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Hey ChatGPT, give me a title for a paper about degree apathy and student use of AI for assignment writing

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ABSTRACT

ChatGPT could allow students to plagiarize the content of their coursework with little risk of detection. Little is known about undergraduate willingness to use AI tools. In this study, psychology undergraduates ($N = 160$) from the United Kingdom, indicated their willingness to use, and history of using, ChatGPT to write university assignments. Almost a third (32%) indicated that they would use such tools; 15% indicated that they had used them already. Neither personality (conscientiousness, agreeableness, Machiavellianism, narcissism), academic performance, nor study skills self-efficacy could predict future use of AI tools. A novel Degree Apathy Scale was the only significant predictor. Willingness to use AI tools was greater when the risk of getting caught was low, and punishment was light, particularly for those high in degree apathy. Findings suggest that degree apathy is a key risk factor in academic misconduct. Wider research and pedagogical applications of degree apathy are discussed.

1. Introduction

In November 2022, OpenAI launched ChatGPT – a generative language AI system capable of answering questions in detailed, human-like ways. This has led to concerns that students may be able to use ChatGPT to write essays or other coursework assignments without it being easily detected (e.g., Cotton, Cotton, & Shipway, 2023; Dehouche, 2021). Indeed, several early reports have demonstrated that essays or exam answers generated using ChatGPT could be of sufficient quality to pass university assignments (Choi, Hickman, Monahan, & Schwarcz, 2023; Malinka, Perešíni, Firc, Hujňák, & Januš, 2023). This poses considerable challenges for higher education. According to Rudolph, Tan, and Tan (2023), one of the major concerns that educators have is that ChatGPT will render the essay obsolete as a form of assessment because students can "outsource" the writing to AI.

Use of AI for assignments is not a foregone conclusion, however. Informal conversations with students themselves, indicate that some are skeptical of AI, thinking that using the tool would not earn them a better grade, and that reliance on it might lead to a blunting of their academic skills. History has shown that the fact that students *could* cheat on assignments does not mean that they *will* cheat, and prevalence rates have been shown to vary across studies (e.g., Haney & Clarke, 2007; Whitley, 1998). Prevalence also seems to vary across assessment type, type of cheating, and method used to detect cheating. Honz, Kiewra, and Yang (2010), for example, showed that the prevalence of cheating on examinations was higher (68.4%) than for take-home tests (59.5%) and reports (44%). Newton (2018) reported the prevalence of "contract cheating", or students actively getting somebody else to do their work (Clarke & Lancaster, 2007), was as low as 3.52% of 54,514 students. None of these prevalence rates reach 100%, indicating that not every student would cheat under the same circumstances.

Our first aim in the current study was to provide prospective prevalence rates for students who reported that they were willing to use, or indeed had used, ChatGPT or other AI tools to write their academic assignments. To our knowledge, no prevalence rates have been established. Our second aim was to examine some of the individual differences and contextual factors that might predict whether students would be likely to misuse AI tools in their assignments. As previous reports of prevalence rates for academic cheating do not reach 100%, it is reasonable to assume that some students are more likely to cheat than others. As this is the first study considering AI-assisted cheating specifically, we based our predictions on existing literature concerning other forms of academic dishonesty: personality, study skills and self-efficacy, and academic motivation. We will briefly outline key literature relating to these possible predictors in the following pages.

We consider that different forms of academic dishonesty are likely to be predicted by different intrapersonal factors (Marsden, Carroll, & Neill, 2005). For example, copying an answer to a multiple-choice

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question in an exam setting is likely to be opportunistic and impulsive whereas commissioning an essay from a paid source requires planning and access to resources. Therefore, it is important to define what we are considering as analogous forms of academic dishonesty before considering likely predictors of student behaviour according to the literature. The most widely researched forms of academic dishonesty (or "counterproductive academic behaviour") are cheating on tests, plagiarism, and accessing help from unauthorised sources (Cuadrado, Salgado, & Moscoso, 2021). In the context of the current study, we are most interested in the literature concerning factors that influence plagiarism. In our view, presenting written coursework that has been generated using ChatGPT or other AI tools is conceptually similar to presenting work written by another human author – the student submitting the work is attempting to claim credit for ideas that are not their own. While we acknowledge that AI can be used legitimately (to improve grammar or to provide a suggested structure for an essay answer, for example), we are considering the "use of AI" in the current paper as meaning that most of the content of one or more sections of an assignment has been generated by AI. See the discussion for more information.

1.1. Personality factors

The first and most obvious potential source of variation in the likelihood of cheating on academic assessments is personality. In the current study we considered the Big-Five personality traits (Costa & McCrae, 1992) as potential predictors of academic dishonesty. Existing literature contains several meta-analyses and empirical studies on the topic of cheating, though it is important to note that precisely which types of academic dishonesty is considered varies. Recent meta-analyses (Cuadrado et al., 2021; Giluk & Postelthwaite, 2015) have examined the relationships between the Big Five and plagiarism and found that conscientiousness and agreeableness were negatively associated with academic dishonesty and plagiarism. In Giluk and Postelthwaite (2015) analysis, extraversion, neuroticism and openness to experience had relationships with academic dishonesty for which the 80% credibility intervals included zero. Hence, the current study focused on conscientiousness and agreeableness as potential predictors in the analysis. Individuals who are high in agreeableness are warm and trusting and, importantly for the context of the current study, they are likely to avoid conflict (Graziano, Jensen-Campbell, & Hair, 1996). In that regard, it has been suggested that students who are highly agreeable are less likely to engage in academic dishonesty to avoid potential conflict with teachers (Giluk & Postelthwaite, 2015). Individuals who are high in conscientiousness are organised and follow rules – both of which are tendencies that would reduce the likelihood of academic dishonesty. The ability and desire to plan carefully would likely mean that conscientious students rarely find themselves in a position where they need to complete an assignment without sufficient time to perform at their best. Even so, if they *were* completing an assignment close to the deadline then their desire to adhere to norms and rules would preclude them from resorting to dishonest behaviour. The theoretical relationships outlined above have been supported by empirical literature (Cuadrado et al., 2021; Giluk & Postelthwaite, 2015). We therefore expected negative relationships between conscientiousness and agreeableness, respectively, and self-reported likelihood, and past use, of using ChatGPT or other AI tools in academic assignments.

A second potential individual differences factor in predicting academic dishonesty is the Dark Triad (Paulhus & Williams, 2002). The Dark Triad is made up of psychopathy, Machiavellianism and narcissism and all three of these traits have been shown to have specific relationships with dishonest behaviour of one kind or another. Williams, Nathanson, and Paulhus (2010), for example, reported that there were significant positive correlations between the Dark Triad and both self-reported cheating behaviour and objective measures of plagiarism generated by Turnitin (iParadigms, L. L. C., 2004). Recent studies have provided further support for this association (e.g., Cheung & Egan, 2021; Curtis, 2023). Given that individuals high in Machiavellianism tend to manipulate others to gain an advantage, that individuals high in narcissism are likely to be arrogant and entitled, and that individuals high in psychopathy are manipulative, impulsive and anti-social, this pattern is hardly surprising. In the context of plagiarism and the use of AI tools such as ChatGPT to cheat on academic assignments, we argue that psychopathy is less likely to be influential than it would be for opportunistic and impulsive forms of academic dishonesty such as copying from another test-taker in an exam situation. Indeed, some studies (e.g., Esteves, Oliveira, de Andrade, & Menezes, 2021) have reported non-significant effects of psychopathy on academic dishonesty and in Lee, Kuncel, and Gau (2020) meta-analysis, the 80% credibility interval for psychopathy included zero. Therefore, we focused on narcissism and Machiavellianism in our analyses. In both cases, we expected higher scores on the Dark Triad to be predict a greater likelihood of using AI to cheat on assignments.

1.2. Factors related to studentship and academic performance

Of course, academic dishonesty is committed by students who vary not only in personality factors, but in their approaches to, strategies for, and competencies in studying. Therefore, we also considered study-related predictors of using ChatGPT or other AI tools to complete assignments. In what follows, we discuss three potential influences on cheating behaviour and plagiarism – study skills self-efficacy, motivation or lack thereof, and grades. Study Skills Self Efficacy (Silver, Smith Jr, & Greene, 2001) refers to the belief of a given student in their ability to complete study-related tasks. This is a specific aspect of "academic self-efficacy" (Chemers & Garcia, 2001) which is itself a subtype of general self-efficacy (Bandura, 1977). Self-efficacy can be broadly defined as confidence in being able to perform the appropriate behaviours to a standard that is necessary to achieve a given outcome or goal. We argue that students who have high self-efficacy in relation to their study skills should be less likely to engage in academic dishonesty because they are confident that completing academic tasks will result in a good enough outcome, and hence there is no need to attempt to gain an unfair advantage (Murdock, Hale, & Weber, 2001). Indeed, the meta-analyses reported by both Lee et al. (2020) and Krou, Fong, and Hoff (2021) reported exactly this pattern – higher self-efficacy was predictive of lower academic dishonesty. This has been shown in more recent empirical studies as well (Fatima, Sunguh, Abbas, Mannan, & Hosseini, 2020; Mukasa, Stokes, & Mukona, 2023). Hence, we expected a negative relationship between study skill self-efficacy and academic dishonesty.

Another factor identified as predictive of engaging in academic dishonesty is academic motivation (or, conversely, apathy). As with academic dishonesty, there are a variety of ways by which academic motivation has been operationalised in the literature. A full consideration of this issue is beyond the scope of the current paper. However, motivation can generally be considered as a force that drives and guides behaviour (Reeve, 2009), and we highlight 3 types of motivation that might be of particular relevance to the study at hand. According to achievement goal theory (Pintrich, 2000), the motivation for a student to engage in their education can be oriented to achieving mastery (i.e., the goal is acquiring the skills or knowledge being taught) or achieving a criterion performance level – usually a certain grade (Krou et al., 2021). It has been demonstrated that students who are motivated by mastery of the content and skills in an academic course are less likely to engage in academic dishonesty, and students who are particularly performance-oriented are more likely to plagiarize (Anderman, Griesinger, & Westerfield, 1998; Anderman & Midgley, 2004; Daumiller & Janke, 2019; Krou et al., 2021; Lee et al., 2020; Marsden et al., 2005; Tas & Tekkaya, 2010). While being motivated by performance or mastery have been shown to relate to academic dishonesty in different ways, students who fall into these categories are at least motivated by something related to their studies. The third type of student we wish to highlight are those who are not motivated by their studies at all, and therefore have no particular drive to complete their courses – this has been termed as amotivation (Ryan & Deci, 2000) or apathy (e.g. Beck & Davidson, 2001) in the literature. Both Orosz, Farkas, and Roland-Lévy (2013) and Krou et al. (2021) have indicated that lack of motivation is positively related to academic dishonesty. Previous research on academic amotivation has considered it to have four facets which relate to beliefs around a) ability, b) effort, c) value and d) the task itself, with questionnaire measures created to tap these beliefs (e.g. Legault, Green-Demers, & Pelletier, 2006). While we agree that a lack of motivation could stem from each of these beliefs, the existing measure presupposes that there *is* a lack of motivation and then tries to determine why. In a general student population, there will be students who are and who are not motivated, and our goal in this study was to identify whether lacking in motivation increased the likelihood of academic dishonesty. Therefore, we developed and administered a short measure designed to capture apathy towards university-level study – the *Degree Apathy Scale* (DAS) – to measure the overall value and investment participants had towards their education. This novel questionnaire asked about the students' approach to their degree including, among other things, the importance of grades, the reasons for enrolling on the degree scheme in the first place and the level of engagement with the course (the complete measure is described during the Measures section of this paper). We did not include questions relating to ability beliefs, because we had included a separate and specific measure of self-efficacy around study skills which would capture that concept, nor did we include questions around the tasks themselves, because we were concerned with general academic dishonesty rather than dishonesty in specific contexts. We predicted that higher DAS scores would predict a greater willingness to engage in academic dishonesty using ChatGPT or other AI tools. To be clear, we are considering "degree apathy" to be counter to *any* type of motivation to complete courses and engage in class work – a lack of desire to expend effort on studying and a low perceived value of the educational experience. Simply put, an apathetic student is not motivated to achieve mastery or to attain high performance. We consider that this is dissociable from a lack of ability (which we measured objectively, see below).

The final predictor we considered in our study was previous academic attainment, as operationalised by grades achieved in courses taught and assessed during the previous semester. There are established relationships between study skills, motivation, and academic achievement (see Friedman & Mandel, 2011; Hsieh, Sullivan, & Guerra, 2007). There are also established relationships between academic achievement and engagement in academic dishonesty. In a meta-analysis, Paulhus and Dubois (2015) indicated that there was a robust negative relationship between academic achievement and likelihood of academic dishonesty. Whether this is an artefact of the relationship between academic achievement and the other study-related variables discussed in this paper or not, we argue that it is important to consider previous academic achievement in the analysis of the likelihood that a student will cheat using ChatGPT or other AI tool. We expect that students who tend to get better grades will be less likely to engage in academic dishonesty, simply because they have no need – they are likely to do better in assessments that they complete themselves than they are in assignments in which they engage in plagiarism or other forms of cheating.

1.3. The current study

In the current study, we asked students to complete a questionnaire concerning the key predictors of academic cheating outlined above, as well as whether they had, or would, use ChatGPT or other AI tools to generate content for their assignments, which would be considered misuse of these tools. We had three key aims – 1) to quantify willingness to misuse, and previous misuse of, AI tools in academic assignments; 2) to examine the individual characteristics of students who might be inclined to misuse AI; and 3) to determine the level of risk that students might accept to use AI to cheat. To meet this final aim, we operationalised risk in two ways – the likelihood of getting caught and the level of punishment received for cheating. These risk factors were chosen because they have been previously argued to be influential in non-academic forms of dishonest behaviour such as sexual deviancy (Thomas, Stone, Bennett, Stewart-Williams, & Kennair, 2021) or criminal activity (Wright, Caspi, Moffitt, & Paternoster, 2004), as well as in academic situations (Corcoran & Rotter, 1987). Simply put, it has been shown that individuals are more likely to engage in dishonest or illegal behaviour if they think it is "safe" to do so – that they will be able to get the outcome they want without repercussions that would make the potential cost-benefit ratio unfavourable. We assume that the same will be true of the use of AI tools to cheat on academic assignments. Specifically, we predict that the likelihood of using ChatGPT in academic assignments will decrease as the likelihood of detection increases and/or as the severity of the punishment increases. The goal of this part of the study was to potentially provide clear guidance for the higher education sector to mitigate the impact of ChatGPT and other AI tools in the short to medium term while universities adjust assessment strategies to circumvent this form of cheating altogether.

2. Methods

2.1. Participants

One-hundred and sixty undergraduate students were recruited from [REDACTED FOR PEER REVIEW]. Participants ranged from 18 to 45 years of age (M = 21.48; SD = 4.10). One-hundred and twenty-four students were female (77.5%), 35 were male (21.9%) while 1 participant responded "other" (0.6%). The sample consisted of 40 first-year students (25%), 68 s-year students (42.5%) and 52 third-year students (32.5%). There were 139 domestic students (86.9%), while 21 participants were international students (13.1%). The mean assessment grade of participants in their previous semester was 67.04% (SD = 9.18; range 18.67–87.33%). Participants took part voluntarily. Ethical approval for the study was received from the [REDACTED FOR PEER REVIEW] Ethics Committee.

2.2. Measures

2.2.1. Degree Apathy Scale (DAS)

The Degree Apathy Scale (DAS) is a novel custom-made measure for this study (see Table 1). The DAS contains eight-items which measure a student's lack of interest, enthusiasm, or concern for undertaking their degree, their level of engagement in the course (e.g., "I feel engaged in my degree"), the perceived importance of their degree for their future career (e.g., "If I did badly at my degree, it would ruin my career plans"), and the extent to which the selection of their course was an arbitrary process (e.g., "I started my degree because I wasn't sure what else to do"). Respondents provide responses on a seven-point Likert-Scale (1 =

Table 1
Individual items of the Degree Apathy Scale.

Item	*M*	*SD*
1. I started my degree because I wasn't sure what else to do	3.13	2.01
2. I started my degree because I didn't want to get a job yet	2.95	2.09
3. My degree is essential to my future career*	2.20	1.43
4. If I did badly at my degree, it would ruin my career plans*	2.81	1.60
5. When it comes to my degree, I just want to pass everything	4.28	2.11
6. What I am learning on my degree will matter to me in the future*	2.03	1.07
7. I feel engaged in my degree*	2.56	1.28
8. My degree is very important to me*	1.88	1.07
Average score	2.73	1.01

* = Reverse scored. Items are answered on 7-point Likert scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree nor disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree.

"Strongly disagree" to 7 = "Strongly agree"). Five of the items are reverse scored and then an average is calculated. Internal consistency was good (α = 0.77).[1]

2.2.2. Big Five-Inventory (BFI)

The *Big Five-Inventory* (BFI; John & Srivastava, 1999) is a measure of the Big Five personality traits (i.e., openness, conscientiousness, extraversion, agreeableness, and neuroticism). The BFI consist of 44 items which measure each of the personality traits via a series of statements that respondents can respond to using a five-point Likert scale (1 = "Disagree strongly"; 2 = "Disagree a little"; 3 = "Neither agree nor disagree"; 4 = "Agree a little"; 5 = "Agree strongly"). Nine items measure conscientiousness and eight items measure Neuroticism. Statements measuring conscientiousness include "I see myself as someone who does a thorough job" and "I see myself as someone makes plans and follows through with them" and statements measuring neuroticism include "I see myself as someone who is depressed, blue" and "I see myself as someone who get nervous easily". The psychometric properties of the scale are robust (BFI; John & Srivastava, 1999). Internal consistency was good for the conscientiousness (α = 0.86) and neuroticism (α = 0.85) subscales.

2.2.3. The Short Dark Triad (SD3)

The *Short Dark Triad* (SD3; Jones & Paulhus, 2014) is a measure of the dark triad of personality traits: Machiavellianism, Narcissism and Psychopathy. The SD3 consists of 27 items. There are nine items each for Machiavellianism (e.g., "Most people can be manipulated"), Narcissism (e.g., "people seem me as a natural leader") and Psychopathy (e.g., "I like to get revenge on authorities"). Respondents can respond using a 5-item Likert Scale (1 = "Disagree strongly" to 5 = "Agree strongly"). The SD3 is deemed to provide a psychometrically robust brief measure of the dark triad (Maples, Lamkin, & Miller, 2014). Internal consistency was good for the sub-scales Machiavellianism (α = 0.80) and acceptable for narcissism (α = 0.69).

2.2.4. Study Skills Self-Efficacy (SSSES)

The Study Skills Self-Efficacy (*SSSE*; Silver et al., 2001) scale is a measure of a student's confidence in their study skills behaviours. The SSSE has 32-items and can be used as a tri-factorial tool (measuring students "Study Routines", "Text-Based Critical Thinking", and "Resource Use") or as a unifactorial tool where the total score is used by summing the responses to all items. In this study we used the total score. Participants are asked "How much confidence do you have in doing these behaviours?" and then respond to items such as "Understanding what I read in a textbook", "Reading critically" and "Taking tests that ask me to compare different concepts". Participants provide responses on a 5-point Likert Scale (1 = "Very Little" to 5 = "Quite a lot"). Silver et al. (2001) note that the scale is both valid and reliable. The internal consistency of the measure was good (α = 0.84).

2.2.5. ChatGPT: Students' experience and future intention

This section of the questionnaire was designed to measure students' experience and intention to use ChatGPT or other AI writing tools. The questionnaire started with a description of ChatGPT:

ChatGPT is an artificial intelligence model developed by OpenAI that is capable of generating human-like text. It is trained on a large corpus of text data from the internet and uses advanced machine learning algorithms to generate responses to questions or prompts. The model has been fine-tuned for various tasks such as answering questions, generating creative writing, and even coding. In summary, ChatGPT is a cutting-edge tool that showcases the power of AI in the field of natural language processing.

Following this, students were asked to respond to the following questions using the options "Yes" or "No". For the latter two questions "Prefer not to say" was added as an additional option.

- Have you ever heard of ChatGPT or AI writing tools?
- Would you ever use ChatGPT or AI writing tools to help you write a university assignment (e.g., an essay)?
- Have you ever used ChatGPT or AI writing tools to help you write a university assignment (e.g., an essay)?

2.2.6. ChatGPT: Intended use by level of risk and punishment

This final section of the questionnaire was designed to see how risk and potential punishment affected student intentions to use ChatGPT/AI. Participants were asked how "likely [they] would be to use ChatGPT or AI writing tools to help [them] write an assignment" under different punishment conditions should they get caught. There were seven punishments in total, increasing in severity from nothing, to failing a particular course module, to expulsion from the university. Next, they repeated the task, only this time they were asked how likely they would use ChatGPT or AI writing tools under different condition of risk. There were seven different chances of "getting caught" ranging from 0%, to 50%, to 99%. For both punishment and risk questions, participants indicated likelihood using a five-point scale from 1 – "Not at all" to 5 - "Extremely".

2.3. Procedure

Participants were asked to take part in the study via an email containing a link to the survey which was hosted online via Qualtrics. If participants took part, they were then required to read through an information sheet and complete a consent form. Following this, participants were required to provide their student number and socio-demographic details including their age, sex, year of study, degree programme, and whether they were a domestic or international student. Participants were then presented with the following questions: "If you were given a month to complete an essay on a topic you know reasonably well, what grade do you think you would be given?" and "What would you consider a 'good grade' to be for an essay?". Participants provided responses to these questions using a sliding scale allowing between 0% and 100%. Participants then completed the questionnaires above presented in a random order. Following completion of these measures they were presented with a debrief form.

2.4. Statistical analyses

The current study had 3 overarching research questions. The first question concerned the extent to which participants were a) aware of ChatGPT or similar AI tool, b) willing to misuse AI in academic assignments and c) had previously misused AI in this way. This research question was addressed by calculating percentages of participants who responded in specific ways to the questions relating to ChatGPT tools. The second research question was as to what characteristics of the participants predicted willingness to use (or prior use of) AI tools in academic assignments. This was examined using logistic regression models. The third research question concerned whether increasing the risk or severity of the penalty for AI misuse would alter the likelihood of engaging in this form of academic dishonesty. This was analysed using repeated measures ANOVAs, where participants had provided separate ratings for their willingness to misuse AI under a variety of hypothetical levels of risk.

[1] The Degree Apathy Scale items were designed to represent one underlying factor. A confirmatory factor analysis on the items showed excellent fit (CFI = 0.98; RMSEA = 0.05; $\chi^2(18) = 25.912$; $p = .102$) when the error of items 1 and 2 (reasons for starting the degree) and 3 and 4 (career applicability) were allowed to co-vary.

3. Results

3.1. Overview of knowledge and usage responses

Knowledge of ChatGPT/AI was high within the sample, with 83.1% of students saying that they had heard of it before. When asked if they would use ChatGPT/AI to help write an assignment, 31.9% answered "Yes" and 1.9% answered "Prefer not to say", with the remaining 66.2% saying that they would not use AI in this way. Predictably, the proportion of students who reported having already used it for an assignment was smaller – 15% said "Yes" and 1.9% answered "Prefer not to say".

3.2. Predicting intention to use and actual use

Next, we ran a multiple binary logistic regression to predict intention to use (the "would you use" question). We coded the "Yes" and "Prefer not to say" as 1 and "No" as 0 for this analysis and included (1) DAS; (2) conscientiousness and agreeableness subscales from the BFI; (3) Machiavellianism and narcissism from the SD3; and (4) SSSE. With student consent, we accessed their student records to give us access to their (5) average grade for the past year, standardized within year group and (6) year of study. Descriptive statistics and correlations for the measures used in the models can be found in Table 2.

The resulting model (see "Would Use" in Table 3) was significant and showed goodness of fit, though it had a poor classification accuracy (46%). Of the variables entered into the analysis, only degree apathy and year of study were statistically significant. Specifically, for every 1 *SD* increase in degree apathy, students were 117.3% more likely to be in the "Yes" category. Compared to first year students, second year students were 67.7% less likely to select "Yes", though there was no difference between first and final year students. Running the same model, but this time predicting actual use (the "Have Used" model in Table 3) produced a significant but weak model with even poorer classification accuracy (15%) and only one significant predictor. For every 1 *SD* increase in SSSE, the likelihood of having used ChatGPT / AI tools decreased by 3.9%.

Because 17% of the students reported never having heard of ChatGPT/AI tools before the study began, it was feasible that these individuals (a) may have not felt they understood the tools well enough to decide if they wanted to use them, and (b) would, by default, have not used them before. If so, these factors could have impacted the sensitivity of the analysis. We decided to run the models again, including only those participants who had previously known about ChatGPT/AI before they began the study. Doing so produced a better model of prospective use ("Would Use (K)" in Table 3) with slightly better classification accuracy (49%) but no other qualitative difference; a 1 *SD* increase in degree apathy was related to a 144.6% increase in likelihood that a participant reported that they would use AI tools, and second year students were 66.6% less likely to use AI in future than first year students. Similarly, modest improvements were found in the "Have Used (K)" model predicting previous use (now correctly classifying 23% of cases), with a 1 *SD* increase in SSSE relating to a 5% decrease in likelihood of having used AI tools in previous assignments, though the model was not a good fit according to the Hosmet & Lemeshow test. No predictors other than study skills were significant.

In sum, the willingness to use ChatGPT or AI writing tools for assignments was positively predicted by level of apathy towards one's degree and cohort effects, though the model was able to classify those who responded "Yes" correctly less than half the time. These predictors did not in turn predict actual past use. Only lack of study skills predicted this, though the model was not particularly sensitive – classifying <25% of cases of use correctly.

3.3. The role of risk and punishment

Using a repeated measures ANOVA, we found a significant effect of risk on likelihood to use ($F(1.765, 954) = 118.989$, $p < .001$). As with all repeated measures ANOVAs and ANCOVAs reported here, we used Greenhouse-Geisser corrections to account for violations of the sphericity assumption. All other assumptions were met. In the case of risk, this significant effect was comprised of linear ($F(1,159) = 141.949$, $p < .001$, $\eta_p^2 = 0.472$), quadratic ($F(1,159) = 167.978$, $p < .001$, $\eta_p^2 = 0.514$), and cubic ($F(1,159) = 14.430$, $p < .001$, $\eta_p^2 = 0.083$) relationships, suggesting that the relationship between risk and likelihood of use to be curvilinear in nature. As can be seen in Fig. 1, likelihood of using ChatGPT / AI decreased rapidly with increasing risk. If there was no risk of getting caught (0%) the average score fell between "Slightly" and "Moderately". Likelihood decreased sequentially every stage of risk above 0% (all *ps* < 0.006 using Bonferroni corrections), however, the effect of increased risk showed diminishing returns and increases risk past 75% showed no subsequent decrease in likelihood (all *ps* > 1.00). Full post-hoc analysis tables for this and all ANOVAs/ANCOVAs are available in the supplementary materials. **Numerical values for the descriptive statistics are also available in the supplementary materials (visual representations are shown in Figs. 1 and 2).**

In terms of consequence, a repeated measures ANOVA also revealed significant within-subjects effect ($F(2.390, 954) = 79.038$, $p < .001$) comprised of linear ($F(1,159) = 124.222$, $p < .001$, $\eta_p^2 = 0.438$), quadratic ($F(1,159) = 54.092$, $p < .001$, $\eta_p^2 = 0.254$), and cubic ($F(1,159) = 60.713$, $p < .001$, $\eta_p^2 = 0.276$) relationships. As can be seen in Fig. 2, likelihood of use decreased with increasing punishment in a similar curvilinear pattern. If there was no punishment, the average score fell between "Slightly" and "Moderately". Likelihood decreased between no punishment and having to re-do the assignment and then again when having to re-do the assignment while being capped at a "pass" (all *ps* < 0.001). However, past this point there was no increased impact of punishment (all *ps* > 1.00) except for the worst punishment possible (expulsion). Likelihood of using ChatGPT when the consequence was expulsion was lower than when the punishment was having to redo the assignment while being capped at a pass (**$p = .003$**). All other punishments were similar to expulsion (all *ps* > 0.074).

Because degree apathy was a significant predictor in the regression analysis, we ran the risk and punishment analyses again including it as a covariate. The data met the additional assumptions of ANCOVA, though it's worth nothing that while degree apathy showed a linear relationship with the dependant variables, there was a minor floor effect because many students gave themselves the lowest degree apathy score. In the risk ANCOVA the effect of risk was now non-significant ($F(1.819, 948)$

Table 2
Descriptive statistics and correlations for the continuous variables used in the regression analyses.

Factor	*M*	*SD*	1.	2.	3.	4.	5.	6.
1. Average Grades	67.04	9.18						
2. Degree Apathy	2.73	1.01	−0.169*					
3. Conscientiousness	31.99	5.70	0.067	−0.386**				
4. Agreeableness	33.96	6.25	−0.001	−0.148	0.263 **			
5. Machiavellianism	2.91	0.70	−0.120	0.208**	−0.157*	−0.472 **		
6. Narcissism	2.46	0.59	−0.161*	−0.115	0.228**	−0.115	0.416**	
7. Study Skills	96.18	13.24	0.206**	−0.328**	0.306**	0.087	−0.026	0.254**

Note: * $p < .05$; ** $p < .01$ All participants ($N = 160$) completed all measures.

Table 3
Logistic regressions predicting participants who would use and have used ChatGPT/AI tools to help with university assignments. Also shown are version of the models (labelled as 'K') including only participants who knew about ChatGPT/AI tools before participating in the study.

	Would Use			Would Use (K)			Have Used			Have Used (K)		
Factor	*B*	*SE*	Exp(B)	*B*	*SE*	Exp(B)	*B*	*SE*	Exp(B)	*B*	*SE*	Exp(B)
Degree Apathy	**0.776*****	**0.223**	**2.173**	**0.894*****	**0.261**	**2.446**	0.171	0.245	1.186	0.203	0.268	1.225
Conscientiousness	−0.014	0.038	0.986	0.002	0.043	1.002	−0.007	0.046	0.993	0.008	0.051	1.008
Agreeableness	0.070	0.041	1.072	0.083	0.045	1.086	0.065	0.050	1.067	0.085	0.053	1.088
Machiavellianism	−0.309	0.369	0.734	−0.227	0.427	0.797	0.579	0.449	1.785	0.388	0.496	1.474
Narcissism	0.079	0.398	1.083	0.281	0.439	1.325	0.195	0.471	1.215	0.406	0.499	1.501
Study Skills	−0.028	0.017	0.972	−0.043	0.019	0.958	**−0.040***	**0.020**	**0.961**	**−0.051***	**0.022**	**0.950**
Average Grades (*z*)	−0.041	0.199	0.960	−0.042	0.218	0.959	−0.186	0.244	0.830	−0.295	0.253	0.745
2nd Year Student	**−1.130***	**0.488**	**0.323**	**−1.096***	**0.534**	**0.334**	−0.658	0.626	0.518	−0.616	0.660	0.540
3rd Year Student	−0.426	0.505	0.653	−0.245	0.541	0.783	0.533	0.598	1.704	0.713	0.615	2.040
Constant	−0.793	2.714	0.453	−1.424	2.916	0.241	−2.515	3.286	0.081	−2.561	3.416	0.077
χ^2	33.047, $df = 9$, $p < .001$			33.638, $df = 9$, $p < .001$			18.863, $df = 9$, $p = .026$			20.867, $df = 9$, $p = .013$		
-2LL	171.549			139.134			126.384			110.559		
Nagelkerke R^2	0.259			0.307			0.186			0.231		
Hosmet & Lemeshow	$p = .095$			$p = .156$			$p = .063$			$p = .039$		
Classification accuracy	0.463			0.489			0.148			0.231		
N for the analysis	160			133			160			133		

Note: * $p < .05$, *** $p < .001$. z = Standardized.

= 1.478, p = .231). However, there were significant risk by degree apathy effect (F(1.819, 948) = 8.413, $p < .001$) comprising of linear (F(1,158) = 17.776, $p < .001$, $\eta_p^2 = 0.066$) and quadratic (F(1,158) = 2.698, $p = .005$, $\eta_p^2 = 0.048$) interactions. To examine the impact of degree apathy on the relationships, we generated estimated marginal means at high (+1 *SD* from the mean) and low (−1 *SD* from the mean) - an approach more rigorous than creating separate artificial high and low degree apathy groups using, say, a median split. Fig. 2 illustrates how high and low levels of degree apathy increase willingness to use ChatGPT or AI for assignments, but only under low risk of getting caught. Specifically, when degree apathy is high, likelihood reduces at every increase in risk level from 0% to 75% (all $ps < 0.006$). However, there is no subsequent reduction in risk beyond this (all $ps = 1.00$). For the low degree apathy group, the effect of risk has a larger diminished returns effect. From 0% to 25% there are reductions (all $ps < 0.001$) but beyond this **a single additional increment of** risk of getting caught did not lead to significantly lower likelihood (all $ps > 0.317$ **for consecutive conditions**). The results are likely driven by the fact that in the absence of risk, those low in degree apathy have lower likelihood scores to begin with, meaning that reduction in likelihood meets a floor effect for this group sooner than the high degree apathy group.

The consequence ANCOVA yielded similar results. There was no longer an effect of consequence (F(2.446, 948) = 0.818, $p = .463$), but there was an interaction between consequence and degree apathy (F(2.446, 948) = 5.322, $p = .003$) marked by a linear relationship (F(1,158) = 11.359, $p < .001$, $\eta_p^2 = 0.067$). Those with higher degree apathy were more willing to use ChatGPT or AI under conditions of no punishment or mild punishment. When degree apathy is high, increased punishment reduced risk incrementally from no punishment to retaking the assignment with a score "cap" (all $ps < 0.001$), but punishments beyond this made little difference to likelihood (all $ps > 0.085$). The only exception was expulsion which did show a reduction effect over retaking the assignment with a score "cap" (p = 0003). For the low degree apathy group, the results were qualitatively the same, though this time the likelihood of use when the punishment was expulsion was no lower than when the publishment was retaking the assignment with a score "capped" at a pass. Together, the results suggest that consequence effects the degree apathy groups in similar ways, though expulsion might be a greater deterrent to those with a particularly high degree apathy score and thus higher "baseline" likelihood of use.

4. Discussion

In this study, we examined the factors that predict the likelihood that students will employ ChatGPT or other AI tools to engage in academic dishonesty, as well as mechanisms that could be employed to reduce AI-assisted cheating from occurring. To our knowledge this is the first study to explore this topic. The choice of predictors that we included in our model was informed by the existing literature on plagiarism in coursework. Previous studies have demonstrated that plagiarism is more likely to occur when students are low in conscientiousness and/or agreeableness (Giluk & Postelthwaite, 2015), high in Machiavellianism and narcissism (Williams et al., 2010), amotivated or apathetic towards their studies (Krou et al., 2021), low in study skills self-efficacy (Lee et al., 2020), and have poor academic ability (Paulhus & Dubois, 2015). Perhaps the most surprising result from the current study is that, despite the strong evidence for personality and study skills being key predictors of cheating and academic misconduct, basic motivation about the student's degree course was the strongest predictor of willingness to use ChatGPT / AI. This confirms empirically what seasoned academics have known for some time, that students who show less interest in their course, just want to "get by", and derive no sense of meaning or purpose from their studies are prone to course disengagement and worse academic outcomes. The newly formed Degree Apathy Scale therefore has potential research and pedagogical value. Possible uses include examining how effective academic and employability skills modules are at helping students see the value of their course, using it as a tool for detecting students who are "at risk" of disengagement from the course, and using it alongside careers guidance to empower students to make informed choices about their education options. Given that this is a new measure, it would be pertinent to conduct further studies to test the reliability and validity of the Degree Apathy Scale beyond the current sample – though the internal consistency of the scale was shown to be good.

The non-significant effects of the personality factors in this study could be accounted for in a number of ways. One explanation could stem from the fact that we asked our participants to provide self-reports of past and probable future cheating behaviour. Although self-reports are efficient methods of collecting data about academic dishonesty (Robinson, Amburgey, Swank, & Faulker, 2004), it is possible that the participants (particularly those who were more inclined to cheat) may have concealed the true nature and extent of their cheating. Credibility is a concern when using this method of measuring academic dishonesty (Paulhus, 1991; Simpson & Yu, 2012). Rates of under-reporting cheating would likely be higher in participants who scored higher in Machiavellianism (which is associated with manipulating others to gain an advantage, such as by withholding information) who were also predicted to be likely to cheat, which might explain the absence of

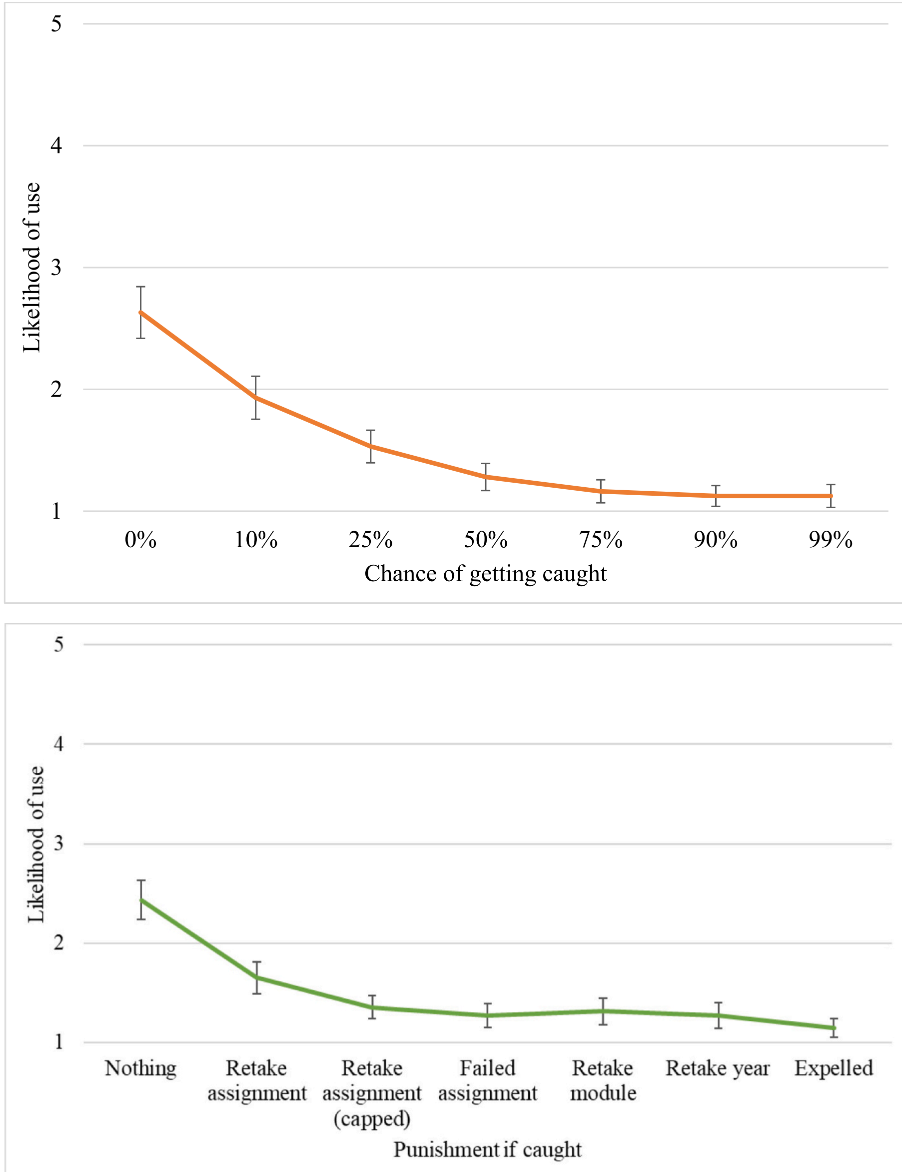

Fig. 1. *Likelihood of using ChatGPT / AI to write an assignment as a function of risk of getting caught (upper, orange) and degree of punishment if caught (lower, green). Error bars represent 95% confidence intervals.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

significant effects of this variable. The same principle would hold for reports of past AI use in assignments. However, while we cannot guarantee that the self-report data is entirely accurate, we would argue that there is value to using this kind of data in studies of AI use to cheat on assignments. For example, Williams et al. (2010) examined factors related to academic dishonesty in two studies – one relied on self-report measures and the other was based on objective scores, generated using Turnitin, which reflected the percentage of the student's assignment that overlapped with existing sources. The pattern of correlations was similar in both studies, and the overall prevalence of cheating was actually lower when measured objectively. In other words, the self-report data *overestimated* the level of academic dishonesty and revealed the same findings as the objective data. Furthermore, there is currently no reliable method of determining whether an essay *was* generated using ChatGPT, so an objective measure is not yet available as an alternative.

Another explanation for the unexpected findings of this paper could be that the sample was self-selecting and therefore liable to be unrepresentative of the wider student population. It could be argued that students who took part were a) more conscientious, b) more agreeable and c) higher achievers than those who did not complete the questionnaire. The first two arguments are refuted by the fact that national UK estimates of personality reveal that our sample had similar levels of conscientiousness ($M = 3.65$ vs 3.55 here) and agreeableness ($M = 3.74$ vs 3.77 here; Rentfrow, Jokela, & Lamb, 2015). As for the sample being high achievers, we used a one-sample *t*-test to compare the standardized degree grades that we used as a measure of previous academic achievement to those of the whole year group. This indicated that the mean scores of our participant group were not significantly different from zero. That is, the sample mean was not dissimilar from the cohort mean. Therefore, the evidence suggests that the pattern of findings that we have reported in the current study are not solely artefacts of a self-selection bias in our sample.

The third aim in this study was to determine the extent to which potential for academic dishonesty could be assuaged by a) increasing the likelihood that cheating would be detected and b) increasing the severity of the punishment should the student get caught engaging in unfair practice. In both cases, the pattern was clear – students were much more likely to cheat if they were not going to be caught or severely punished.

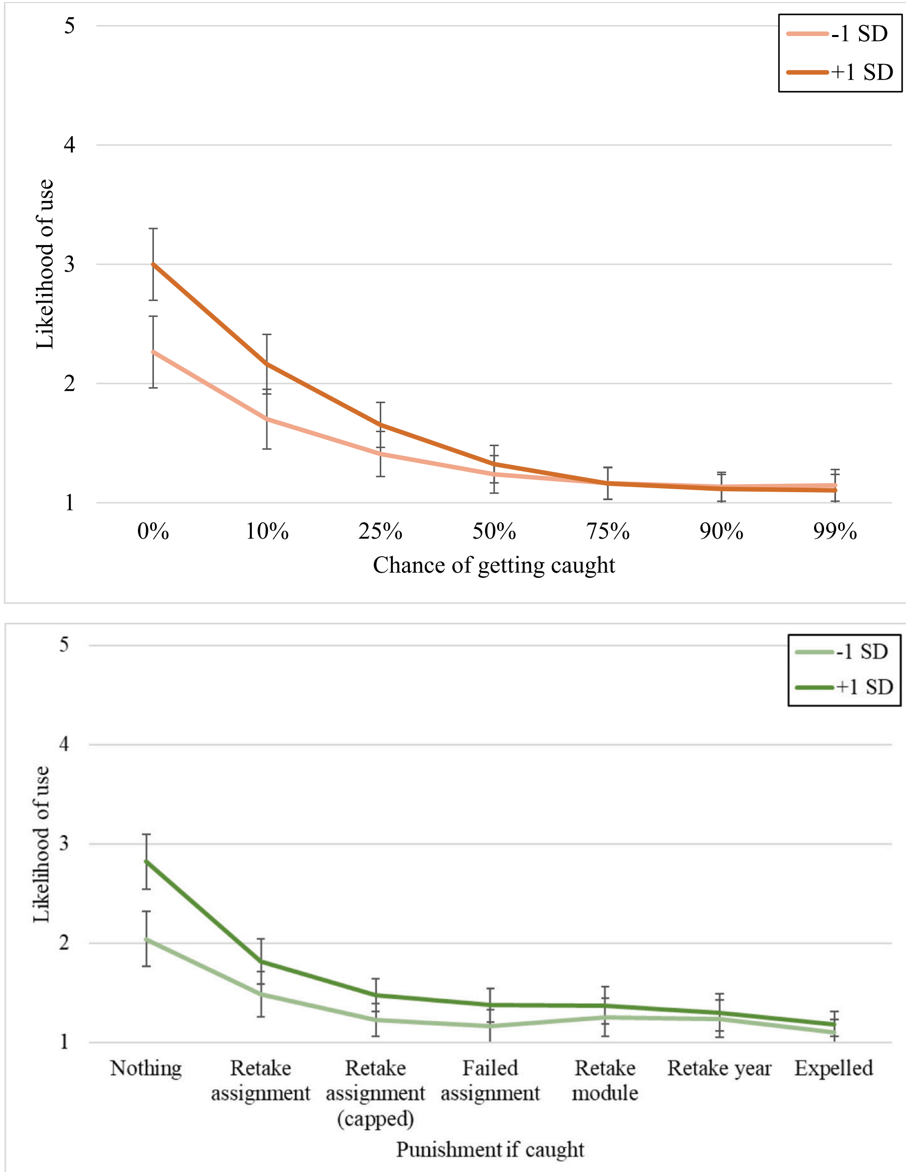

Fig. 2. *Likelihood of using ChatGPT / AI to write an assignment as a function of risk of getting caught (upper, orange) and degree of punishment if caught (lower, green). Separate lines are displayed for those high (+1 SD) and low (−1 SD) in degree apathy. Error bars represent 95% confidence intervals.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Participants reported significantly lower likelihood of cheating with each increment of risk of detection up to a 50% chance of getting caught. Participants also reported significantly lower likelihood of cheating with each increase in punishment up to reducing the maximum attainable grade to the minimum passing grade.At lower levels of risk and consequence, the likelihood of cheating was higher among students who scored high on the DAS. This indicates that a) there are straightforward methods to dramatically reduce the likelihood of academic dishonesty related to AI use and b) that a lack of motivation is more likely to result in unfair practice, as well as the established risks of disengagement, withdrawal from the programme of study, and lower academic achievement. It's also worth noting that the effect of risk and punishment on likelihood of use followed a curvilinear pattern. This suggests that moderate risk and punishment serve as similar levels of deterrent to high risk and severe consequences. Educators seeking to reduce AI tool abuse among their students may not need infallible detection and scorched earth punishments to do so.

It is important to note that participants use of ChatGPT or AI tools does not always constitute “cheating” or academic misconduct. For example, how a student may use these tools can vary drastically (e.g., using AI tools to generate an entire essay is different to using these tools to rephrase a sentence or explain a technical term). If participants in our sample who used AI tools simply as an editing or education tool responded in the affirmative to the questions about using ChatGPT or AI tools to help them with their assignment this may well dilute our results, thus accounting for some of our unexpected findings. We argue that the fact that the likelihood of using these AI tools was impacted by the level of risk indicates that the participants were probably considering this as academic dishonesty rather than a legitimate study technique, but the current data does not allow us to draw a definitive conclusion in this regard. However, we acknowledge that the fact that we did not explicitly state that participants should answer with reference to “cheating” may limit the application of our findings, and that future research could aim to determine what predicts legitimate use of AI tools as a study skill by explicitly differentiating between the two potential use cases in the questions posed to participants. At the same time, it is worth recognising that this research was conducted in early March 2023 when ChatGPT was first entering public awareness and discussed primarily in context of its use as a tool for cheating. This, coupled with the study's emphasis on anonymity and questions around “risk” and “punishment”. Thus, we are confident that the study's context was clear to the participants.

Assuming this confidence to be misplaced, it could be that differences in the interpretation of “AI use” in the study is a contributing factor in the number of participants who were correctly classified by our regression models. If a proportion of participants were interpreting the questions as pertaining to legitimate AI use rather than dishonesty, then the relationship between established predictors of cheating and the outcome variable in our study would necessarily be weaker. Nevertheless, our results still provide evidence of who is likely to use these tools and the conditions under which they are likely to use them. In conclusion, it appears that the circumstances under which students are more prone to using AI-tools to cheat on assignments are similar to those that lead to increased likelihood of cheating by other methods or plagiarising text from another student. This is not surprising, but it could be argued that it is evidence that the concerns of educators are overblown – AI will not necessarily cause an increase in the prevalence of academic dishonesty, merely provide an alternative method for those students who were inclined to cheat in any case. We have also provided empirical evidence that simple steps could be taken to prevent the use of AI to outsource student assignments in the short term. In the longer term, however, we would suggest that methods of assessing students are designed such that using ChatGPT would not be possible (e.g. oral presentations, video blogs), would not be effective (e.g. application of theoretical knowledge to solving real-world problems) or is a necessary component (e.g. ask ChatGPT to answer this question, then critique the response that is generated).

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CRediT authorship contribution statement

David Playfoot: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Martyn Quigley:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Andrew G. Thomas:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iheduc.2024.100950.

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