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Investigating students' perspectives on the integration of generative artificial intelligence in university curricula and assessments

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Abstract

The incorporation of Generative Artificial Intelligence (GenAI) in education offers new opportunities to enhance students' learning experiences. Using a Chi-square Automatic Interaction Detection (CHAID) analysis, this study examined how the frequency of GenAI use for higher-order learning tasks and for supporting learning, as well as various demographic factors, influence students' attitudes towards GenAI.

The first decision tree analysis revealed that the respondents' GenAI usage frequency for higher-order learning was the most important factor determining their desire to see GenAI incorporated into the university's curriculum and assessment. In addition, for some learners, the study found that age was a significant factor, with the younger learners having a more positive attitude towards this technology than those who were older. An analysis of the second decision tree found that the frequency of GenAI use for learning support was the most important determinant of the students' willingness to have GenAI mark their assignments. An understanding of how demographic and contextual factors influence the students' attitudes towards the role of GenAI in education can guide academic institutions and educators in the development of effective educational strategies and policies that facilitate its acceptance by a diverse student population.

Introduction

Since its inception in 1956, the term "artificial intelligence" (AI) has surged in popularity and today, thanks to the recent development of very promising real-world applications (Górriz et al., 2020), few doubt the potential that this technology has to transform all domains of human activities (SAS, n.d.). Generative Artificial Intelligence (GenAI) applications have also garnered widespread interest in education, where it has triggered some of the most profound transformations the field has ever experienced (Dwivedi et al., 2023).

As GenAI technologies evolve and become more common, they offer new opportunities for educators to enhance their students' learning experiences and performance assessment. It is, therefore, timely to explore how the very individuals who interact with GenAI on a daily basis, in the case of this study, tertiary students, perceive the implications of the incorporation of GenAI tools into their programme curriculum and assessment.

Previous studies have shown that the effective use of technology depends on various factors, including the frequency and context of use, as well as the demographic characteristics of the users, such as their age and gender (Draxler et al., 2023; Morris & Venkatesh, 2000; Robinson et al., 2015; Stöhr et al., 2024; Venkatesh & Morris, 2000). However, as the specific drivers of the students' desire for GenAI incorporation into curriculum and assessment remain underexplored, they warrant further investigation.

This study used the Chi-square Automatic Interaction Detection (CHAID) analysis to identify and understand the key factors influencing students' desire to incorporate GenAI into their university curriculum and assessment. By examining how different demographic and contextual factors affect these students' preferences, this study aimed to provide timely insights that inform the development of educational strategies and policies that align with students' needs, providing actionable insights for educators, researchers, and policymakers. These insights are crucial as they ensure that the GenAI-enhanced teaching and assessment practices that are designed and implemented take students' perspectives into account.

This research is guided by a conceptual framework that examines how the frequency of GenAI use for higher-order learning tasks and for supporting learning influences students' enthusiasm for GenAI integration. The framework also considers the role of demographic and educational factors, including age, gender, race, and year of study, in shaping students' attitudes towards GenAI.

The following sections successively present the literature review, outline the research methodology, present the results of our analysis, and discuss the implications of our findings for educators, researchers and policymakers.

Literature review

In today's world of fast-paced technological changes, GenAI represents one of the most formidable forces that have revolutionised how individuals work and interact with the world around them (Bahroun et al., 2023). Among the many domains of human activity, education stands out as one where GenAI is showing the most significant impact (Dwivedi et al., 2023) as evidenced by recent studies that have examined the potential of GenAI to enhance learning outcomes and transform traditional educational practices (Ali et al., 2024; Bahroun et al., 2023; Bower et al., 2024; Kim et al., 2022).

This literature review synthesises the existing research on GenAI in education, focusing on its role and use in teaching, curriculum development and assessments as well as how students perceive and use it for learning.

Some AI tools can be used to support educators in assessment tasks by generating assessment questions, automating student essay marking and grading, assessing learning processes, and developing personalised assessments (Swiecki et al., 2022). Other AI tools may also enhance the ability of educators to focus on process-oriented assessment, which seeks to understand the process students go through when completing a learning task, rather than just evaluating the final result (Kim et al., 2022). In addition, GenAI tools can be used in course development, more specifically, for tasks such as generating course outlines, lesson plans, learning objectives, identifying topics, curating learning resources, facilitating personalised learning, and designing learning activities (Hadi et al., 2023).

The increasing adoption of GenAI in education also has an impact on teaching practices. AI can be utilised in the curriculum to foster higher-order thinking skills such as problem-solving and creativity (Kim et al., 2022). Educational institutions can enhance learning by integrating AI within the curriculum and providing opportunities for students to develop key areas of AI literacy, regardless of the students' academic field of study (Southworth et al., 2023). In addition, it is important to teach students the responsible use of GenAI, including critically assessing the quality and accuracy of its outputs (Bower et al., 2024).

Because GenAI is relatively new, the research literature on its role in education is still nascent. Existing studies that primarily focused on the applications of GenAI in education highlighted its benefits, the ethical challenges and inaccuracy issues it raises, and the deleterious effect it has on students' critical thinking (Ali et al., 2024; Zhu et al., 2023). Some researchers (e.g., Bahroun et al., 2023) have proposed that future research should seek to better understand the use of GenAI in education, particularly on the acceptance and adoption of GenAI by students, focusing on understanding the factors that shape their attitudes towards it as well as on the strategies that can positively influence their acceptance of such technology (Bahroun et al., 2023). Although a few studies have examined student perceptions of GenAI (Baidoo-Anu et al., 2024; Chan & Hu, 2023; Johnston et al., 2024), further research is needed to explore factors that influence students' attitudes towards the integration of GenAI into the programme curricula and assessments, a gap that this research aims to fill.

Prior research shows that demographic factors, including age and gender, do affect technology usage and attitudes towards technology (Draxler et al., 2023; Morris & Venkatesh, 2000; Robinson et al., 2015; Venkatesh & Morris, 2000). A study conducted by Draxler et al. (2023) found that among a sample of US citizens, females were less likely to use GenAI than their male counterparts and that younger users were more likely to use GenAI than older ones. In addition, the study found that the effect of gender is most pronounced among young adults, while it becomes only marginal for users from older age groups. However, the role of gender and other demographic factors requires further investigation in the context of GenAI within the education context. More generally, an understanding of the demographic patterns in the use of GenAI in education can guide academic institutions and educators in the development and implementation of effective policies that facilitate its acceptance by a diverse student population.

The frequency with which students use GenAI tools for learning influences their attitudes towards GenAI. Stöhr et al. (2024) found a strong positive correlation between familiarity with ChatGPT and favourability of attitude towards such tools. Individuals who are more familiar with these tools tend to perceive greater benefits from their use. However, it is not immediately clear that frequency of usage of GenAI tools in various contexts influences students' attitudes towards incorporation of such tools into curriculum and assessment. Even if students frequently use GenAI tools, they might question the appropriateness of integrating these tools into educational assessments or curricula. Students might have reservations about using GenAI because of their concerns about academic integrity, reliability and potential biases relating to its outputs.

While the potential benefits of the use of GenAI in higher education are evident, the literature reveals a gap in understanding the specific factors that influence students' desire for the incorporation of such tools in curricula and assessments. This study aims to fill this gap by exploring how the frequency of GenAI use across different types of learning activities, along with demographic and educational factors such as age, gender, race, and year of study, influence students' desire for the integration of GenAI in their studies. By building on the existing literature and addressing this research gap, this research seeks to provide insights that can inform institutions and policymakers tasked with developing and implementing policies and strategies that guide the integration of GenAI into university curricula and assessments.

Conceptual framework

The incorporation of GenAI into university curricula and assessments has the potential to enhance students' educational experiences (Chan & Hu, 2023). To realise this potential, it is essential to understand the factors that influence students' desire for such integration. The conceptual framework of this study (Figure 1) examines how the frequency of GenAI use for higher-order learning and frequency of GenAI use for supporting learning, as well as various demographic factors—including age, gender, race, and year of study— might affect students' desire for incorporating GenAI into the university's curriculum and assessments, and their receptivity to have GenAI mark their assignments.

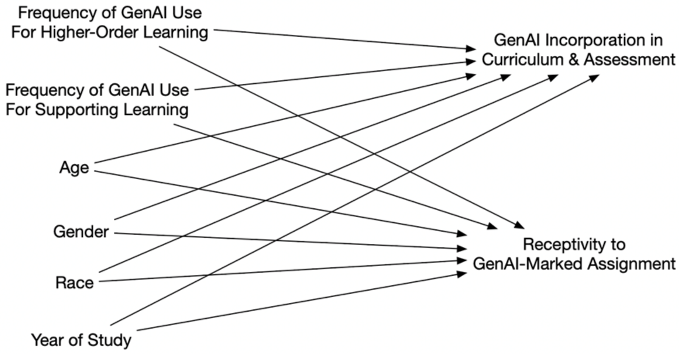

Figure 1. Conceptual framework for the study.

Methodology

Research design

This quantitative research used a survey questionnaire to gather data on the use and perceptions of GenAI among part and full-time students from a Singapore university. An analysis of the patterns and relationships found within the data led to meaningful conclusions about the students' experiences and attitudes towards GenAI.

Procedures

The recruitment of participants was conducted through various channels. Email invitations containing the survey link giving access to the online questionnaire were sent to all students. In addition, participants were recruited by posting on the university's learning management system (Canvas) invitations to participate that contained the survey link. Instructors of courses managed by the Online Learning Unit also assisted in the recruitment by making announcements to their students, inviting them to take part in the survey. Interested participants were provided with a participant information sheet containing a brief description of the study. Participants proceeded to answer the eligibility questions before the main survey. The main survey contained questions about their usage of GenAI, their perception of GenAI tools as well as demographic questions.

Participants

A total of 790 students from a university in Singapore participated in the survey. For the participants to be able to provide meaningful responses to the questions in our study, respondents needed to meet four criteria outlined in the following four screening questions:

- Are you currently enrolled in an undergraduate/ postgraduate programme at the university?
- Are you aged 18 years or above?
- Have you heard of generative AI?
- Have you ever used generative AI tools for tasks such as text generation?

Respondents who answered “no” to any of these questions were excluded from the survey. From the initial 790 participants, 85 of them discontinued the survey during the screening questions stage while 45 respondents did not meet the initial eligibility criteria laid out in the first three questions. Specifically, ten students did not meet the requirement of being enrolled in an undergraduate or postgraduate programme at the university, two did not meet the age requirement of being 18 years or older, and 33 students had not heard of GenAI. The other 660 participants responded to the question on their prior use of GenAI tools for tasks such as text generation. Among these, 531 participants (80.5%) reported prior use of GenAI, meeting the inclusion criteria. The remaining 129 participants (19.5%) indicated no prior use and were thus excluded from the study.

The first column of Table 1 presents the demographic and educational profile breakdown of all participants who met the inclusion criteria (n=531). The second column shows the demographic breakdown of the participants (n=355) who responded to the questions used as dependent variables in the decision tree analysis.

Table 1. Demographic & educational characteristics of survey participants.

Demographic & Educational Characteristics	Participants who met inclusion criteria (n = 531)	Participants included in decision tree analysis (n = 355)
Age		
18 to 24 years of age	20% (105)	29% (103)
25 to 34 years of age	24% (126)	35% (125)
>35 years of age	19% (101)	28% (98)
Missing	37% (199)	8% (29)
Gender		
Male	34% (182)	51% (181)
Female	27% (146)	40% (141)
Missing	38% (203)	9% (33)
Year of Study		
Year 1	20% (104)	29% (102)
Year 2	19% (103)	28% (100)
Year 3 and above	23% (124)	35% (123)
Missing	38% (200)	8% (30)
Race		
Chinese	45% (239)	66% (234)
Malay	10% (53)	15% (52)
Indian	3% (18)	5% (18)
Eurasian	0.4% (2)	0.6% (2)
Other	3% (15)	4% (15)
Missing	38% (204)	10% (34)

Note. Each cell in Table 1 shows both the percentage and the actual number of participants (in parentheses) that fall into each category.

From Table 1, it is apparent that the number of participants listed in the first and second columns does not show a significant difference. This can be attributed to the placement of the demographic questions towards the end of the survey. About 200 of the 531 participants who met the inclusion criteria did not reach the end of the survey, missing the demographic questions. Consequently, the number of participants in the first column who answered the demographic questions does not differ significantly from those in the second column who responded to the questions used as dependent variables in the decision tree analysis. These dependent variable questions are positioned close to the end of the survey, before the demographic section, hence, most participants who reached these questions also completed the demographic section. As a result, the number of missing responses is much smaller when the population is defined as those who answered the dependent variable questions used in the decision tree analysis.

Independent variables

Respondents were asked about their usage of GenAI in the form of the frequency with which they use GenAI tools in each of the following study contexts (on a 5-point Likert scale from 1= “Never” to 5 = “Very frequently”):

a) To complement the course material
b) As a virtual tutor or study companion to explain or clarify basic concepts, models, theories, or processes contained in the course materials
c) To summarise the course material
d) To learn more advanced or specialised topics
e) To develop my critical thinking and analysis skills
f) To translate or learn new languages
g) To get creative inspiration e.g. generate artistic or design suggestions
h) To brainstorm and generate ideas in general
i) To find references to research papers
j) To evaluate my own ideas
k) To generate partial answers to my graded assignments
l) To generate full answers to my graded assignments
m) To review and improve my writing
n) To provide feedback on my answers to graded assignments before submission
o) To generate quizzes for practice and immediate feedback
p) To generate personalised study guides
q) Other purpose – Please specify only one: __________

Other independent variables are demographic and educational factors, i.e. the respondents’ age, gender, race, and year of study.

Factor analysis

Factor analysis is used to simplify data and uncover patterns within a set of variables (Child, 2006). It works by clustering variables that share common variance, thereby identifying underlying constructs (Yong & Pearce, 2013). Factor analysis was used in this study so as to easily identify and group related activities associated with GenAI usage into various larger study contexts, reducing in the process the relatively large number of variables into a smaller number of factors reflecting patterns of GenAI usage in learning processes. Grouping related behaviours into coherent factors, such as the use of GenAI for higher-order learning or for supporting learning, provides insights into the patterns of students’ engagement with GenAI in their learning activities. Factor analysis enhances parsimony (Harman, 1976), facilitating the meaningful interpretation of the data.

The data were analysed using factor analysis, employing Principal Component Analysis and Varimax rotation, to identify underlying factors that represent distinct patterns of use of GenAI among students.

The Kaiser-Meyer-Olkin (KMO) test for sampling adequacy produced a coefficient of 0.927, which is greater than the benchmark of 0.5. Kaiser (1974) recommended values greater than 0.5 as barely acceptable. Values between 0.8 and 0.9 are deemed meritorious, and values of 0.9 and above are classified as marvellous (Kaiser, 1974). Additionally, Bartlett's test of sphericity is significant ($p < 0.001$). These indicate that factor analysis is appropriate, and the results can be relied upon.

Table 2 presents the factor loadings of the individual items onto the two factors identified from the data.

Table 2. Factor analysis results.

	Frequency of GenAI Use for Higher-order Learning	Frequency of GenAI Use for Supporting Learning
To complement course material	**0.814**	0.225
To act as a virtual tutor/study companion	**0.798**	0.197
To learn more advanced/specialised topics	**0.780**	0.242
To develop critical thinking & analysis skills	**0.749**	0.278
To brainstorm/generate ideas	**0.733**	0.176
To evaluate ideas	**0.695**	0.388
To review & improve writing	**0.674**	0.379
To summarise course material	**0.665**	0.367
To get creative inspiration	**0.494**	0.367
To generate quizzes for practice & feedback	0.148	**0.835**
To generate personalised study guides	0.249	**0.801**
To generate full answers to assignments	0.168	**0.739**
To provide feedback on answers to assignments	0.449	**0.616**
To translate/learn new languages	0.279	**0.570**
To generate partial answers to assignments	0.467	**0.568**
To find references to research papers	0.369	**0.544**
% of Variance	33.591%	25.175%
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.927	
Bartlett's Test of Sphericity		
Approx. Chi-Square	4051.457	
Df	120	
Sig.	.000	

Note: The numbers in the table indicate factor loadings, with the major ones shown in bold.

A total of two factors were identified. The first factor explains 33.591% of the variance in the data after rotation, and the cumulative variance explained by the two factors is 58.766%. The literature recognises that there are generally two qualitatively different approaches to learning - the surface and the deep approaches (Aharony, 2006; Biggs, 2003; Dinsmore & Alexander, 2012). As defined by Baeten et al. (2008), the "deep approach to learning is associated with student intention to understand and to distil meaning from the content to be learned", whereas the surface approach to learning "is characterised by a student's intention to cope with course requirements" (pp. 359–360).

As shown in the factor analysis results (see Table 2), the nature of the nine items loaded onto the first factor suggests that the first factor can be labelled as "Frequency of Using GenAI for Higher-Order Learning". The activities associated with this factor involve the use of GenAI in ways that actively engage students in their learning processes, pertaining to more complex cognitive functions such as critical thinking, evaluating ideas, generating ideas, and engaging in creative activities, rather than merely performing surface-level tasks. As such, this factor can be deemed to represent the active and deep learning processes that students experience when using GenAI. A deep approach to learning is characterised by students' desire to thoroughly understand and meaningfully engage with the material. It involves focusing on key concepts and principles and applying strategies that effectively foster the creation of meaning (Asikainen & Gijbels, 2017; Vanthournout et al., 2014). Strategies used by students who have a deep approach to learning include connecting new ideas with prior knowledge, identifying patterns, evaluating ideas and critically assessing arguments (Baeten et al., 2008).

The second factor comprises seven items (see Table 2). Based on the nature of these items, the second factor was named "Frequency of GenAI Use for Supporting Learning". The activities associated with this factor involve the use of GenAI in tasks that provide learning support to students, without engaging with students' higher-order cognitive skills such as critical thinking or creativity. Examples of such activities are generating quizzes, generating study guides, generating answers to assignments – which suggest students seeking shortcut to receive straightforward answers, providing feedback, translating languages, and finding references to research papers. These are activities involving the use of GenAI for supportive, lower-level tasks that streamline the assignment preparation process and do not require deep, complex cognitive engagement. According to Vanthournout et al. (2014), the surface approach to learning involves behaviour driven by external motivations or intentions that are unrelated to the true purpose of learning, such as a fear of failure.

Dependent variables

The dependent variables of interest in this study are:

1. "I would like to see generative AI being formally incorporated into the university curriculum."

2. "I would like to see generative AI being formally incorporated into the university assessment."

3. "I am receptive to the idea of having my assignment marked, graded and commented by AI instead of my instructor."

The first dependent variable of this study (desire for GenAI incorporation into the university curriculum *and* assessment) was derived by calculating the average response to Questions 1 and 2.

Questions 1 and 2 represent the respondents' attitudes toward incorporating GenAI into the university curriculum and assessment, in other words, the interest in integrating GenAI into the university's educational system. The curriculum, as defined by Organisation for Economic Co-operation and Development (1998, p. 33), is a field of enquiry and action on all that bears on schooling, including content, teaching, learning and resources. It covers the design and delivery of educational content, while assessment involves evaluating and measuring learning outcomes. Given that assessment is an essential and integrated part of the curriculum, both areas are closely related. Hence, this construct was named "GenAI Incorporation in Curriculum and Assessment."

Question 3 was examined separately as the second dependent variable. It was prudent to do so, given the potential for differing attitudes towards using GenAI for marking as opposed to general integration of GenAI into curriculum and assessment. This enabled a better understanding of whether there was a significant difference in how respondents view the general integration of AI into education versus its evaluative role in taking over human marking, grading and feedback. The idea of GenAI taking over such duties might provoke a response that is different from students' general attitude towards GenAI integration in curriculum and assessment. It is possible that respondents could be comfortable with GenAI being part of the curriculum and assessment design, but less so with GenAI making evaluative decisions that directly impact their academic outcomes. Separating the analysis helps to capture these nuances accurately, providing clearer insights into specific attitudes towards GenAI's role in marking. If the average of Questions 1 and 2 were to indicate a high level of acceptance, while Question 3 showed a lower receptiveness, it would suggest that while respondents were open to GenAI as a tool for enhancing education, they may still have reservations about entrusting GenAI with marking, grading and feedback responsibilities. Discovering varying levels of acceptance or resistance towards the use of GenAI for marking as opposed to general integration of GenAI into the curriculum and assessment can help educators and policymakers develop more targeted strategies or interventions regarding GenAI's role in education.

Analysis and discussion

Data analysis

This study aimed to identify the key determinants of the respondents' desire to see GenAI incorporated into the university's curriculum and assessment as well as the main factors influencing the respondents' willingness to have GenAI mark their assignments.

A total of 790 participants were surveyed, but only 531 met the respondent profile requirements set out by four qualification questions requiring that they be 18 or older and enrolled in an under or postgraduate programme at that university, that they had heard of generative AI and had used it for text generation. However, only 355 of these 531 qualified survey participants responded to the questions pertaining to GenAI incorporation into the university's curriculum and assessment as well as the one about their willingness for GenAI to mark their assignments. To determine whether the fact that only 355 out of 531 qualified survey participants responded to the questions might affect our study's results, statistical tests were conducted to compare the attitudinal profiles—specifically, the GenAI usage frequency—of respondents and non-respondents to these questions. An analysis was carried out to determine whether there were significant differences between the two groups in terms of their GenAI usage frequency for higher-order learning and for supporting learning. The results indicated no significant differences between respondents and non-respondents in these measures. Therefore, there is no evidence to suggest that the 176 participants who did not respond had any adverse effects on the results derived from the 355 respondents who answered the questions.

To analyse the data collected, a chi-square automatic interaction detection (CHAID) model was used with IBM SPSS Modeler. The CHAID algorithm is a decision tree technique commonly used for effect assessment and prediction. Generally, the most important determinant among the independent variables (as indicated by its p-value) splits the sample analysed into two or more subgroups, called nodes (Koh, 2005). Following preset split condition parameters (such as statistical significance thresholds and minimum post-split sample size), the process is repeated with the next most important determinant/s, splitting one/some of these subsets into smaller subgroups further down the tree. The splitting process terminates when no further significant variables can be associated with the independent variable, giving the final decision tree.

In this study, CHAID was used to generate two distinct decision trees. The first one analysed the relationship between the respondents' desire to see GenAI incorporated into the university curricula or assessment and five socio-educational factors as determinant variables, namely: age, gender, race, frequency of GenAI use for higher learning, and frequency of GenAI use to support learning. The second decision tree carried out a similar analysis on the association between these same determinants and the respondents' willingness to let GenAI mark their assignments.

To identify the best determinants of the respondents' desire to see GenAI incorporated into the university curricula or assessment, the CHAID algorithm created a 9-node, 3-layer decision tree (Figure 2).

Node 0 comprises the final sample of 355 survey participants who were asked the extent to which they agreed with the statement, "*I would like to see generative AI being formally incorporated into the university curriculum and assessments*". The average response score was 3.565, which falls mid-way between "neutral" to "somewhat agree".

At the first level, the decision tree indicates a very statistically significant ($p=0.000$) positive association between the respondents' desire for the university to incorporate GenAI into its programme curricula and assessments and their GenAI usage frequency for higher-order learning. The monotonic relationship reveals that the more frequently the respondents used GenAI for higher-order learning, the more

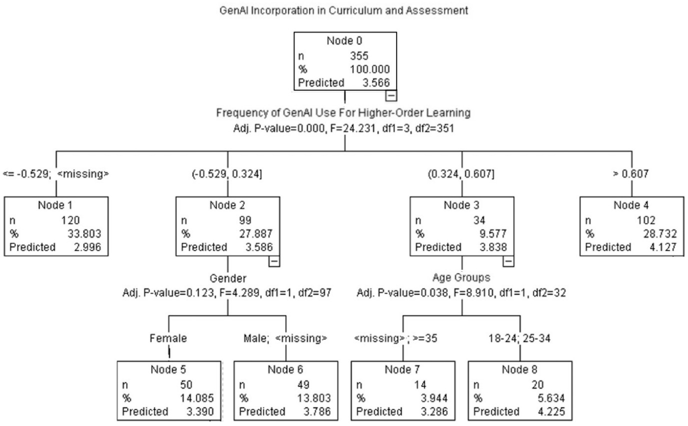

Figure 2. Decision tree for GenAI incorporation in curriculum and assessment.

they would like to see it formally incorporated into their curriculum and assessment (see nodes 1 to 4 in Figure 2).

Furthermore, for the group of respondents whose GenAI usage frequency for higher-order learning was above average but not very high (node 3), the younger group of 18-34 (node 8) tended to have a stronger desire to see GenAI incorporated into the curriculum or assessment as compared to the older group of 35 year-old and above (n=11) as well as those who did not state their age (n=3) (node 7).

Finally, it was noted that in the group of respondents whose GenAI usage frequency for higher-order learning was average (node 2), there is a marginal statistically significant difference (p=0.123) between male (n=41) and those who did not indicate their gender (n=8) versus female respondents, with the former (node 6) having expressed a stronger desire to see GenAI incorporated into the curriculum and assessment than the latter (node 5).

The CHAID algorithm was also used to identify the determinants of the respondents' willingness for GenAI to mark their assignments, resulting in a second 6-node, 3-layer decision tree (Figure 3).

As shown by the splits below node 0, there was a very significant (p=0.000) positive association between how receptive the respondents were to having GenAI mark their assignment and their GenAI usage frequency to support their learning – that is, the more frequently they used GenAI in learning support contexts, the more receptive they were to letting it mark their assignments (see nodes 1 to 3).

Furthermore, it is noted that within the group of respondents whose GenAI usage frequency in learning support contexts was low (node 1), 70.34% of those whose GenAI usage frequency for higher order learning was also low tended not to be receptive to the idea of letting GenAI mark their assignments (node 4). On the other hand, however, 51.85% of the respondents whose GenAI usage frequency for higher-order learning was high (n=92) or missing (n=16) either had no objection or were agreeable to GenAI being used to mark their assignments (node 5). It can be argued that as these respondents use GenAI in contexts involving in-depth and

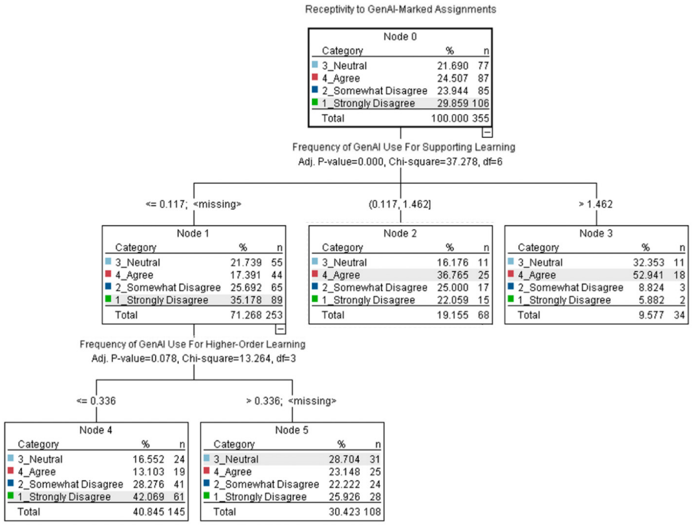

Figure 3. Decision tree for receptivity to GenAI-marked assignments.

more complex learning, they might be perceiving GenAI's knowledge but also analytical and reasoning capabilities to be sufficiently sophisticated for them to consider GenAI to possess sufficient domain expertise to mark their assignments.

Finally, although they were included in both CHAID analyses, it should be noted that neither *race* nor *years of study* were found to be determinant of the two dependent variables that this study examined.

Discussion

This study used two CHAID analyses to examine the strongest determinants of the respondents' desire to see GenAI incorporated into their course curriculum and assessment as well as with their willingness to let GenAI mark their assignments.

An analysis of the data reported by the first decision tree found that the respondents' GenAI usage frequency for higher-order learning was the most important factor determining their desire to see GenAI incorporated into the university's curriculum and assessment while gender was found to be a marginally significant determinant, but only for a subgroup of those whose GenAI usage frequency for higher-order learning was above average, but not very high. It is suggested that the GenAI use for higher-order learning was found to be a determinant of the respondents' willingness to incorporate GenAI in Curriculum & Assessment because many of the higher-order learning variables relate to course content (therefore to curriculum), such as GenAI use for complementing course materials, learning advanced topics, and summarising content, as well as for assignment preparation (assessment), including developing critical thinking skills, gaining creative inspiration, brainstorming and evaluating ideas, and reviewing and improving writing, as shown in Table 2. Hence, since this particular group already uses GenAI informally in these contexts, they are more familiar with its capabilities and it therefore appears likely that to maximise its benefits, they would want the university to formally incorporate GenAI in the development and content of the course curriculum and assessment.

An analysis of the second decision tree found that the frequency of GenAI use for learning support was the most important determinant of the students' willingness to have GenAI mark their assignments, followed by its frequency of use for higher-order learning. This could be explained by the fact that many of the learning support variables relate to assignment preparation, such as GenAI use for generating partial or full answers to assignments, finding references for research papers, and providing feedback on assignment answers before submission. Similarly, some higher-order learning variables (as shown in Table 2), such as developing critical thinking skills, getting creative inspiration, brainstorming, evaluating ideas, and improving writing, also contribute to this willingness. As such, it appears logical and, as the results showed, that it is likely the respondents who frequently use GenAI to prepare their assignments would tend to understand and trust its capabilities and would hence be more receptive to having GenAI mark their graded submissions.

Conclusions and recommendations

The purpose of this research was to identify the factors that affect the learners' openness to integrate GenAI in the curriculum, assessment methods, and assignment marking of the courses they take at the university.

The study found that the respondents' familiarity with GenAI, as measured by how frequently they use it, was positively associated with their attitude and trust towards it as they were more willing to see it being incorporated in their studies, for content and assessment development as well as for assignment marking. This is aligned with Stöhr et al. (2024) whose research concluded that a strong positive correlation exists between familiarity with ChatGPT and favourability of attitude towards such tools.

In addition, for some learners with an above-average familiarity with GenAI, the study findings suggest that age was also a significant factor, with the younger 18-34 learners having a more positive attitude and trust towards this technology than those 35 and above. Although this research investigated Singapore learners at a local university, its findings are coherent with those of Draxler et al. (2023), who concluded that younger US citizen users were more likely to use GenAI than older ones.

These findings should prompt universities to implement the following recommendations.

Firstly, universities should develop and issue a formal statement describing, but also circumscribing the role that GenAI plays at their institution so as to broadly address both the opportunities and challenges presented by this technology. This is especially important so that the students and faculty easily understand what they are allowed and not allowed to do with GenAI.

To operationalise that statement, universities should then develop clear, transparent and comprehensive policies governing how GenAI ought to be used in learning, assessment, and assignment marking, including clear guidelines on the ethical use of GenAI tools, particularly in the context of academic integrity, to prevent misuse such as plagiarism or over-reliance on AI-generated content.

They should also ensure that prior to the beginning of every semester, these policies are communicated effectively to all students and faculty while paying particular attention to the concerns of those who may be less familiar or less trusting of this technology.

Thirdly, universities should promote GenAI literacy by developing training courses on the use of AI technologies in an academic setting, encouraging, in particular, its older student population to learn to engage with GenAI through a series of online or face-to-face workshops and tutorials. Similar training could also be developed for faculty so that they can learn to integrate GenAI into the course curriculum and assessment as well as into their teaching practices.

Fourthly, starting with one or two courses in each discipline, universities should gradually incorporate AI into the content and assessment of its courses so as to allow students and faculty to gradually adapt to this new reality and become sufficiently confident to engage it within the limits set out by the institution. During the implementation of these pilot programmes, it should also gather feedback from both younger and older learners to refine its implementation approach.

Fifthly, universities should continuously seek inputs and feedback through formal channels of communication and forums for students and faculty to discuss the use of GenAI in education. This can help them address concerns, share experiences, and build a community of practice around GenAI, enhancing trust and positive attitudes across all age groups.

Finally, with the feedback gathered on the effective use of GenAI in education, universities should regularly revisit and refine both their GenAI statement and policies so that they remain current, relevant and useful in addressing the new benefits and challenges of this fast-evolving technology.

At the same time that this research was conducted, there were parallel GenAI policy and practice developments within the university where the data was collected (hereinafter "the University"). Although developed independently, our research and the University initiatives outlined below do complement and often reinforce each other. The University's initiatives validate the study's recommendations, and the latter provide support for the parallel developments at the University.

In early 2024, the University formed an AI taskforce comprising faculty representatives from its various schools, Teaching and Learning Centre as well as from its learning technology and E-learning media and resource departments. Given a six-month mandate, the taskforce was asked to explore the challenges and opportunities that GenAI bring to higher education and offer faculty and staff guidance on best practices for implementing GenAI in adult learning environments.

A comprehensive "Generative Artificial Intelligence Policy" was added to the Student Handbook, describing in detail the contexts, learning situations and conditions under which students are allowed and not allowed to use it, along with the disciplinary sanctions they could face when these rules are violated. To raise awareness of this policy, every teaching faculty use a set of slides explaining its main tenets to their students. In addition, the University also provides its staff and teaching faculty a GenAI policy for teaching and learning. Furthermore, the University's Teaching and Learning Centre developed a series of short courses for students regarding the responsible use of GenAI in their assignments, highlighting the citation requirements as well as the guidelines to follow in order to avoid sanctions pertaining to plagiarism.

To guide the faculty on the use of GenAI for course development, assessment and teaching, the taskforce developed a series of documents on the assessment modes and GenAI usage that are appropriate to the learning outcomes of different course levels and subjects so that through their assignments, students can develop their core skills independently of GenAI while ensuring that they also learn to effectively use it during their studies, ensuring that they are ready when they embark or continue their career.

Finally, the University library has published a microsite on GenAI outlining the main categories of AI tools along with specific AI applications that students and instructors can use, along with resources on their responsible use. It also provides additional links to subscribed resources.

Limitations & future research

While providing some valuable insights, this study is affected by a number of limitations. Firstly, the respondents' profile was restricted to students from a Singapore-based autonomous university and this may limit the generalisability of the findings to broader populations. Hence, a larger, more diverse sample would have enhanced the external validity of the results.

Secondly, the research design and methodology, while robust, may not fully capture all relevant variables, potentially overlooking nuanced aspects of the respondents' attitude towards GenAI that was under investigation.

Future research should address these limitations by using sampling methods that target larger and more diverse samples that better represent the overall student population. Furthermore, as GenAI is quickly becoming more pervasive, these studies should focus more on the perceived or real impact it has on, for instance, the students' learning journey, their achievement of course learning outcomes, the skills that they need to properly harness its power as well as the skills that they should develop so that they remain employable and relevant in the job market.

Regardless of the focus of future studies on GenAI, it is undeniable that this technology has barely started to disrupt how students learn, instructors teach, and faculty develop courses and conduct research. As GenAI becomes increasingly more powerful and sophisticated, its influence will only spread wider and deeper into every aspect of education. The pace as much as the scope of its growing influence presents governmental as well as educational authorities with the particularly difficult challenge of harnessing this technology to enhance teaching, learning and research while ensuring that its adoption and integration do not destroy the learners' ability and motivation to acquire knowledge nor the faculty's incentive to participate in its creation. To avoid such a negative outcome, universities should set up a formal GenAI usage feedback mechanism to ensure that its GenAI policies and practices keep up not only with the current GenAI implementation but, as importantly, with the rapid advancement of GenAI tools in both versatility and sophistication.

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