and no offense, but a lot of our teachers are academics. They struggle simplifying the concepts to people who have no idea what they're talking about. And so, we often have to go to something like YouTube or even ChatGPT to get like a simplified explanation with an example. Then we can go back to the lecture and the textbook content, and now we sort of understand it. (S1)

Table 7
AI tools used by students (n = 126 multiple selections permitted)

Student AI tools	Percent
ChatGPT	46.8%
Grammarly	11.1%
None	10.3%
Dall-E	6.3%
Canva	3.2%
Co-pilot	2.4%
Pytorch	2.4%
Quillbot	2.4%
Other	15.1%

Several students also indicated that they have not used AI tools at all (10.3%). While this lack of engagement with AI could be attributed to awareness and relevance to learning domain, a fear of overreliance was also evident in both survey feedback (Table 8) and student interviews:

> I try not to use it like for everything because I don't want to like, become dependent on it. (S1)

> I'm still terrified, I haven't started an account. I feel like once I do, I won't stop. (S6)

Academic integrity, inaccuracy of information a fear of replacing teachers, misalignment with learning and misuse of personal data were also fears expressed by students:

> So, one thing I would be concerned about is sort of replacing teachers entirely. So, I don't want to end up in a situation where it's just like the AI's teaching the course and the, I don't know, I guess the lecture's just sort of tinkering with the algorithm. (S5)

Table 8
Concerns of students (n = 56) around the use of AI in teaching and learning

Student AI concerns	Percent
Overreliance	28.6%
Academic integrity	21.4%
Loss of human element	16.1%
Inaccuracy of information	16.1%
Misalignment with learning	14.3%
Use of personal information	3.6%

Discussion

This investigation surveyed undergraduate and postgraduate students from three faculties to evaluate student characteristics that inform blended learning personalisation (RQ1). The study also employed semi-structured interviews to explore student motivation and engagement in blended learning as well as the role AI can play (RQ2). In the next section, we use the conceptual framework as a guide to discuss the findings and implications for practice and research.

Students and curriculum

More than 70% of students surveyed agreed that face-to-face teaching provided a better experience than online teaching, highlighting the importance of social constructivist features in blended learning (Al-Huneidi & Schreurs, 2012). Consistent with this pattern, interview data elaborate the stated preference for face-to-face teaching. Students described their attendance decisions as influenced by the availability of lecture recordings, travel time, content relevance and assessment requirements. This qualitative insight contextualises the quantitative pattern: students generally value face-to-face interactions theoretically but make pragmatic attendance decisions based on the perceived value of the activity. This conditional preference for in-person interaction is consistent with Armellini et al. (2021), where practical activities, workshops and tutorials were preferred delivery methods.

Student characteristics effectively inform the personalisation of feedback types, aligning with findings by Kim and Kim (2021) on key factors for student satisfaction and achievement in asynchronous online learning. Age and disability were associated with the personalisation of learning materials, while other demographics (gender, language, enrolment status and year level) were indicators of preferred curriculum structure. Additionally, dispositions associated with the enjoyment of learning and satisfaction with course resources diminished by year level, emphasising the need for continuous review of student learning preferences.

Interview accounts expanded on the limited association between student demographics and learning material formats reported in Table 3. Students explained that format preferences depend on content difficulty and relevance, believing that their motivation declined when material was perceived as outdated or overly complex. This suggests that context and perceived value could matter more than learner characteristics in shaping material format. This is notable given that personalised teaching materials are currently the most widely used feature of learning personalisation (Fariani et al., 2023). Rather than creating multiple learning formats, effective personalisation may be better achieved through a human-in-the-loop model (Bhutoria, 2022) utilising teacher-guided learning activities and targeted feedback aligned with demographic patterns identified in feedback preferences.

Students and technology

Age, language, enrolment status and year level are relevant to learning personalisation models and warrant further evaluation. Learners aged 25–34 reported greater comfort with AI, and students under 35 expressed more confidence in its potential to improve teaching quality, indicating that younger cohorts may be receptive to the early adoption of AI tools to support personalised learning. The aspects of comfort (ease of use) and improved quality (perceived usefulness) align with technology acceptance model constructs (Davis, 1989), suggesting that specific AI tools should be evaluated using this approach.

Interview insights contextualise the apparent contradiction between students' positive views of AI potential (60.6% for teaching quality and 70.3% for learning quality) and low trust in AI feedback (24.4%). Students distinguished functional support, where AI assists with explanations, from relational validation, where human recognition matters. This suggests students accept AI as a cognitive tool but not as a relational substitute. Willingness to use AI may not generalise to willingness to receive AI feedback.

Large language models, such as ChatGPT, are not specifically trained for educational personalisation. Consequently, student experience varies, with misinformation risk increasing with learning complexity (Kocoń et al., 2023). Broad-scale AI tools require close educator guidance and informed institutional understanding to ensure successful outcomes. The absence of AI use was reported by 10.3% of students, with concerns of overreliance and academic integrity, aligning with research on trust in AI technologies (Choung et al., 2023). While greater exposure may increase willingness to use these tools, clear expectations around appropriate use remain essential.

Students and teachers

The concept of "humanness" was evident in student surveys and interviews, reflecting sentiments by Yang et al. (2021) regarding AI as both an enabler and inhibitor of best practices in education. Students believed they learned better with the guidance of a teacher and identified the most important aspects of educator's role as knowledge facilitator, followed by subject matter expert and then designer of learning. This suggests that teachers do not need to be the sole conduits of knowledge and highlights the evolving role of the educator, a factor of blended learning that receives less attention than it may require (Li & Wong, 2019). This also builds on the academic communities of engagement framework developed by Borup et al. (2020), adding further understanding to the forms of teacher support required to promote academic success.

Quantitative data showed that enjoyment of study was significant for first-year, postgraduate and international students. While year level significance suggested a positive experience, international students reported lower overall enjoyment. Interview data complicates this pattern, with students identifying teacher enthusiasm and content relevance as key drivers of motivation. This suggests that the quantitative signal of enjoyment may be a partial proxy for perceived teaching quality, rather than a stable dispositional characteristic. In practice, this shifts the relational focus from targeting individual enjoyment of study to their evaluation of the learning environment, particularly for international cohorts.

Conclusion

This exploratory study offers four insights to educational literature on blended and technology enhanced learning that inform future directions for researchers and universities addressing blended learning personalisation using AI.

First, student characteristics as a construct of learner demographics and dispositions show potential to inform blended learning personalisation approaches. While this study measured preferences rather than outcomes, the patterns identified provide opportunities for future studies to investigate whether characteristic-based personalisation facilitates engagement and improves learning outcomes.

Second, universities may benefit from blended learning models that prioritise face-to-face interactive activities such as tutorials and workshops, though further research is needed to determine whether preference-based designs improve learning outcomes.

Third, student characteristics associated with demographics and dispositions showed limited association with personalised learning materials but stronger patterns in feedback preferences. Therefore, feedback may represent a more promising target for characteristic-based personalisation that warrants further investigation. The demographic patterns identified in this study offer a starting point for hypothesis-driven intervention research.

Finally, students in this study expressed preference for rubrics and written feedback, which have the potential for automation using AI in the form of large language models. Investigating effective methods to support this approach appears warranted given only 24.4% of students believed AI could provide feedback equivalent to teachers. Building student trust in AI-supported feedback will depend on educator and institutional guidance that engages with the variation in student characteristics identified in this study.

Limitations

This exploratory study has several limitations. Our sample was drawn from a single research-intensive Australian university through voluntary participation, limiting generalisability. The sample lacked Aboriginal and Torres Strait Islander students, had limited mature-age learners (7.1%) and included very small subgroups (e.g., non-binary students: n = 3; students with learning disabilities: n = 9), requiring cautious interpretation of associated findings. Critically, we measured stated preferences rather than learning outcomes. Students may prefer approaches that feel comfortable but do not optimise learning. Establishing whether personalisation based on these characteristics improves outcomes requires experimental designs testing actual implementations.

While the survey instrument demonstrated acceptable reliability and content validity for exploratory research, it has not been validated across multiple samples or tested for temporal stability. Future research should examine factorial structure and measurement invariance across demographic groups. Additionally, this cross-sectional study captured preferences during late 2023 amid rapid AI evolution; perceptions and usage patterns will continue to evolve.

Author contributions

Shaun McCarthy: Conceptualisation, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review and editing; **Edward Palmer:** Methodology, Validation, Writing – review and editing; **Nickolas Falkner:** Methodology, Validation, Writing – review and editing.

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