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Using the Reasoned Action Approach to Predict Students' Misuse of Generative Artificial Intelligence in the Production of University Assessments

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ABSTRACT: We tested whether the Reasoned Action Approach (RAA) model could predict both students' intentions and the frequency with which they had previously misused generative artificial intelligence (GenAI) for producing assessment content (behaviour). We also tested the extent to which the additional constructs of moral norm and anticipated regret improved the predictive validity of the RAA in respect of this behaviour. The participants (N = 369 psychology undergraduates) completed an online questionnaire measuring the RAA and additional constructs. Hierarchical linear regressions showed that the RAA accounted for 74% of the variance in students' intentions and 65% of the variance in behaviour. Moral norm and anticipated regret led to a significant (1% point) increment to explained variance in the prediction of intentions but not behaviour. The independent predictors of intentions were instrumental attitude, injunctive norm and anticipated regret. Intention was the sole predictor of behaviour. The results demonstrate, for the first time, that the RAA is a useful model for predicting university students' misuse of GenAI in the production of assessment content, and that anticipated regret constitutes a useful addition to the model in this context. Practical implications for decreasing GenAI misuse are discussed.

Keywords: Generative AI misuse, university students, Reasoned Action Approach, moral norm and anticipated regret

1. INTRODUCTION

Generative artificial intelligence (GenAI) produces original and creative content (e.g., text, code, images, audio and video) in response to a prompt or a series of prompts by human users. Within higher education, there is a growing literature on the use of GenAI for faculties and students. Since its introduction, faculty staff have begun to use GenAI to increase operational efficiencies, support administrative

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workloads and research activities, develop policies, produce teaching and assessment content, and improve student support and feedback (e.g., Lu *et al*., 2024; Qian, 2025; Watermeyer *et al*., 2024; Watson, 2024). Students have used it to support their learning and assessment, for example by asking it to act as a tutor, summarise topics or articles, explain concepts, brainstorm and discuss ideas, and help structure and refine thoughts and writing (e.g., Chan and Hu, 2023; Johnston *et al*., 2024).

With respect to student learning and assessment, emerging evidence suggests that GenAI can improve students' academic achievement, enhance student motivation and engagement, and support higher-order thinking and self-directed learning (e.g., Deng *et al*., 2024; Liu *et al*., 2025). However, academics and educational practitioners have also raised concerns over students' use of GenAI, including its fallibility (e.g., the production of factual errors or citation of non-existent sources), and its risk to the development of critical or creative thinking, problem-solving, and students' ability to engage with source material independently (e.g., Alasadi and Baiz, 2023; Yan *et al*., 2024). Indeed, there is evidence that, while it increases academic achievement (grades), it does not increase knowledge and increases meta-cognitive laziness (Fan *et al*., 2025). Related to this study, students' use of GenAI can impact the academic integrity of assessments (e.g., Bittle and El-Gayar, 2025). Non-invigilated/non-proctored assessments (e.g., coursework reports) provide the opportunity for students to submit GenAI produced content as their own work, and therefore bypass learning outcomes (e.g., Sallai *et al*., 2024). Such content can be produced to a high standard, typically resulting in a passing grade, and it is difficult to detect through academic dishonesty practices (March *et al*., 2026; McGroarty *et al*., 2026; Pudasaini *et al*., 2024; Scarfe *et al*., 2024). A recent survey by the Higher Education Policy Institute (2024) also showed that 13% of UK undergraduate students reported including GenAI produced content in their assessed work after editing it themselves, which amounts to paraphrasing and, therefore, plagiarism in most universities. Even worse, 5% reported that they had included GenAI produced content in their assessed work after editing it with further prompts and 3% reported that they had included completely unedited GenAI produced content.

Invigilated assessments, where students are denied access to GenAI tools, are a solution to the problem of GenAI misuse in the assessment process because they ensure that the final product (i.e., the exam answer) is produced by the student, even if GenAI has been used in the preparation process (e.g., to generate, in advance, answers to possible exam questions). However, reliance on this type of assessment can be problematic. In particular, such assessments are typically time-constrained, which can limit the exploration and development of ideas and the attainment of some learning outcomes (Parker *et al*., 2021). Some authors have also argued that invigilated examinations are low in inclusivity and authenticity (French *et al*., 2024). Non-invigilated assessments therefore remain important to achieve diverse assessment batteries. In this research, we therefore aimed to identify predictors of university students' use of GenAI for producing content for inclusion in formal

assessments (i.e., students' *misuse* of GenAI). To address this issue, we employed the Reasoned Action Approach model (RAA; Fishbein and Ajzen, 2009). We employed this model because it contains potentially modifiable constructs as predictors of behaviour. Those constructs can therefore: (a) help provide an understanding into why some students might decide to misuse GenAI in higher education assessments; and (b) inform the development of remedial measures (e.g., communications or assessment strategies that target the predictors of this behaviour, with a view to promoting responsible GenAI use).

The RAA (see Figure 1) is an elaboration on the theory of planned behaviour (Ajzen, 1985, 1991). Both the theory of planned behaviour and the RAA

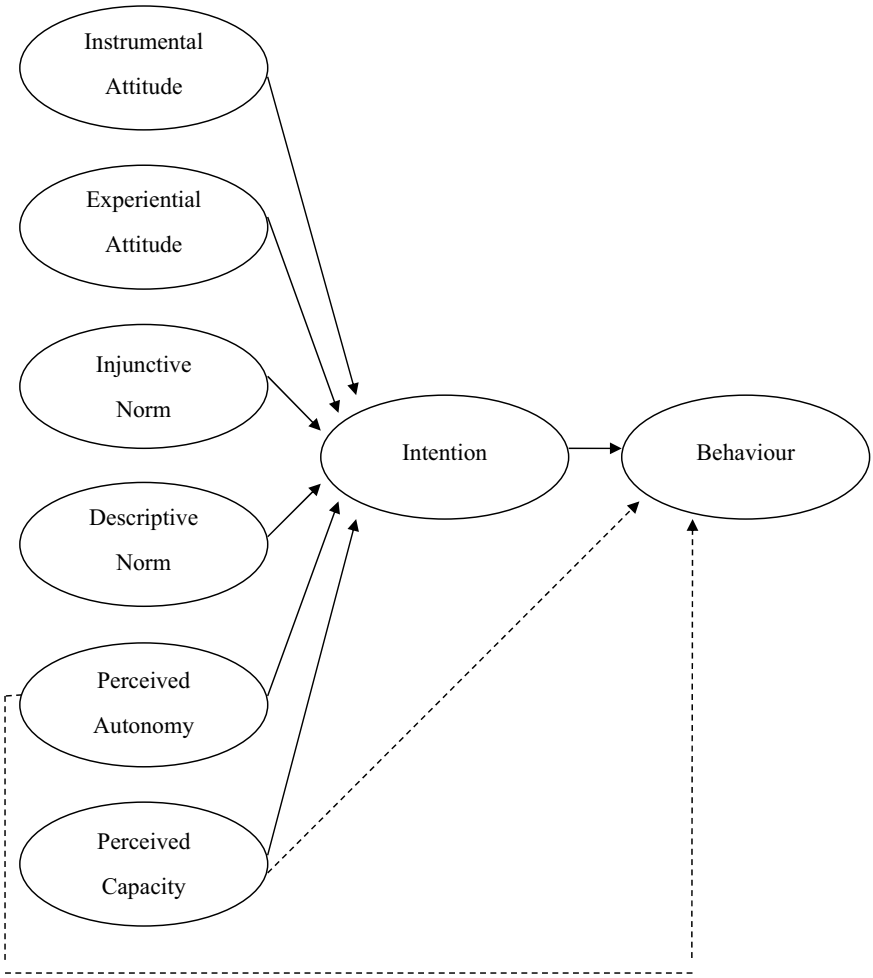

Figure 1. The RAA model.

propose that intention (motivation to behave) is the main predictor of behaviour. Both models also propose that intentions are underpinned by attitudes (positive or negative evaluations about performing a behaviour), subjective norms (perceived social pressure to behave) and perceived behavioural control (the perception of whether a behaviour can be performed), with perceived behavioural control also predicting behaviour directly, along with intention, for behaviours that are non-volitional (i.e., not under complete intentional control). However, the RAA explicitly treats subcomponents of attitudes, subjective norms and perceived behavioural control as independent, albeit related, constructs rather than single, higher-order constructs (e.g., Elliott and Thomson, 2010; McEachan *et al*., 2016). Attitudes are separated into instrumental and experiential components. Instrumental attitudes are utilitarian evaluations about performing a behaviour (e.g., 'for me, using GenAI to produce assessment content would be beneficial/harmful'), whereas experiential attitudes are affective evaluations (e.g., 'for me, using GenAI to produce assessment content would be enjoyable/unenjoyable'). Subjective norms are separated into injunctive and descriptive norms. Injunctive norms reflect perceived social pressure to perform a behaviour stemming from beliefs about the extent to which important others would approve or disapprove (e.g., 'people important to me would want me to use GenAI to produce assessment content'). Descriptive norms reflect perceived social pressure to perform a behaviour stemming from beliefs about the extent to which the behaviour is typical (e.g., 'other students are likely to use GenAI to produce assessment content'). Perceived behavioural control is separated into perceived autonomy and perceived capacity. Perceived autonomy taps the degree to which individuals believe a behaviour is under their own internal control (e.g., 'I have full control over whether or not I use GenAI to produce assessment content'). Perceived capacity is the extent to which individuals believe they have the ability to perform a behaviour (e.g., 'I am capable of using GenAI to produce assessment content').

Meta-analytic evidence supports the RAA. McEachan *et al*. (2016) showed that, across 14 independent studies, the model's constructs accounted for 59% of the variance in intentions and 31% of the variance in behaviour. These effect sizes are regarded as 'large' (i.e., greater than $R^2 = .25$) according to conventionally accepted criteria in the social sciences (e.g., Cohen, 1992). They, therefore, attest to the predictive validity of the RAA (for further meta-analytic support also see Conner *et al*., 2017; Hagger *et al*., 2018).

The RAA is also likely to be a useful model for predicting university students' misuse of GenAI in their assessed work. The salient factors that are associated with GenAI usage (e.g., Acosta-Enriquez *et al*., 2025; Aldreabi *et al*., 2025; Choudhuri *et al*., 2024; Liu *et al*., 2026), map well onto the RAA's constructs. These include: attitudinal factors (e.g., improved grades [instrumental attitude] and relief from assignment stress and worry [experiential attitude]); normative factors (e.g., perceived acceptability of GenAI usage [injunctive

norm] and perceived usage by other students [descriptive norm]); and control factors (e.g., access to GenAI [perceived autonomy] and ability to use the technology [perceived capacity]). Additionally, a small number of studies have shown that the RAA's predecessor, the theory of planned behaviour, can predict GenAI usage intentions (Ahadzadeh *et al*., 2024; Ma, 2025; Wang *et al*., 2024) and behaviour (Ivanov *et al*., 2024), and completion of GenAi usage declarations (e.g., Gonsalves, 2025) in university student populations.

To date, however, no previously published studies have tested whether the RAA can predict university students' misuse of GenAI in the production of assessed work. Such research is warranted for several reasons. First, while the above cited research has shown that university students are attuned to possible attitudinal, normative and control factors associated with GenAI misuse, integrating those factors in a single predictive framework, such as the RAA, can help researchers and practitioners to identify which of them are most and least important in potentially dictating students' behaviour. In turn, this is important for identifying suitable targets for remedial measures. Second, while previous research has tested whether the theory of planned behaviour can predict university students' use of GenAI, the RAA is a superior predictive model (see Elliott and Ainsworth, 2012) and allows a more fine-grained analysis of the predictors of behaviour (i.e., the identification of which *components* of attitudes, subjective norms and perceived behavioural control independently predict intentions and behaviour). The RAA is therefore likely to provide a greater understanding of students' GenAI use than the theory of planned behaviour. Third, the pattern of independent predictors in both the theory of planned behaviour and the RAA can vary across behaviours and populations (e.g., Ajzen and Cote, 2008; Conner *et al*., 2017). The above cited research has focused on general usage in university contexts (e.g., the adoption of GenAI), not specifically on the *misuse* of GenAI in the production of university assessments. It has also been conducted mainly in populations from Eastern societies (e.g., China) and, while globalisation and internationalisation have produced increasing convergence between Eastern and Western education systems (e.g., Ryan and Louie, 2007), comparative education research has identified systematic differences between Confucian-heritage and Anglo-Western higher education systems that could potentially impact the extent to which the RAA might predict GenAI usage. These include differences in assessment regimes and pedagogical structures, social expectations, governance, and cultural attitudes towards authority, learning and technology (e.g., Hu, 2024; Li, 2012; Li *et al*., 2025; Zhao *et al*., 2025). Further research, specifically on the misuse of GenAI in academic assessments, and research in western societies is therefore warranted. More generally, it is worth noting that virtually all tests of the RAA have taken place in the context of health-related behaviours (see Conner *et al*., 2017; Hagger *et al*., 2018; McEachan *et al*., 2016). Research testing the RAA in other contexts (e.g., education) would contribute towards a demonstration of the model's generalisability. In this study, we therefore tested whether the RAA

could predict the use of GenAI to produce assessment content in a sample of UK university students.

We also tested whether moral norms and anticipated regret could improve the predictive validity of the RAA in this context. Moral norms (e.g., 'I think that using GenAI to produce assessment content is wrong') reflect internalized moral rules about whether performing a behaviour is correct or incorrect (Ajzen, 1991). Anticipated regret refers to the expectation of a negative affective response (regret) following the performance, or non-performance, of a behaviour that transgresses one's moral code (e.g., 'I would regret it if I used GenAI to produce my assessments'). Moral norm and anticipated regret have been found to be important predictors of behaviours that have an ethical dimension, increasing the proportion of variance that is accounted for in intentions, over and above the variance that is accounted for by the constructs in the theory of planned behaviour (e.g., Beck and Ajzen, 1991; Elliott, 2012; Sandberg and Conner, 2008) and the RAA (e.g., Elliott and Thomson, 2010). These constructs, in particular anticipated regret, have also been found to account for unique variance in the direct prediction of behaviour (e.g., Elliott and Thomson, 2010; Sandberg and Conner, 2008). Given that the misuse of GenAI in the production of university assessments constitutes academic dishonesty, and therefore compromises ethical principles in academia, students' moral norms, and their sense of regret for transgressing them, are likely to be important in dictating the development of their intentions and the extent to which they engage in this behaviour, over and above the RAA.

Study Aims and Hypotheses

The aims of the study were to test the extent to which the RAA can predict university students' intentions to use GenAI for producing assessment content and the extent to which moral norm and anticipated regret improve the prediction of students' intentions to perform this behaviour. We also tested the extent to which the RAA can predict the frequency with which students report having used GenAI to produce assessment content and the extent to which moral norm and anticipated regret improve the prediction of this behaviour. The research was conducted within an Undergraduate Psychology course at the authors' institution, in which the students are informed (e.g., through the course handbook and assessment handouts) that, while GenAI can be used as a learning tool (e.g., to research and better understand topics and concepts), the production of GenAI content (e.g., text, code) for use in assessments (e.g., essays, reports), violates learning outcomes, and therefore constitutes academic dishonesty and misuse of the technology.

The hypotheses were as follows:

H1. The RAA will account for a significant proportion of the variance in university students' intentions to use GenAI for producing assessment content.

H2. Moral norm and anticipated regret will account for a significant increment to explained variance in university students' intentions, over and above the RAA.

H3. The RAA will account for a significant proportion of the variance in university students' use of GenAI for producing assessment content.

H4. Moral norm and anticipated regret will account for a significant increment to explained variance in the frequency with which this behaviour is carried out, over and above the RAA.

2. METHOD

Participants

The sample comprised $N = 369$ university students who were enrolled in a 4-year, undergraduate, Psychology degree programme at a large University in Scotland. Table 1 shows the profile of the sample and the population (i.e., all students on the degree programme) in terms of age, gender and year of study. As the table shows, the profile of the sample closely matched the profile of the population.[1]

The achieved sample size was within the range specified for the target sample in the pre-registration for this study. The range for the target sample specified in the pre-registration was between $N = 200$, which power analyses showed was sufficient for detecting an effect size of $f^2 = 0.04$, and $N = 400$, which power analyses showed was sufficient for detecting an effect size of $f^2 = 0.08$. This range, therefore, ensured that the analyses would be not be under-powered, as they would be able to detect small but meaningful effect sizes, or over-powered, as they would not be able to detect negligible effect sizes, lower than the lower boundary for a small-sized effect ($f^2 = 0.02$; Cohen, 1992).

Table 1. Sample and population characteristics

		Sample ($N = 369$)	Population ($N = 1212$)
Age	Mean (*SD*):	20.40 (4.91)	20.21 (3.75)
Gender			
Males	*n* (%):	40 (11)	237 (20)
Females	*n* (%):	319 (86)	970 (80)
Other	*n* (%):	10 (3)	n/a
Year of study			
1st year	*n* (%):	145 (39)	513 (42)
2nd year	*n* (%):	112 (30)	306 (25)
3rd year	*n* (%):	83 (23)	253 (21)
4th year	*n* (%):	29 (8)	140 (12)

Note. University records provided data on sex (i.e., male or female) only, hence the 'n/a' entry for the 'other' option in the population's gender profile.

Design & Procedure

A cross sectional, correlational, self-reported survey design was employed. The participants were sampled from all four levels of the undergraduate Psychology programme, during the first semester of the 2024–2025 academic year (September to November 2024). Advertisements were posted within the SONA research participation system, which was used within levels 1 to 3 of the programme to advertise research projects and award course credits for research participation. Advertisements were also posted on the virtual learning environments of the students' classes at level 4 of the programme. Announcements were also made in lectures, alerting the students to the electronic advertisements, either on SONA or the level 4 virtual learning environments. The advertisements contained a link to an online questionnaire.

The online questionnaire took approximately 15 minutes to complete and was designed and administered using Qualtrics. At the start of the questionnaire, the participants were presented with an information sheet, followed by a consent form. The information sheet explained that the study was an investigation into students' attitudes towards the use of GenAI for producing content (e.g., text or code) for assessed work (e.g., essays and reports), and made the participants aware of standard ethical information, including anonymity of the data. The participants who consented to proceed with the study were presented with items to measure their age, gender and level of study, and the constructs from the RAA model, along with the additional constructs (moral norm and anticipated regret). The items to measure the RAA and additional constructs were standard items, as recommended by Fishbein and Ajzen (2010); they were items that had been commonly used in previous research to measure the RAA's constructs with regard to other target behaviours and found to generate psychometrically valid measures (e.g., Elliott and Thomson, 2010; McEachan *et al*., 2016). In this study, the wording these items were designed so they focused on behaviour of using GenAI to produce content (e.g., text, code) for use in assessments (e.g., essays, reports), over the course of a teaching semester. The items were presented one at a time, on separate screens, in a random order to minimise the risk of consistency biases (e.g., Budd, 1987). The response scales were reversed for half the items to minimise the risk of response set biases (e.g., Coolican, 2014). The participants navigated from one screen to the next by clicking on a NEXT button at the bottom of each page of the online questionnaire. At the end of the questionnaire, the participants were presented with a debriefing form.

At the end of the semester, the data from the online questionnaires were downloaded from Qualtrics into SPSS for running the statistical analyses. The study was granted ethical approval by the Departmental Ethics Committee of the authors' institution (ethics approval code: 86.7 May 2024).

Measures

All of the items that were used to measure the study constructs are presented in the Appendix. The following text provides example items, for illustrative purposes.

RAA Model

Intention. Intention was measured with six items (e.g., 'I want to use GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester'). The participants responded to the items on a 9-point scale (e.g., strongly disagree [scored 1] to strongly agree [scored 9]). The mean of the six items served as the final measure of intention (Cronbach's $\alpha = .88$).

Instrumental and Experiential Attitudes. The participants were presented with the sentence stem: 'For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be . . . ' The participants were asked to complete the sentence stem using six, 9-point semantic differential scales that measured instrumental attitude (e.g., extremely useful [scored 9] to extremely useless [scored 1]) and six, 9-point semantic differential scales that measured experiential attitudes. The mean of the six instrumental attitude items served as the final measure of instrumental attitude (Cronbach's $\alpha = .91$). The mean of the six experiential attitude items served as the final measure of experiential attitude (Cronbach's $\alpha = .93$).

Injunctive and Descriptive Norms. Four items were used to measure injunctive norm (e.g., 'People important to me would approve of me using GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester'). Another four items were used to measure descriptive norm (e.g., 'People important to me will, themselves, be using GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester'). The participants responded to these items using 9-point scales (e.g., strongly disagree [scored 1] to strongly agree [scored 9]). The mean of the four injunctive norm items was used as the final measure of injunctive norm (Cronbach's $\alpha = .84$). The mean of the four descriptive norm items was used as the final measure of descriptive norm (Cronbach's $\alpha = .82$).

Perceived Autonomy and Capacity. Perceived autonomy was measured with three items. For example, 'I have full control over whether or not I will use GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester'). The participants responded to the these items using 9-point scales (e.g., strongly agree [scored 9] to strongly disagree [scored 1]. The final measure of perceived autonomy was the mean of the three items (Cronbach's $\alpha = .70$).

Perceived capacity was measured with four items (e.g., 'I am capable of using GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester'). The participants also responded to these items using 9-point scales (e.g., strongly disagree [scored 1] to strongly agree [scored 9]). The mean of the four items was used as the final measure of perceived capacity (Cronbach's $\alpha = .82$).

Measurement of the Additional Constructs

Moral Norm. The mean of four items was used as the final measure of moral norm (Cronbach's $\alpha = .84$; e.g., 'It would be wrong for me to use GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester': strongly agree [scored 1] to strongly disagree [scored 9]).

Anticipated Regret. The mean of four items also served as the final measure of anticipated regret (Cronbach's $\alpha = .89$; e.g., 'I would regret it if I used GenAI in order to produce content [e.g., text, code] for use in my assessments [e.g., essays, reports] this semester': strongly disagree [scored 1] to strongly agree [scored 9]).

Measurement of Behaviour

Finally, four items were used to measure how often the participants had previously used GenAI to produce assessment content. One item asked the participants to rate, 'on a scale of 0 (never) to 10 (many times), how many times have you used GenAI to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) while at university?' (score from 0 to 10 entered). The participants responded to the remaining items using 9-point scales (e.g., 'How often have you used GenAI to produce content [e.g., text, code] for use in your assessments [e.g., essays, reports] while at university?': never [scored 1] to very often [scored 9]). The mean of the four items served as the final measure of behaviour (Cronbach's $\alpha = .90$).

4. RESULTS

Descriptive Statistics and Correlations

The means and standard deviations for each measure are presented in Table 2. As the table shows, the participants, on average, reported misusing GenAI infrequently (i.e., the mean behaviour score towards the lower end of the scale). They also reported, on average, negative intentions and attitudes (both instrumental and experiential) towards using GenAI for producing assessment content and a low amount of social pressure to engage in this behaviour stemming from their perceptions of what important others would want them

Table 2. Means (Standard deviations), scale ranges and correlation matrix for all measures

Variable	*M* (*SD*) range	*r* (*p*)									
		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Behaviour	2.38 (2.06) 0.75 to 9.25	–	.80 (<.001)	.74 (<.001)	.65 (<.001)	.55 (<.001)	.49 (<.001)	−.20 (<.001)	.38 (<.001)	.59 (<.001)	−.66 (<.001)
2. Intention	2.79 (1.72) 1 to 9		-	.85 (<.001)	.77 (<.001)	.64 (<.001)	.49 (<.001)	−.25 (<.001)	.40 (<.001)	.71 (<.001)	−.77 (<.001)
3. Instrumental Attitude	2.93 (1.66) 1 to 9			-	.87 (<.001)	.67 (<.001)	.55 (<.001)	−.28 (<.001)	.43 (<.001)	.79 (<.001)	−.82 (<.001)
4. Experiential Attitude	3.17 (1.72) 1 to 9				-	.61 (<.001)	.48 (<.001)	−.26 (<.001)	.46 (<.001)	.68 (<.001)	−.76 (<.001)
5. Injunctive Norm	3.01 (1.82) 1 to 9					-	.54 (<.001)	−.15 (.004)	.31 (<.001)	.61 (<.001)	−.65 (<.001)
6. Descriptive Norm	5.56 (1.81) 1 to 9						-	−.05 (.360)	.43 (<.001)	.39 (<.001)	−.46 (<.001)
7. Perceived Autonomy	7.82 (1.48) 1 to 9							-	.04 (.451)	−.26 (<.001)	.26 (<.001)
8. Perceived Capacity	5.64 (2.10) 1 to 9								-	.27 (<.001)	−.37 (<.001)
9. Moral Norm	2.36 (1.54) 1 to 9									-	−.79 (<.001)
10. Anticipated Regret	7.40 (1.76) 1 to 9										-

to do (injunctive norm). However, they perceived a moderate amount of social pressure stemming from their perceptions of how many other students are likely to use GenAI for producing assessment content (descriptive norm), a moderate amount of control over this behaviour stemming from their perceived ability (perceived capacity), and a high amount of control stemming from the perception of whether the behaviour was up to them versus external factors (perceived autonomy). Finally, the participants, on average, perceived that the misuse of GenAI for producing assessment content was not morally correct and they anticipated high amounts of regret for performing this behaviour. On average, therefore, the sample was not positively orientated towards misusing GenAI in the production of university assessments. Nevertheless, the standard deviations indicated dispersion around the means and the full range of responses on the response scales was utilised (see Table 2).

In line with the RAA model, the correlations (also shown in Table 2), showed that students' use of GenAI for producing assessment content, increased with intentions and perceived capacity, and decreased with perceived autonomy. Intentions to use GenAI for producing assessment content increased with instrumental and experiential attitude, injunctive and descriptive norm, and perceived capacity, and decreased with perceived autonomy. Also in line with expectations, students' use of GenAI for producing assessment content, and their intentions to do so, increased with moral norm and decreased with anticipated regret.

Predicting Intentions

A hierarchical multiple regression was conducted to test both H1 (the RAA will explain a significant proportion of the variance in university students' intentions to use GenAI for producing assessment content) and H2 (moral norm and anticipated regret will account for a significant increment to explained variance in university students' intentions to use GenAI for producing assessment content). The dependent variable was the measure of intention. The independent variables at step 1 were the RAA constructs that are posited as predictors of intention: instrumental and experiential attitudes, injunctive and descriptive norms, and perceived autonomy and capacity. At step 2, the additional constructs of moral norm and anticipated regret were added to the regression model, as independent variables.

In support of H1, Table 3 shows that the RAA constructs accounted for 74% of the variance in intention, at step 1 of the regression, which was statistically significant. Hypothesis 2 was also supported as moral norm and anticipated regret accounted for a statistically significant increment to explained variance in intention (1%), at step 2 of the regression (also see Table 3). The independent predictors of intention in the final step of the model were instrumental attitude, injunctive norm and anticipated regret. Experiential attitudes, descriptive norm, perceived autonomy and capacity, and moral norm did not independently predict intention.

Table 3. Hierarchical linear regression predicting intention to use GenAI for producing assessment content from the RAA (instrumental and experiential attitudes, injunctive and descriptive norms, perceived autonomy and capacity) and the additional constructs (moral norm and anticipated regret)

Step	Variables	R^2	R_{change}	F_{change}	*df*	*p* for F_{change}	Final β	*t*	*p* for *t*
1	RAA Constructs	.74	.74	168.32	6, 362	<.001			
	Instrumental Attitude						.53	7.77	<.001
	Experiential Attitude						.07	1.33	.183
	Injunctive Norm						.08	2.13	.034
	Descriptive Norm						.01	0.27	.786
	Perceived Autonomy						−.02	−0.65	.515
	Perceived Capacity						.04	1.19	.234
2	Additional Constructs	.75	.01	7.72	2, 360	.001			
	Moral Norm						.04	0.83	.406
	Anticipated Regret						−.17	−3.25	.001

Predicting Behaviour

Another hierarchical multiple regression was conducted to test both H3 (the RAA will explain a significant proportion of the variance in university students' use of GenAI for producing assessment content) and H4 (moral norm and anticipated regret will account for a significant increment to explained variance in university students' use of GenAI for producing assessment content). The dependent variable was the measure of behaviour. The independent variables at step 1 were the RAA constructs that are posited as predictors of behaviour: intention, and perceived autonomy and capacity. At step 2, the additional constructs of moral norm and anticipated regret were added, as independent variables, to the regression model.

As shown in Table 4, the RAA constructs accounted for 65% of the variance in behaviour, at step 1 of the regression. In support of H3, this was a statistically significant proportion of variance. Hypothesis 4 was not supported because moral norm and anticipated regret did not account for a statistically significant increment to explained variance in behaviour, at step 2 of the regression. Intention was the sole independent predictor of behaviour in the final step of the regression.

6. Discussion

This study was conducted to test, for the first time, the extent to which the RAA could predict university students' use of GenAI for generating assessment content and the extent to which moral norm and anticipated regret could improve the prediction of this behaviour, over and above the RAA. It was hypothesised that the RAA will explain a significant proportion of the variance in university students' intentions to use GenAI for producing assessment content (hypothesis 1) and that moral norm and anticipated regret will account for a significant increment to explained variance in intentions to perform this behaviour (hypothesis 2). It was also hypothesised that the RAA will explain a significant proportion of the variance in university students' use of GenAI for producing assessment content (hypothesis 3), and moral norm and anticipated regret will account for a significant increment to explained variance in the frequency with which this behaviour is carried out (hypothesis 4).

In support of hypothesis 1, the RAA accounted for a large proportion of the variance in intentions (74%). This finding is consistent with, and extends, previous studies in which the RAA has been found to account for large proportions of variance in intentions to perform other social behaviours (e.g., Conner *et al*., 2017; Hagger *et al*., 2018; McEachan *et al*., 2016). It also extends previous research on general GenAI usage in higher education, which has shown that the theory of planned behaviour can predict students' intentions to adopt this technology (e.g., Ahadzadeh *et al*., 2024; Ivanov *et al*., 2024; Ma, 2025; Wang *et al*.,

Table 4. Hierarchical linear regression predicting use of GenAI for producing assessment content (behaviour) from the RAA (intention, and perceived autonomy and capacity) and the additional constructs (moral norm and anticipated regret)

Step	Variables	R^2	R_{change}	F_{change}	*df*	*p* for F_{change}	Final β	*t*	*p* for *t*
1	RAA Constructs	.65	.65	224.36	3, 365	<.001			
	Intention						.71	13.59	<.001
	Perceived Autonomy						.00	−0.10	.917
	Perceived Capacity						.06	1.80	.073
2	Additional Constructs	.65	.00	2.06	2, 363	.129			
	Moral Norm						−.03	−0.47	.636
	Anticipated Regret						−.11	−1.93	.055

2024). Importantly, the current findings add the literature on GenAI use in educational settings because previous studies have tended to focus on a single or narrow range of variables (e.g., academic stress or anxiety) when investigating the motivators for students' GenAI use (e.g., Acosta-Enriquez *et al*., 2025; Liu *et al*., 2026). These studies may suffer spuriousness (Herbert, 1954), where an unmeasured variable (e.g., instrumental attitude) is responsible for the correlation between the measured variable(s) (e.g., academic stress) and an outcome (e.g., GenAI misuse). The present study, on the hand, is less likely to suffer this limitation because it employed a comprehensive theoretical framework, which captured a wide range of multiple potential influences upon behaviour, and investigated the independent effect of all those potential influences, independently. Specifically, the results showed that instrumental attitudes and injunctive norms were the constructs in the RAA that independently predicted intentions. Experiential attitudes, descriptive norm, and perceived autonomy and capacity, did not. These results imply that students' intentions to use GenAI in the production of assessment content are underpinned by utilitarian (cost-benefit) considerations (e.g., a higher grade weighed against the risk of detection for academic dishonesty) and perceptions about whether important others would approve of their behaviour, or what important others believe they should do. On the other hand, there was no evidence that intentions to use GenAI to produce assessment content were underpinned by affective considerations (e.g., relief from assignment stress or worry), considerations about the extent to which this behaviour is typical, or control factors relating to autonomy (e.g., access to the technology) or capacity (e.g., ability to use the technology).

In support of hypothesis 2, moral norm and anticipated regret together accounted for a statistically significant increment to explained variance in students' intentions to use GenAI for producing assessment content. This finding is consistent with previous research in which these constructs have been shown to increase the prediction of intentions to perform ethically-related behaviours, over and above the theory of planned behaviour (e.g., Beck and Ajzen, 1991; Elliott, 2012) and the RAA (e.g., Elliot & Thomson, 2010). For students' use of GenAI for producing assessment content, anticipated regret was found to be an independent predictor of intentions, but moral norm was not. The implication is that students' expectation of a negative emotion for breaching moral norms (i.e., feelings of regret), rather than those norms *per se*, are important in the prediction of their intentions to use GenAI for producing assessment content. Given that anticipated regret is an affect-based cognition, this finding is potentially interesting when contrasted with the null finding for affective attitude, discussed above. This contrast suggests that while more general affective considerations tapped by affective attitudes may not impact students' decisions to misuse GenAI, affective considerations relating specifically to the expectation of a negative affective response following the performance of a behaviour that transgresses one's moral code (i.e., anticipated regret) does; students who anticipate regret are less like to decide to use GenAI for producing their assessment content.

Hypothesis 3 was also supported as the RAA accounted for a large proportion of variance in students' reported use of GenAI for producing assessment content (65%). This finding is also consistent with, and extends, previous studies in on other social behaviours (e.g., Conner *et al*., 2017; Hagger *et al*., 2018; McEachan *et al*., 2016) and research on general GenAI usage in higher education (e.g., Ahadzadeh *et al*., 2024; Ivanov *et al*., 2024; Ma, 2025; Wang *et al*., 2024). Intention was the sole RAA predictor of students' reported use of GenAI for producing assessment content. Perceived autonomy and capacity did not predict students' GenAI misuse behaviour. These results imply that intentions are readily enacted, once they are formed following considerations of instrumental attitudes, injunctive norms and anticipated regret. The null results for perceived autonomy and capacity imply that students' misuse of GenAI is under their complete volitional control (i.e., dictated by their intentions).

Contrary to hypothesis 4, moral norm and anticipated regret were not found to account for a statistically significant increment to explained variance in students' reported use of GenAI for producing assessment content. Although not consistent with several studies on other behaviours, which have shown that anticipated regret, in particular, can account for unique variance in the direct prediction of behaviour (e.g., Elliott and Thomson, 2010; Sandberg and Conner, 2008), this finding is consistent with other studies and the proposition that intention is the main direct predictor of behaviour, which mediates the effects of other motivational constructs (e.g., Ajzen, 1991). In the present context, the findings further imply that students' use of GenAI for producing assessment content is underpinned solely by intention; anticipated regret is important in so far as it predicts intention, along with instrumental attitude and injunctive norm (see above).

Practical Implications

The present findings have several implications for educators seeking to reduce students' misuse of GenAI within assessed work. The results indicate that instrumental attitudes, injunctive norms, and anticipated regret shape students' intentions to misuse GenAI, and those intentions, in turn, increase the likelihood of this behaviour. Interventions should therefore target these specific behavioural determinants. Many universities already make efforts to inform students about GenAI usage (e.g., through websites course handbooks, virtual learning environments, assignment handouts, or inductions). However, these messages tend to be based on academics' intuition rather than evidence and, as a result, they tend be non-targeted, generic and vary, both across and within Faculties (e.g., Fu *et al*., 2026; Wilson, 2025; An *et al*., 2025). While generic messaging (e.g., covering all the potential reasons for why students should not misuse GenAI) maybe be useful in a broad context, the present findings imply that it would be beneficial to place additional emphasis on communications that target

instrumental attitudes, injunctive norms and anticipated regret with a view to demotivating GenAI misuse.

For instrumental attitude, educators should seek to reduce the perceived utility of GenAI misuse while increasing the perceived value of legitimate engagement. Specifying the negative outcomes of unauthorised GenAI usage (e.g., poor attainment of learning outcomes and therefore missed opportunities for skill development; potential detection and punishment through academic dishonesty procedures) and the positive outcomes of responsible GenAI use (e.g., attainment of learning outcomes; avoidance of academic misconduct investigations) is, therefore, to be encouraged. Additionally, existing academic integrity guidance recommends embedding authentic and process-oriented practices throughout the assessment lifecycle, including formative tasks and staged submissions that foreground evidence of learning and judgement (e.g., Ajjawi *et al*., 2024). Such approaches have been discussed in the context of GenAI use in educational settings (e.g., Chapman and Dalgarno, 2025; Sharma, 2026). They may reduce the functional usefulness of copying and pasting AI-generated text, while simultaneously supporting learning.

For injunctive norms, clear and consistent normative messaging regarding acceptable GenAI practices is required. This is consistent with recent published articles on GenAI and educational integrity, where authors have argued that institutions should make expectations and standards highly visible and embedded within assessment design rather than relying primarily on detection and punishment approaches (e.g., Sallai *et al*., 2024; Xia *et al*., 2024). Making clear to students that GenAI misuse is not approved by institutions as it violates integrity in university cultures, of which they are a part, might also constitute a useful approach. In addition, messages emphasise that GenAI misuse is not approved by fellow students, accrediting bodies and professional organisations that are students' potential future employers may be effective at targeting injunctive norms. Such messages could be supported by testimonials, which widely used in marketing, including the marketing of university courses, and are effective at influencing consumer choices because they act as a form of social endorsement and provide proof that important others support the required behaviour (e.g., Cialdini, 2009; Knoll and Matthes, 2017). In the present context, testimonials may be effective at discouraging GenAI misuse by providing social endorsement and proof of normative standards.

For anticipated regret, previous research in other contexts shows that asking people to consider negative affect for performing or not performing a behaviour can be an effective strategy for changing behaviour (O'Carroll *et al*., 2016). In the present context, encouraging students to think about how they would regret it if they used GenAI to produce their assessment content may be an effective strategy for reducing this behaviour. This could be achieved by asking students to reflect upon possible adverse future consequences, both individual (e.g., possible academic dishonesty investigation and punishment) or social (e.g.,

violation of established normative standards). In addition to helping educators to target students' injunctive norms (see above), consistent and strong normative messaging surrounding GenAI misuse may therefore be a useful strategy to help create an environment in which educators can more easily manipulate students' sense of anticipated regret for misusing GenAI.

The suggested strategies, informed by the results of this study and designed to encourage students to avoid misusing GenAI in the production of their assessments, should also be supported by the wider academic context. Consistent approaches within courses and the wider institutional frameworks are needed to avoid confusion among students (Fu *et al*., 2026). Explicit guidance should be provided on the specific tasks that constitute acceptable and unacceptable GenAI usage, within degree courses and each individual assignment. Messages targeting instrumental attitudes, injunctive norms and anticipated regret can then be interpreted by students within an environment that provides clear specification of academic integrity with respect to GenAI usage, while still leveraging the potential benefits of advanced AI tools for educational enhancement (e.g., improved learning, skill development).

Additionally, established practices that are relatively secure against GenAI misuse can be more widely embedded into more vulnerable assessment types. For example, oral examinations (Vivas) allow examiners to quiz students on a set topic of learning. Such assessments have been found to assess different skills to written work (e.g., Nunnink *et al*., 2010) but can be used in conjunction with written work to promote acquisition of a broader suite of learning outcomes than written work alone, whilst serving as check of students understanding, as demonstrated in their written work. Similarly, objective structured clinical examinations (OSCEs) allow students to role play vignettes from clinical practice, with their decision-making and competencies in a controlled, 'real-world' setting (Vhora *et al*., 2023). Whilst these types of assessments are more costly, like invigilated exams, they remain reasonably unaffected by GenAI use, even if GenAI is used to pre-prepare answers (i.e., this amounts to question-spotting, which typically does not generate high grades). Such practices should be considered when feasible.

Possible Limitations

A potential limitation is that the measure of behaviour used in this study was self-reported. Self-reported behaviour measures are potentially vulnerable to cognitive (e.g., Luchins, 1957), affective (e.g., Bower and Cohen, 1982) and self-presentational biases (e.g., Paulhus, 2002). However, self-reports are commonly used in the social sciences and are regarded as a valuable methodology, allowing efficient collection of large samples such as the one used in the present study. Self-reported measures are also known to correlate well with objective measures across a range of behaviours (e.g., De Waard & Rooijers, 1994; Freda

et al., 2021; Verbeij *et al*., 2022) and models such as the RAA have been shown to predict objective measures of behaviour in addition to subjective measures in previous studies (see Armitage and Conner, 2001). Furthermore, participation in the present study was completely anonymous, which is known to reduce socially desirable responding (e.g., Ong and Weiss, 2000; Ramachandran *et al*., 2023). That said, objective measures of GenAI use in assessment submissions can be obtained from AI detection software. While these are known to produce false positive and negatives, they do vary significantly in their sensitivity and specificity (Elkhatat *et al*., 2023), and may provide sufficient proxies for behaviour to aid the testing of models such as the RAA. Testing the RAA with objective measures of GenAI misuse in university assessments is a potential avenue for future research.

A cross sectional, correlational design was also employed. Cross sectional designs are potentially limiting because the contemporaneous measurement of RAA constructs and behaviour means that the measures of behaviour relate to past, not subsequent, action. This violates the causal sequencing proposed by the RAA (i.e., RAA → behaviour). Research employing prospective, correlational designs ensures that behaviour is measured after the RAA's constructs, consistent with the theoretically supposed causal sequencing of the model (e.g., Elliott and Ainsworth, 2012; Elliott and Thomson, 2010). However, cross sectional designs mean that participants' anonymity can be preserved because researchers do not need to obtain information to match participants' time 1 (RAA) and time 2 (behaviour) data. This is important for reducing self-reporting biases in studies that target morally questionable, rule-breaking behaviour, such as this one. Also, many studies have demonstrated that the RAA predicts prospectively measured behaviour (see McEachan *et al*., 2016). The present findings are therefore held with confidence.

It should also be noted that, correlational research (cross sectional or prospective), does not permit a test of the causal impact on one construct (e.g., attitudes) on another (e.g., intention). To provide evidence of causal relations between constructs, such as those proposed by the RAA, experimental research is needed in which successful manipulation of independent variables (e.g., attitudes) is shown to generate corresponding changes in dependent variables (e.g., intentions). Such research, in other domains, has shown that the constructs within the RAA can exert a causal impact on intentions and behaviour (e.g., Elliott and Armitage, 2009; Sheeran *et al*., 2016; Webb and Sheeran, 2006). However, experimental research is difficult as it relies on the development of effective intervention techniques (e.g., methods that can successfully change RAA constructs). Such techniques need to be developed in the present context. A useful avenue for future research, therefore, might be to identify effective techniques for modifying the constructs found in this study to independently predict students' intentions to misuse GenAI. This would not only permit a causal test of the relationships demonstrated in this research but it would also identify effective interventions that are likely to discourage the misuse of GenAI in university assessments.

Finally, the present sample comprised 86% females. However, that gender profile was reflected in the population from which the sample was drawn (see Table 1). That profile is also reflective of UK Psychology students more generally, as over 80% of Psychology students in UK higher education are female (Johnson *et al*., 2020). Additionally, there was no evidence that gender altered the findings of this study (see footnote 1) and there is currently no research evidence indicating differences between males and females in their misuse of GenAI in the production of university assessments. That said, future research could explore this issue and investigate the predictors of GenAI misuse in other populations containing predominantly male students, such as those found in Engineering subjects, where the proportion of males is over 80% (e.g., Engineering, 2023).

8. Conclusions

This research showed that the RAA was a good model for predicting university students' misuse GenAI in relation to the production of assessed work. It also showed that anticipated regret is a useful addition to the model for this behaviour. The evidence showed that students' use of GenAI for producing assessment content is underpinned by intentions, which are, in turn, underpinned by instrumental attitudes, injunctive norms and anticipated regret. Consistent policies and supporting documentation, around what constitutes appropriate and inappropriate GenAI usage, is required, along with consistent messaging and assessment designs that target these constructs. Future research could usefully test those methods, targeting the constructs identified in this study (e.g., using controlled experiments), in order to develop evidence-base practice. and provide a causal test of the relationships that were identified in this correlational study.

9. Disclosure Statement

No potential conflict of interest was reported by the author(s).

10. Data Availability Statement

The dataset that supports the analysis reported in this paper is available from the corresponding author upon reasonable request.

11. Pre-registration Statement

The pre-registration for this research is on the Open Science Framework: https://osf.io/w27ev

12. Ethics Approval Statement

This research received ethical approval from the Department of Psychological Sciences and Health's Research Ethics Committee, University of Strathclyde (ethics approval code: 86.7 May 2024).

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14. Note

[1] Note that the analyses presented in this article were re-run with the sample characteristics (age, gender and level of study) as covariates (note that the extremely small number of participants who self-identified as an 'other' gender than male or female were not included in these analyses to avoid violating the linearity assumptions of the analyses). The findings presented in the main article did not change. The significant predictors of intentions and behaviour remained significant predictors. The non-significant predictors remained non-significant predictors.

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APPENDIX

Items used to Measure the RAA (Intention, Instrumental and Experiential Attitude, Injunctive and Descriptive Norm, Perceived Autonomy and Capacity), Additional Constructs (Moral Norm and Anticipated Regret) and Behaviour (Misuse of GenAI)

Items to Measure Intention

- I want to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- I intend to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).
- I plan to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- I think that I will use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).
- I would be willing to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester if necessary (e.g., if I am running out of time, feel unable to complete the task on my own, or can't be bothered to do it myself) (strongly agree [scored 9] to strongly disagree [scored 1]).
- I would consider using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).

Items to Measure Instrumental Attitude

- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely useful (scored 9) to extremely useless (scored 1).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely unnecessary (scored 1) to extremely necessary (scored 9).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely worthwhile (scored 9) to extremely worthless (scored 1).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely harmful (scored 1) to extremely beneficial (scored 9).

- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely honest (scored 9) to extremely dishonest (scored 1).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely foolish (scored 1) to extremely wise (scored 9).

Items to Measure Experiential Attitude

- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely enjoyable (scored 9) to extremely unenjoyable (scored 1).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely sad (scored 1) to extremely happy (scored 9).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely fun (scored 9) to extremely boring (scored 1).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely unpleasant (scored 1) to extremely pleasant (scored 9).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely satisfying (scored 9) to extremely unsatisfying (scored 1).
- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely displeasing (scored 1) to extremely pleasing (scored 9).

Items to Measure Injunctive Norm

- People important to me would approve of me using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- People important to me are likely to encourage me to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).
- People important to me would want me to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1])

- If I used GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester, people important to me would . . . ' (greatly disapprove [scored 1] to greatly approve [scored 9]).

Items to Measure Descriptive Norm

- How many students do you think will be using GenAI in order to produce content (e.g., text, code) for use in their assessments (e.g., essays, reports) this semester? (a lot [scored 9] to none [scored 1]).
- Of the people you know, how many do you think will be using GenAI in order to produce content (e.g., text, code) for use in their assessments (e.g., essays, reports) this semester? (none of them [scored 1] to many of them [scored 9]).
- People important to me will, themselves, be using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- Other students are likely to be using GenAI in order to produce content (e.g., text, code) for use in their assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).

Items to Measure Perceived Autonomy

- I have full control over whether or not I will use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- Whether or not I use GenAI to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester is under my control (strongly agree [scored 9] to strongly disagree [scored 1]).
- How much control do you think you will have over whether or not you will use GenAI in order to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) this semester? (no control at all [scored 1] to complete control [scored 9]).

Items to Measure Perceived Capacity

- For me, using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester would be: extremely easy (scored 9) to extremely difficult (scored 1).
- I have the resources to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).
- I have the ability to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- I am capable of using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).

Items to Measure Moral Norm

- It would be wrong for me to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 1] to strongly disagree [scored 9]).
- It would be morally acceptable for me to use GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly agree [scored 9] to strongly disagree [scored 1]).
- How proper would it be if you used GenAI in order to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) this semester? (not proper at all [scored 1] to very proper [scored 9]).
- Do you think it would be wrong for you to use GenAI in order to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) this semester? (definitely no [scored 9] to definitely yes [scored 1]).

Items to Measure Anticipated Regret

- I would feel absolutely fine with using GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester? (strongly disagree [scored 9] to strongly agree [scored 1]).
- I would regret it if I used GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (strongly disagree [scored 1] to strongly agree [scored 9]).
- How much would you regret it if you used GenAI in order to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) this semester? (very much [scored 9] to not at all [scored 1]).

- I would feel guilty if I used GenAI in order to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) this semester (not at all [scored 9] to very much [scored 1]).

Items to Measure Behaviour

- On a scale of 0 (never) to 10 (many times), how many times have you used GenAI to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) while at university? (score from 0 to 10 entered).
- I have used GenAI to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) while at university? (strongly agree [scored 9] to strongly disagree [scored 1]).
- How often have you used GenAI to produce content (e.g., text, code) for use in your assessments (e.g., essays, reports) while at university? (never [scored 1] to very often [scored 9]).
- I have never used GenAI to produce content (e.g., text, code) for use in my assessments (e.g., essays, reports) while at university? (strongly disagree [scored 9] to strongly agree [scored 1]).