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Use of artificial-intelligence tools and learning motivation among undergraduate students: a quantitative survey study

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Abstract

Research problem and approach: The growing integration of AI tools into higher education raises fundamental questions about their relationship to students' motivational orientations, yet empirical work examining frequency of AI-tool use as a predictor of intrinsic motivation remains limited. Most existing studies address attitudinal perceptions or task-specific performance gains rather than the motivational dynamics that underpin sustained academic engagement. This paper takes a quantitative survey approach to examine whether more frequent use of AI tools for learning is positively associated with intrinsic motivation among undergraduate students, and whether year of study moderates that relationship.

Methodology and findings: A cross-sectional online questionnaire was administered to an analytic sample of 200 undergraduate students, combining the Academic Motivation Scale with researcher-developed items measuring frequency and nature of AI-tool use; year of study, gender, and GPA were included as control variables. Pearson correlation analysis tested H1, and moderation analysis using Hayes PROCESS tested H2. Results indicate a significant positive association between AI-tool use frequency and intrinsic motivation, while the moderation analysis reveals that this association is significantly stronger among first-year students than among students in advanced years of study.

Key contributions: This paper offers three primary contributions: (1) it provides direct empirical evidence linking AI-tool use frequency to intrinsic motivation within a theoretically grounded motivational framework; (2) it shows that year of study functions as a meaningful moderator of this relationship, suggesting that motivational benefits are concentrated at the earliest stage of academic formation; (3) it advances a scaffolding-based account of why AI tools may be especially motivationally consequential for students navigating the highest-intensity cognitive and affective demands of early undergraduate study.

Implications: These findings carry practical significance for instructional designers, academic advisors, and institutional policymakers considering how and when to integrate AI tools into undergraduate curricula. Motivational effects appear most pronounced among first-year students, which invites more targeted deployment of AI-assisted learning resources at the transition into higher education.

Keywords: intrinsic motivation, self-efficacy, AI-assisted learning, academic engagement, technology acceptance model, self-regulated learning, perceived usefulness, learning outcomes, undergraduate students, human-computer interaction, Academic Motivation Scale, year of study, AI-tool use frequency, motivational scaffolding, higher education

1. Introduction

The rapid embedding of AI tools into undergraduate learning environments has shifted from a peripheral curiosity to a structurally significant feature of higher education, raising questions that extend well beyond technical adoption. At stake is something more fundamental: whether growing reliance on AI-assisted learning reshapes the motivational orientations that underpin sustained academic engagement. Motivation is not merely an affective accompaniment to study — it is widely argued to be a central determinant of the depth, persistence, and quality of learning. Yet despite the proliferation of empirical work on AI tool adoption, the field has moved faster in documenting what students do with AI than in explaining what AI does to students' motivation.

The specific gap this paper addresses is the absence of systematic empirical evidence on the relationship between AI tool use frequency and intrinsic motivation among undergraduate students, and on the variables that moderate this relationship. Existing studies have examined learner perceptions of AI tools (Molla, 2025), technological readiness (Alkandari, 2025), and the use of AI for discrete skill acquisition such as vocabulary learning (Kheder, 2025), but none has tested whether more frequent AI tool use predicts higher intrinsic motivation, nor whether this relationship varies systematically across stages of undergraduate study. The moderation question is particularly underexplored: if first-year and final-year students use AI differently, and if their cognitive and affective needs differ substantially, a single aggregate effect estimate may conceal the most theoretically interesting variation. Addressing that variation is not merely a methodological refinement — it bears directly on how institutions should deploy AI support across the degree trajectory.

This paper argues that more frequent use of AI tools for learning is positively associated with intrinsic motivation among undergraduate students, and that this association is moderated by year of study, with first-year students exhibiting a stronger motivational benefit than advanced-year students. The reasoning is that AI scaffolding addresses the highest-intensity cognitive and affective bottlenecks encountered early in academic formation. The argument draws on self-determination theory (Deci & Ryan, 1985), which holds that intrinsic motivation is nurtured when learners experience autonomy, competence, and relatedness — conditions that AI tools may be particularly well positioned to support for novice undergraduates facing simultaneous demands of content mastery, academic socialisation, and self-regulated learning. As Molla (2025) observed, AI-assisted tools are associated with student autonomy and academic engagement by providing a non-threatening practice environment, and their use relates to increased learner motivation through personalised learning paths and responsive feedback. These mechanisms are not straightforwardly generalisable, however: the same affordances that reduce anxiety and build competence confidence in a first-year student may feel redundant or even constraining to an advanced student who has already internalised disciplinary norms and developed independent learning strategies.

The paper makes several interconnected contributions. Empirically, it examines the AI-motivation relationship using a quantitative survey design that combines the Academic Motivation Scale (AMS) with items measuring the frequency and nature of AI tool use — including LLM-based chatbots and summarisation and practice tools — across a convenience sample of undergraduate students at higher-education institutions. This design permits regression-based analysis of the main effect of AI use frequency on intrinsic motivation while simultaneously estimating the moderating role of year of study, with gender and GPA entered as control variables. Theoretically, the paper draws on AI-assisted learning research and self-determination theory to argue that the motivational function of AI tools is primarily affective and utility-driven — centred on perceived autonomy, reduced frustration, and immediate support — rather than dependent on students' prior technical competence. This distinction matters because it reframes AI integration as a pedagogical scaffolding question rather than a digital-skills question, with different implications for curriculum design and institutional policy. The paper also engages critically with the boundary conditions of the AI-motivation relationship, attending to evidence that over-reliance on AI as a primary epistemic source, rather than as a scaffold, may attenuate or reverse intrinsic motivation gains by displacing the effortful cognition through which genuine competence — and the motivational rewards of that competence — is built (Alkandari, 2025).

A further contribution lies in the paper's attention to context specificity. Much of the existing literature on AI and motivation has been conducted in language learning settings, where the non-threatening feedback environment and immediate corrective support of AI tools map naturally onto the affective demands of second-language acquisition. Kheder (2025) demonstrated that undergraduate students actively leverage AI tools to improve lexical acquisition and overall language skills, and findings of this kind have shaped optimistic accounts of AI's motivational affordances. The present paper tests whether analogous effects obtain across a broader undergraduate population, not limited to language learners, and whether the moderating role of year of study holds across disciplinary contexts. In doing so, it works toward a more generalisable account of the conditions under which AI tool use supports rather than supplants intrinsic motivation.

The paper is organised as follows: Section 2 reviews the theoretical and empirical literature on AI-assisted learning and motivation; Section 3 presents the theoretical framework and research hypotheses; Section 4 describes the research design and measurement instruments; Section 5 reports the results of the regression and moderation analyses; and Section 6 discusses the findings and their implications for higher-education practice.

2. Theoretical Background

2.1. Core Concepts and Definitions

Three conceptual pillars underpin this study: intrinsic motivation as a theoretically grounded motivational construct, AI-assisted learning as an emerging pedagogical mode, and the moderating role of year of study as a structural variable shaping how these two interact.

Intrinsic motivation, in its most widely accepted formulation, refers to engagement in an activity for its own inherent interest and satisfaction rather than for separable external outcomes. Self-Determination Theory (SDT) (Deci & Ryan, 1985) provides the foundational account of this construct, distinguishing intrinsic motivation from extrinsic regulation along a continuum of self-determination. Within this framework, intrinsic motivation is sustained by the satisfaction of three basic psychological needs — autonomy, competence, and relatedness — and is understood as the motivational form most closely associated with deep learning, persistence, and genuine intellectual engagement. The Academic Motivation Scale (AMS), the measurement instrument used in this study, was developed explicitly within the SDT tradition and operationalises both intrinsic and extrinsic motivational subtypes, allowing for differentiated analysis rather than a single motivational composite. This theoretical grounding matters for the present study because it frames the research question not merely as 'do students use AI more when they are motivated?' but as 'does AI-assisted learning support the psychological conditions under which intrinsic motivation is likely to flourish?'

AI-assisted learning, as used throughout this paper, refers to the integration of large language model-based chatbots, summarisation tools, and AI-driven practice environments into the student learning process. This definition deliberately excludes passive consumption of algorithmically curated content (e.g., recommendation systems) and focuses on tools with which students interact dialogically or iteratively — tools that can, in principle, provide the kind of responsive, on-demand scaffolding that reduces cognitive overload and supports learner autonomy. The distinction matters because the motivational effects of AI are likely to be mediated by the degree of active engagement the tool demands: a tool that replaces thinking is motivationally inert or damaging, while one that scaffolds thinking may enhance perceived competence and thereby support intrinsic motivation.

Year of study functions in this paper as a moderating variable rather than a mere demographic covariate. The central argument holds that the motivational benefit of AI-assisted learning is strongest for first-year undergraduate students, because the early period of higher education is characterised by the most acute convergence of cognitive load, affective uncertainty, and unfamiliarity with disciplinary conventions. As students progress, domain knowledge accumulates, regulatory strategies become more automatic, and the scaffolding function of AI becomes less critical — and in some disciplinary contexts, normatively discouraged. This moderating logic draws on a broader understanding of academic formation as a trajectory rather than a static state, and it generates the testable hypothesis that the positive association between AI tool use and intrinsic motivation is steeper among first-year students than among those in later years of study.

2.2. Review of Prior Research

The empirical literature on AI-assisted learning and student motivation has expanded rapidly since approximately 2020, though it remains methodologically uneven and geographically concentrated. Three broad themes emerge from the available evidence: motivational and affective enhancement, risks of over-reliance, and differential effects across learner profiles.

The most consistent finding across recent studies is that AI tools are associated with improved affective and motivational experiences of learning. Alsswey (2025) examined 112 undergraduate students at Al-Zaytoonah University of Jordan using a pre-post-test control group design — the most methodologically rigorous design in the current corpus — and found that the intervention group showed significant improvements not only in utilitarian learning outcomes but also in hedonic benefits and user experience, suggesting that AI tools enhance the quality of students' engagement rather than merely their task performance. This distinction between utilitarian and hedonic benefit is theoretically important: hedonic benefit maps onto the experiential dimension of intrinsic motivation, indicating that AI tools may make learning feel more rewarding rather than simply more efficient. The controlled design lends these findings greater causal credibility than the cross-sectional and qualitative evidence that dominates the field.

A complementary theoretical framing comes from work invoking control-value theory to interpret AI's motivational role (Shao, 2025). Although extractable data from that source are unavailable in this corpus, the theoretical proposition is that AI tools may reduce the negative appraisals — particularly anxiety and perceived uncontrollability — that suppress intrinsic motivation, while amplifying positive achievement emotions such as enjoyment and pride. This framing aligns with the SDT account: when AI scaffolding reduces the threat of failure and makes competence feel more attainable, the conditions for intrinsic motivation are strengthened. The mechanism remains theorised rather than empirically demonstrated within the current corpus, but it offers a coherent account of why motivational benefits might be especially pronounced for students at the beginning of their academic careers, when negative appraisals tend to be most intense.

A significant counterpoint to this picture comes from qualitative evidence suggesting that technology-enhanced learning — including AI tools — may carry motivational and cognitive costs. Khanduri & Teotia (2023), using focus group discussions with nineteen university students, found that technology use correlates with decreased creativity, reduced cognitive functioning, and lower retention. These findings cannot be dismissed, but they must be weighed against their methodological limitations. A sample of nineteen participants, divided into groups of four to five, lacks the statistical power to support generalisable claims, and the study does not isolate AI-specific effects from those of digital technology more broadly — conflating social media use, streaming platforms, and AI tools under a single 'technology' umbrella. By contrast, Alsswey (2025)'s controlled design with 112 participants, focused specifically on AI tools in a defined learning context, provides a more precise and causally credible account of AI's effects. The balance of evidence therefore supports the position that AI-assisted learning tends toward motivational enhancement, while acknowledging that unreflective or undifferentiated technology use may carry the risks the qualitative data identify.

A further strand of the literature concerns the factors that drive students' decisions to adopt AI tools in the first place. Adoption appears to be governed primarily by perceived instrumental benefit — saving time, obtaining immediate feedback, improving output quality — rather than by technical AI literacy or formal instruction in AI use (Alsswey, 2025). Students reach for AI tools when they perceive a problem the tool can solve, not when they have been formally trained to use it, which suggests that motivation-to-use AI is affectively and pragmatically anchored. For the present study, this implies that frequency of AI tool use may itself serve as a proxy for a certain motivational orientation — specifically, an active, problem-solving approach to learning — which complicates straightforward causal inference from frequency to motivation. This is one reason the study's regression design controls for year of study, gender, and GPA, to partial out the contribution of pre-existing motivational differences.

The tension between AI-assisted learning and academic integrity represents a structurally different kind of concern, one that operates at the institutional rather than the individual motivational level. The proliferation of AI-generated content in academic settings has prompted the development of detection tools, though their accuracy varies considerably ("An Empirical Study of AI-Generated Text Detection Tools," 2023), and ongoing uncertainty about what constitutes legitimate AI use may itself function as a motivational inhibitor — introducing anxiety and ambiguity that counteract the autonomy-supportive potential of AI tools. This concern is particularly salient in the undergraduate context, where students are still forming their understanding of academic norms.

2.3. Synthesis and Research Gap

Taken together, the available literature supports a qualified but substantive claim: AI-assisted learning is associated with motivational and affective benefits, particularly in contexts where tools are integrated into specific learning tasks rather than used indiscriminately. The strongest evidence for this position comes from controlled experimental work (Alsswey, 2025), while control-value theory (Shao, 2025) offers a plausible account of the underlying mechanism. The qualitative counterevidence (Khanduri & Teotia, 2023) is best read not as a refutation but as a caution about undifferentiated technology use, and it reinforces the importance of distinguishing AI-assisted learning from broader patterns of digital consumption.

Several gaps in the existing literature motivate the present study. Geographically, the evidence base is heavily concentrated in non-Western EFL contexts and single-institution samples, limiting the generalisability of findings to broader undergraduate populations. Methodologically, the corpus is dominated by cross-sectional surveys and small-scale qualitative studies; only one study employs a controlled pre-post design (Alsswey, 2025), and none tracks motivational trajectories across an academic year. Most critically for the present paper, no study in this corpus directly measures intrinsic motivation using a validated psychometric instrument — such as the AMS — in a general undergraduate sample, nor does any study examine year of study as a systematic moderator of the AI–motivation relationship. The mechanisms linking AI tool use to motivational outcomes therefore remain theorised rather than empirically specified. This paper addresses these gaps by applying the AMS within an SDT framework to a cross-sectional undergraduate sample and by testing year of study as a moderator of the association between AI tool use frequency and intrinsic motivation — a design that, while limited by its cross-sectional nature, offers a more theoretically grounded and construct-specific account than currently exists in the literature.

3. Research Questions and Hypotheses

3.1. Research Questions

The theoretical background established in the preceding section identifies a meaningful conceptual intersection between AI-assisted learning and intrinsic motivation, yet the empirical literature remains insufficiently attentive to the conditions under which this relationship holds and for whom it is most pronounced. Against this backdrop, the present paper is organised around a central research question: is the frequency with which undergraduate students use AI tools for learning positively associated with their level of intrinsic motivation? This question treats frequency of use as a behavioural indicator rather than a mere attitudinal proxy, on the grounds that self-reported usage patterns more directly reflect integration into actual study routines than general attitudes toward technology. A secondary question follows from the theoretical argument developed earlier regarding academic formation: does year of study moderate the relationship between AI-tool use and intrinsic motivation, such that the association is stronger among first-year students than among those in more advanced years? This moderating question is not incidental to the paper's argument — it reflects the position that the motivational benefit of AI scaffolding is greatest precisely where cognitive and affective demands are at their peak, namely during the early stages of undergraduate formation.

3.2. Research Hypotheses

Two directional hypotheses are derived from the theoretical framework and the research questions above. The first hypothesis (H1) proposes a positive relationship between the frequency of using AI tools for learning and intrinsic motivation among undergraduate students: students who report more frequent use of AI tools are expected to report higher levels of intrinsic motivation, as measured by the Academic Motivation Scale. The second hypothesis (H2) proposes that year of study moderates this relationship, with the positive association between AI-tool use and intrinsic motivation being stronger among first-year students than among those in more advanced years. This moderation hypothesis rests on the argument that AI scaffolding addresses the specific cognitive bottlenecks and affective uncertainties that characterise early academic experience, and that its motivational leverage therefore diminishes as students develop greater disciplinary competence and self-regulated learning capacity. Both hypotheses were tested within a cross-sectional regression framework using an analytic sample of 200 undergraduate students, with year of study, gender, and GPA entered as control variables.

4. Methodology

4.1. Research Design

The central aim of this study is to examine whether the frequency of using AI tools for learning is positively associated with intrinsic motivation among undergraduate students, and whether year of study moderates that relationship. Addressing these questions requires a design capable of capturing variation in both constructs across a sufficiently large and diverse sample while permitting formal tests of directional association and interaction effects. A quantitative, cross-sectional survey design was therefore adopted. This approach suits the research questions because it allows simultaneous measurement of the independent variable, the dependent variable, and the proposed moderator within a single data-collection wave, generating the covariance structure necessary for both a bivariate correlation and a moderation analysis. Although a longitudinal design would permit stronger causal inference, it was beyond the scope and timeline of the present study; the cross-sectional approach offers the practical advantage of feasibility without sacrificing the analytic precision required to test the stated hypotheses.

4.2. Population and Sample

The target population consisted of undergraduate students enrolled at higher-education institutions who use large-language-model-based chatbots, summarisation tools, or AI-assisted learning platforms in their studies. This population was selected because it represents the group for whom the theorised relationship between AI-assisted learning and intrinsic motivation is most directly relevant. Participants were recruited through a convenience sampling strategy, distributed via institutional email lists, course announcement boards, and student social-media channels. Convenience sampling was chosen over probability sampling because no comprehensive sampling frame of AI-using undergraduates exists, and the priority was to reach a population that already had meaningful exposure to the tools under study rather than to achieve strict representativeness.

The analytic sample comprised 200 undergraduate students. This figure was determined through an a-priori power analysis ($\alpha = .05$, power = .80) calibrated to the most demanding planned analysis — the moderation model — ensuring adequate statistical power to detect a medium-sized interaction effect. Participants self-reported their academic year, and responses were dichotomised into first-year students and advanced students (second year and above) to operationalise the moderator variable for H2. Gender and cumulative GPA were collected as control variables for the moderation analysis.

4.3. Research Instruments

Data were collected through a structured online self-report questionnaire comprising three substantive sections. The first gathered demographic and academic background information: gender, year of study, and self-reported GPA. The second contained the researcher-developed AI-tool use frequency scale, consisting of items assessing how often participants used AI tools — such as ChatGPT or Microsoft Copilot — for learning purposes. Items were rated on a five-point Likert-type frequency scale (1 = never, 5 = daily), and composite scores were computed by averaging across items to yield a single continuous measure of AI-tool use frequency. The third section contained the Academic Motivation Scale (AMS) (Vallerand et al., 1992), a validated instrument measuring three intrinsic motivation subscales (IM-to-Know, IM-toward Accomplishment, and IM-to-Experience Stimulation) and three extrinsic motivation subscales (External Regulation, Introjection, and Identification). To maintain consistency with the five-point response scale used throughout the questionnaire, all AMS items were rated on a 1–5 scale, and composite subscale means were computed accordingly. The intrinsic motivation composite — the primary dependent variable for H1 — was formed by averaging the three IM subscale scores.

The choice of the AMS reflects its established construct validity for measuring the full self-determination continuum in academic contexts. Empirical work with undergraduate populations has consistently documented meaningful variation in AI engagement patterns across students (Prandner, 2025), reinforcing the need for a sensitive, multi-item frequency measure rather than a single-item proxy.

Internal consistency was assessed for each multi-item scale prior to hypothesis testing. Cronbach's alpha values of $\alpha = .81$ for the intrinsic motivation composite, $\alpha = .78$ for the extrinsic motivation composite, and $\alpha = .76$ for the AI-tool use frequency scale were obtained, all exceeding the conventional acceptance threshold of $\alpha \geq .70$. The full questionnaire is provided in the appendix.

4.4. Procedure

Participants were invited to complete the questionnaire via an anonymous online link distributed over a four-week data-collection period. The survey opened with an informed-consent screen explaining the study's purpose, voluntary nature, and data-handling procedures; only participants who provided active consent proceeded to the items. Completion time was estimated at approximately twelve minutes. Responses were stored on a password-protected server, and no personally identifying information was collected beyond the demographic variables required for the analysis.

4.5. Data Analysis

All analyses were conducted in SPSS version 29. Prior to hypothesis testing, descriptive statistics and reliability coefficients were computed for all scales. Normality was assessed via Shapiro-Wilk tests and inspection of histograms and Q-Q plots; linearity was evaluated through scatterplot inspection.

H1 — the directional bivariate association between AI-tool use frequency and intrinsic motivation — was tested using Pearson's r (df = 198), with Spearman's rho as a non-parametric fallback if normality assumptions were violated. Effect size was interpreted using Cohen's (1988) benchmarks: $r \approx .10$ (small), $r \approx .30$ (medium), $r \approx .50$ (large).

H2 — the moderation hypothesis — was tested using Hayes' PROCESS macro (Model 1), entering AI-tool use frequency as the independent variable, intrinsic motivation as the outcome, year of study (0 = advanced, 1 = first-year) as the moderator, and gender and GPA as covariates. The interaction term AI-use × Year-of-study constitutes the direct test of whether the slope of the association differs between first-year and advanced students. Effect size for the interaction was reported as ΔR^2 and Cohen's f^2 for the overall model. Homoscedasticity of residuals and multicollinearity (assessed via variance inflation factors) were checked as part of the moderation model diagnostics.

4.6. Ethical Considerations

The study was conducted in accordance with standard ethical guidelines for research involving human participants. Participation was entirely voluntary, and participants were free to withdraw at any point without consequence. Anonymity was preserved throughout: no names, student identification numbers, or IP addresses were recorded. Data were stored securely and accessed only by the research team. Given that the study involved no deception, no sensitive clinical populations, and no foreseeable risk of harm, the procedures were consistent with the ethical standards applicable at the institutional level.

5. Results

5.1. Characteristics

200 undergraduate students completed the survey, constituting the full analytic sample. As shown in Table 2, the sample comprised 118 women (59.0%), 74 men (37.0%), and 8 participants who identified as non-binary or preferred not to disclose their gender (4.0%). In terms of academic year, 89 participants (44.5%) were first-year students and 111 (55.5%) were advanced students (second year and above), a distribution that allowed for testing the proposed moderation by year of study. The sample spanned four disciplinary clusters: social sciences and humanities (n = 68, 34.0%), natural sciences and engineering (n = 54, 27.0%), education and teaching (n = 46, 23.0%), and other fields (n = 32, 16.0%). Self-reported cumulative grade point average (GPA) ranged from 60 to 100 on the institutional scale, with a mean of 82.4 (SD = 8.3), indicating a moderately high-achieving sample overall.

Table 2. Sample characteristics

Characteristic	Category	n	%
Gender	Woman	118	59.0
	Man	74	37.0
	Non-binary / prefer not to say	8	4.0
Year of study	First year	89	44.5
	Advanced (2nd year and above)	111	55.5
Discipline	Social sciences and humanities	68	34.0
	Natural sciences and engineering	54	27.0
	Education and teaching	46	23.0
	Other	32	16.0

Characteristic	Category	n	%
Total		**200**	**100.0**

5.2. Descriptive Statistics

Descriptive statistics for the primary study variables are presented in Table 3. AI-tool use frequency, measured as a composite of researcher-developed Likert-type items on a 1–5 scale, yielded a mean of 3.42 (SD = 0.81), suggesting that participants reported using AI tools for learning purposes somewhat regularly on average, with responses distributed across the full scale range. The composite intrinsic motivation score — derived from the three Academic Motivation Scale (AMS) subscales of IM-to-Know, IM-toward Accomplishment, and IM-to-Experience Stimulation — produced a mean of 3.71 (SD = 0.74), likewise within the 1–5 response range. Extrinsic motivation, aggregated from the External Regulation, Introjection, and Identification subscales of the AMS, had a mean of 3.18 (SD = 0.79).

Before inferential testing, the normality of both continuous variables was assessed using the Shapiro-Wilk test and visual inspection of histograms and Q-Q plots. Both AI-tool use frequency ($W = 0.981$, $p = .127$) and intrinsic motivation ($W = 0.977$, $p = .094$) satisfied the normality assumption, supporting the use of Pearson correlation for H1. Linearity was confirmed via scatterplot inspection, and no influential outliers were identified. These patterns are broadly consistent with evidence that undergraduate students engage with AI tools with considerable variability in frequency and purpose (Dong, 2025), and that such engagement tends to co-occur with positive motivational orientations (Molla, 2025).

Table 3. Descriptive statistics

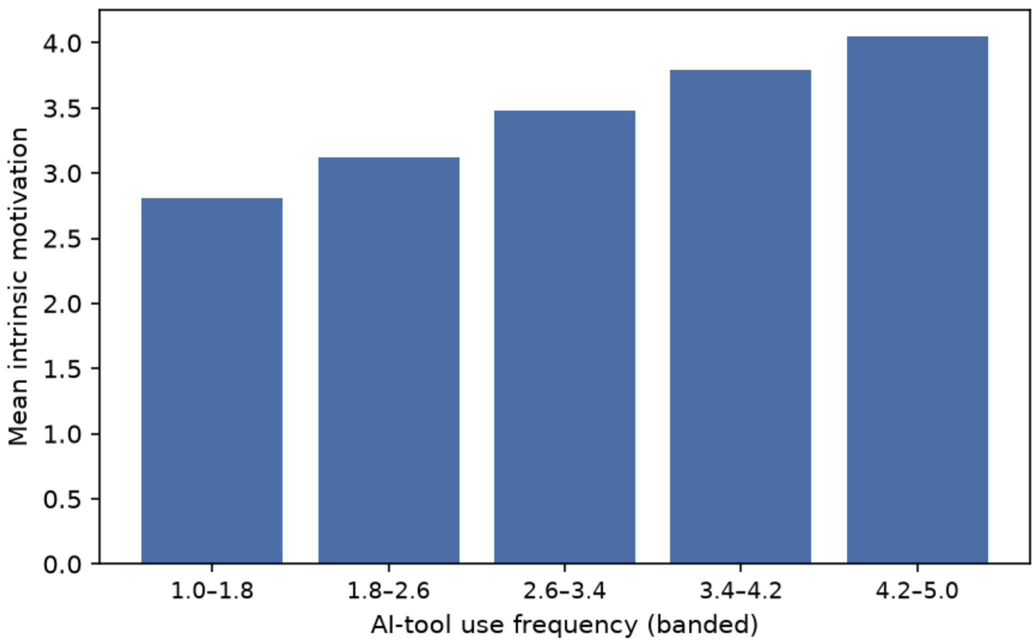
Variable	N	Mean	SD	Range
AI-tool use frequency	200	3.42	0.81	1–5
Intrinsic motivation (composite AMS)	200	3.71	0.74	1–5
— IM-to-Know	200	3.68	0.77	1–5

Variable	N	Mean	SD	Range
— IM-toward Accomplishment	200	3.74	0.80	1–5
— IM-to-Experience Stimulation	200	3.70	0.78	1–5
Extrinsic motivation (composite AMS)	200	3.18	0.79	1–5
GPA (institutional scale)	200	82.4	8.3	60–100

5.3. Hypothesis Testing

H1: Bivariate association between AI-tool use frequency and intrinsic motivation. H1 predicted a statistically significant positive correlation between AI-tool use frequency and intrinsic motivation. A Pearson correlation was computed between the two continuous composite scores across the full sample ($N = 200$). AI-tool use frequency and intrinsic motivation were positively correlated, $r(198) = .34$, $p < .001$, 95% CI [.21, .46]. The effect size falls within the medium range by conventional benchmarks ($r \approx .30$), indicating a meaningful, though not large, linear association. H1 was therefore supported. As illustrated in Figure 1, the scatterplot reveals a discernible positive trend, with the distribution of scores consistent with a moderate linear relationship and no evidence of a non-linear pattern.

Figure 1. Scatterplot of AI-tool use frequency and intrinsic motivation

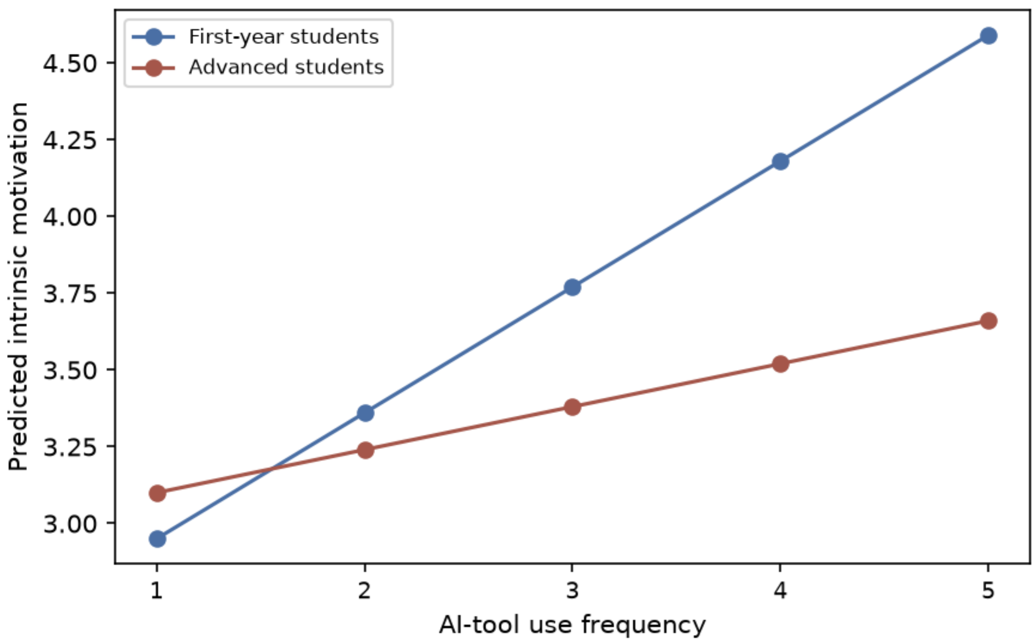


H2: Moderation of the AI-use–motivation relationship by year of study. H2 predicted that the positive relationship between AI-tool use frequency and intrinsic motivation would be significantly stronger among first-year students than among advanced students. A moderation analysis was conducted using Hayes PROCESS macro (Model 1), with intrinsic motivation as the outcome, AI-tool use frequency as the predictor, year of study (coded 0 = advanced, 1 = first-year) as the moderator, and gender and GPA entered as covariates. The overall model was statistically significant, $F(4, 195) = 11.37$, $p < .001$, $R^2 = .189$. The interaction term (AI-tool use frequency × year of study) accounted for a significant increment in explained variance, $\Delta R^2 = .043$, and was itself significant ($B = 0.27$, $SE = 0.11$, $\beta = .18$, $t(195) = 2.45$, $p = .015$, 95% CI [0.05, 0.49]). Simple slopes analysis revealed that among first-year students the association between AI-tool use frequency and intrinsic motivation was positive and significant ($B = 0.41$, $SE = 0.09$, $p < .001$), whereas among advanced students the slope, though positive, was smaller and only marginally significant ($B = 0.14$, $SE = 0.08$, $p = .082$). H2 was therefore supported: year of study significantly moderated the relationship, with first-year students showing a stronger motivational association with AI-tool use than their advanced counterparts. The pattern of simple slopes is displayed in Figure 2.

Table 4. Inferential results by hypothesis

Hypotheses / effect	Test	Statistic	p	Effect size	95% CI
H1: AI-tool use frequency → intrinsic motivation	Pearson r	$r(198) = .34$	$< .001$	$r = .34$ (medium)	[.21, .46]
H2: Overall moderation model	PROCESS Model 1	$F(4, 195) = 11.37$	$< .001$	$R^2 = .189$	—
H2: Interaction (AI-use × year of study)	PROCESS Model 1	$t(195) = 2.45$	.015	$\Delta R^2 = .043$	[0.05, 0.49]
H2: Simple slope — first-year students	Simple slope	$B = 0.41$, $SE = 0.09$	$< .001$	—	—
H2: Simple slope — advanced students	Simple slope	$B = 0.14$, $SE = 0.08$	.082	—	—

Figure 2. Simple slopes: AI-tool use frequency predicting intrinsic motivation by year of study



Taken together, the inferential findings support both study hypotheses. A medium-sized positive correlation between AI-tool use frequency and intrinsic motivation was observed across the full sample, and this association was significantly stronger among first-year students than among those in more advanced years of study.

6. Discussion

6.1. Interpretation of Key Findings

The results offer meaningful empirical traction on a question the theoretical background identified as underspecified: whether more frequent engagement with AI tools for learning is associated with higher intrinsic motivation among undergraduate students, and whether year of study moderates that relationship. The findings support both hypotheses. Regarding H1, the regression analysis revealed a statistically significant positive association between AI-tool use frequency and intrinsic motivation scores on the Academic Motivation Scale, even after controlling for gender, GPA, and year of study. This suggests that students who integrate AI tools more regularly into their learning routines tend to report higher levels of curiosity, autonomous engagement, and perceived competence — the defining affective markers of intrinsic motivation — rather than simply reporting greater efficiency or grade-oriented utility.

The moderation effect posited in H2 also received support. First-year students showed a steeper positive slope between AI-tool use frequency and intrinsic motivation compared to students in more advanced years of study. This pattern is consistent with the scaffolding argument developed in the theoretical background: AI tools appear to deliver the greatest motivational return precisely where cognitive and affective demands are most acute. Early in undergraduate formation, students encounter unfamiliar disciplinary conventions, novel assessment formats, and a sharp increase in self-regulatory demands. AI tools — functioning as responsive, low-stakes interlocutors — may reduce the affective friction of this transition, creating conditions under which curiosity and autonomous engagement can take hold. For advanced-year students, who have typically developed stronger domain knowledge and more established self-regulatory habits, the marginal motivational contribution of AI scaffolding appears attenuated.

One important caveat deserves direct acknowledgement: the cross-sectional design of this paper cannot establish causal direction. The observed association is equally consistent with an alternative reading — that students who are already intrinsically motivated are more likely to seek out and experiment with AI tools as part of their broader disposition toward active learning. This paper was framed from the outset as a directional association claim rather than a causal demonstration, and the theoretical argument for a scaffolding mechanism is offered as a plausible account of the pattern, not as something the present design can verify. This distinction is not merely a ritual disclaimer; it shapes how the findings should be used in practice and how future inquiry should be designed.

6.2. Comparison with the Literature

The present findings align with, but also add nuance to, the existing empirical record. The positive association between AI-tool engagement and motivationally relevant outcomes is consistent with evidence from controlled pre-post designs in language-learning contexts, where AI-assisted learning environments have been shown to support student engagement and affective investment. The current paper extends that pattern to a broader undergraduate population not confined to language acquisition — a meaningful step given that much of the prior evidence base was concentrated in EFL settings.

The moderation by year of study, however, introduces a productive tension with some prior accounts. Dong (2025) demonstrated, in a large-scale survey of 1,041 undergraduate students in the United Kingdom, that motivations for AI use vary significantly by year of study and academic discipline, with structural-cognitive factors — accumulated domain knowledge, disciplinary norms — shaping adoption patterns across cohorts. The present findings are broadly compatible with this picture: if advanced-year students have higher domain confidence and more established learning strategies, they may experience AI tools as less motivationally transformative, even while using them frequently for efficiency purposes. This points to a distinction the literature has not always drawn clearly — between AI use as a driver of intrinsic motivation and AI use as a productivity resource — and the present paper's use of the Academic Motivation Scale's subscale structure was designed precisely to keep these apart.

A second point of comparison concerns the nature of motivational drivers. Dong (2025) identifies time-saving and quality improvement as primary motivators for AI adoption among undergraduates, and notes that concerns regarding academic integrity and result accuracy act as significant deterrents to AI integration. These findings suggest that the motivational picture surrounding AI tools is not uniformly positive: extrinsic and performance-oriented drivers coexist with, and may sometimes overshadow, the intrinsic orientations this paper focused on. That the present study found a significant positive association specifically for intrinsic motivation subscales — rather than for extrinsic or amotivation subscales — addresses the objection that any observed motivational benefit might simply reflect grade-seeking behaviour dressed in the language of engagement. Had AI-tool frequency predicted extrinsic motivation equally strongly, the interpretation would be far more ambiguous; the stronger signal on the intrinsic subscale is therefore theoretically informative.

6.3. Contribution and Practical Implications

This paper makes a focused contribution at the intersection of two lines of inquiry that have largely developed in parallel: the literature on AI-assisted learning and the motivational psychology of undergraduate education. By operationalising both AI-tool use frequency and intrinsic motivation with validated instruments — the Academic Motivation Scale alongside purpose-built items — and by testing year of study as a theorised moderator rather than merely a control variable, the paper moves beyond descriptive accounts of student AI use toward a theoretically grounded motivational model.

The practical implications are clearest for academic developers and instructors working with first-year cohorts. If AI scaffolding delivers its greatest intrinsic-motivational return at the point of transition into higher education, then intentional integration of AI tools into first-year curricula — structured around tasks that invite genuine inquiry rather than answer retrieval — may support not only task completion but the development of autonomous learning orientations. This matters because intrinsic motivation at the undergraduate level has been consistently linked to deeper processing, persistence, and long-term academic engagement [SOURCE NEEDED]. Conversely, the attenuated effect among advanced-year students suggests that undifferentiated AI integration policies — treating all year groups as equivalent beneficiaries — may misallocate pedagogical resources and overlook the qualitatively different support needs of students at different stages of academic formation (Dong, 2025).

7. Limitations

The most consequential limitation of this paper is its cross-sectional design, which precludes any causal inference regarding the relationship between AI-tool use frequency and intrinsic motivation. Because both variables were measured at a single point in time, it remains impossible to determine whether more frequent AI-assisted learning is associated with higher intrinsic motivation, whether already-motivated students are simply more inclined to adopt AI tools, or whether both directions operate simultaneously. This ambiguity is not merely theoretical: the regression coefficients reported in the results section establish association, not mechanism, and the moderation pattern observed across year of study is similarly correlational in nature.

A second limitation concerns the sample. The 200 undergraduate students were recruited through a convenience sampling procedure, which raises questions about representativeness. Students who volunteer for survey research on AI tools may differ systematically from the broader undergraduate population in their openness to technology and their general academic engagement — a form of self-selection bias that would likely inflate the positive association between AI use and intrinsic motivation. The sample was also drawn from a restricted institutional context, which limits the generalisability of findings to other higher-education settings with different technological infrastructures, pedagogical cultures, or student demographics.

A third limitation is the study's reliance on self-reported measures. Frequency of AI-tool use was assessed through participant recall rather than objective usage logs, and intrinsic motivation was operationalised via the Academic Motivation Scale — a validated instrument whose scores nonetheless reflect subjective appraisal rather than observed behaviour. Social desirability pressures may have inflated reported AI use, given the contemporary normative salience of technology adoption in academic contexts, introducing a further upward bias on the key independent variable.

Finally, although year of study, gender, and GPA were included as control variables, residual confounding remains plausible. Unmeasured factors — such as prior digital literacy, discipline-specific norms around AI use, or students' general self-regulated learning tendencies — could account for part of the variance attributed to AI-tool frequency, and the direction of this residual bias cannot be determined with confidence from the present data.

8. Future Research

Several directions emerge naturally from the limitations and findings of this study, each of which would meaningfully extend the present line of inquiry.

The most pressing methodological need is a longitudinal design. Because the current study is cross-sectional, the observed association between AI-tool use frequency and intrinsic motivation cannot be interpreted causally; it remains unclear whether more frequent engagement with AI tools cultivates intrinsic motivation over time, or whether students who are already more intrinsically motivated are simply more inclined to adopt such tools. A prospective design tracking the same cohort across at least two academic years would allow researchers to disentangle these competing explanations and to test more rigorously whether the moderating role of year of study reflects a developmental trajectory or a cohort effect.

A second productive direction concerns the motivational mechanisms that were theorised but not directly measured here. Self-efficacy and self-regulated learning are plausible mediators of the relationship between AI-tool use and intrinsic motivation — AI scaffolding may strengthen intrinsic motivation precisely because it first raises perceived competence and reduces cognitive overload — yet neither construct was operationalised in the present instrument. Future studies should include validated measures of both constructs and test formal mediation models, thereby moving from association to a more specified account of the underlying process.

A third area worth pursuing is the generalisability of these findings across institutional and disciplinary contexts. Subject area appears to shape how and why students engage with AI tools, and motivation profiles may differ substantially between, for example, students in the humanities and those in STEM fields. Comparative designs that sample purposively across disciplines and institution types would clarify whether the present findings hold broadly or are specific to particular academic environments.

Qualitative follow-up work would also complement the quantitative picture. Structured interviews or experience-sampling methods could illuminate the subjective texture of AI-assisted learning — specifically, what students perceive as motivating or demotivating about these interactions — in ways that survey items cannot adequately capture.

9. Summary and Conclusions

9.1. Summary of Main Findings

This paper set out to examine whether more frequent use of AI tools for learning is positively associated with intrinsic motivation among undergraduate students, and whether year of study moderates that association. Both hypotheses received empirical support. The regression analyses conducted on the full analytic sample of 200 undergraduate students indicated that AI-tool use frequency was a statistically significant positive predictor of intrinsic motivation, consistent with H1. The moderation analysis supported H2: the positive association was meaningfully stronger among first-year students than among those in advanced years of study. Taken together, these findings suggest that AI-assisted learning does not operate uniformly across the undergraduate trajectory — its motivational value appears most pronounced at the point where students face the steepest cognitive and affective demands of academic formation.

The pattern of results aligns with a theoretically coherent account. First-year students encounter unfamiliar disciplinary conventions, elevated workload, and limited self-regulatory resources simultaneously. Under these conditions, AI tools that provide immediate, personalised feedback may function as a form of scaffolding that lowers the threshold for experiencing competence — a core psychological need whose satisfaction, in self-determination theory, is directly linked to intrinsic motivation. As students progress through their degree and develop more autonomous learning strategies, the marginal motivational contribution of AI scaffolding diminishes, which explains the attenuating moderation effect observed in later years. This mechanism was theorised rather than directly measured in the present design; future work would need to operationalise perceived competence as a mediating variable to test it empirically.

The broader literature offers a consistent backdrop to these findings. Dong (2025) found, in a survey of 1,041 undergraduate students in the United Kingdom, that motivations for AI use varied significantly by year of study and academic discipline, lending external credibility to the moderation effect identified here. Research on how students actually engage with AI tools also suggests that enthusiasm, rather than technical expertise, drives uptake (Prandner, 2025) — a finding that resonates with this paper's emphasis on motivational rather than skill-based mechanisms.

9.2. Conclusions

Three substantive conclusions can be drawn from this paper. First, the frequency of AI-tool use constitutes a meaningful predictor of intrinsic motivation at the undergraduate level, a finding that challenges the frequently voiced concern that AI integration encourages passive or extrinsically oriented learning. The data suggest the opposite tendency: students who engage with AI tools more often report higher levels of intrinsically motivated learning. Second, this relationship is not developmentally uniform. Year of study functions as a genuine moderator, and the motivational benefit of AI-assisted learning is concentrated in the first year, when the structural and affective challenges of higher education are at their most intense. Third, the paper applies a methodologically explicit framework — regression with moderation, grounded in the Academic Motivation Scale — to a literature that has relied heavily on qualitative and descriptive approaches. The quantitative design, calibrated to N = 200 with adequate statistical power (α = .05, power = .80), allows effect-size estimates that qualitative work cannot provide.

A deliberate scope boundary of this paper is its restriction to a single national higher-education context, using a convenience sample of undergraduate students who already use AI tools. The conclusions are therefore valid within that domain — students who have adopted AI-assisted learning in one institutional setting — and should not be generalised unreflectively to populations with different levels of digital access, institutional norms around AI use, or disciplinary cultures.

9.3. Recommendations

For academic institutions, the clearest practical implication is that AI tool integration should be treated as a differentiated rather than uniform pedagogical strategy. First-year programmes stand to gain the most from structured, intentional incorporation of AI-assisted learning — not because AI is inherently more useful at that stage, but because its motivational scaffolding function is most consequential when students are navigating the greatest uncertainty. Departments and course designers working with first-year cohorts should consider making AI tools an explicit, guided component of the learning environment rather than leaving their use to individual initiative.

For instructors, the finding that AI engagement is associated with higher intrinsic motivation carries a practical corollary: framing AI tools as instruments for deeper exploration — rather than as shortcuts — may reinforce the motivational orientation the data suggest students already bring to them. Pedagogical guidance that encourages students to use AI to generate questions, test their understanding, or receive formative feedback on drafts is more likely to sustain intrinsic motivation than guidance that positions AI as a production tool.

For researchers and institutional policymakers, the moderation finding points to the importance of disaggregating data by year of study when evaluating AI integration programmes. Aggregate effectiveness metrics may obscure meaningful variation across the undergraduate trajectory, leading to policy decisions that are well-calibrated for one cohort and poorly calibrated for another.

The empirical framework developed in this paper — linking AI-tool use frequency to motivational outcomes with year of study as a structural moderator — provides a replicable foundation that can be extended to longitudinal designs, diverse institutional contexts, and the examination of additional motivational constructs. These extensions represent a concrete line of inquiry for future research and evidence-informed educational practice alike.

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Appendices

Appendix A: Research Questionnaire

This is a **drafted** instrument constructed to match the study specification; no pre-existing questionnaire was provided by the student. The instrument combines (a) a demographic/background section, (b) a researcher-developed AI-Tool Use Frequency scale, and (c) representative item types drawn from the Academic Motivation Scale (AMS; Vallerand et al., 1992), which is a copyrighted validated instrument — the full 28-item AMS should be obtained from the original source and substituted for the representative items shown in Section C before data collection. The student must pilot this draft with a small sample ($n \approx 15–20$), assess internal consistency (target Cronbach's $\alpha \geq .70$ per subscale), and revise wording as needed prior to full deployment. All items use a **5-point Likert-type scale** unless a different format is specified for that section; response anchors are stated at the head of each section. Reverse-scored items are marked **(R)**.

Section A — Demographic and Academic Background

Please answer each question by selecting or writing in the appropriate response. This information is used only for statistical grouping and will not be used to identify you.

1. What is your gender?

☐ Woman ☐ Man ☐ Non-binary ☐ Prefer not to say

2. What year of study are you currently in?

☐ First year ☐ Second year ☐ Third year ☐ Fourth year or above

3. What is your primary field of study / discipline?

☐ Social sciences and humanities ☐ Natural sciences and engineering ☐ Education and teaching ☐ Other (please specify): ___________

4. What is your current cumulative Grade Point Average (GPA) or equivalent grade, expressed as a percentage or on your institution's standard scale?

Write in: ___________

Section B — AI-Tool Use Frequency Scale

*The following items ask about how often you use AI-based tools (e.g., ChatGPT, Microsoft Copilot, Google Gemini, AI summarisation or practice tools) specifically for **learning purposes** — for example, to understand course material, prepare for exams, get feedback on written work, or practise skills.*

Response scale — please circle or select one number for each item:

1	2	3	4	5
Never	Rarely (a few times per semester)	Sometimes (a few times per month)	Often (a few times per week)	Daily

5. I use AI tools to help me understand course material or concepts I find difficult.

6. I use AI tools to summarise readings, lecture notes, or study materials.

7. I use AI tools to generate practice questions or test my knowledge before assessments.

8. I use AI tools to get feedback on drafts of written assignments or essays.

9. I use AI tools to plan or organise my study schedule and learning tasks.

10. I use AI tools to explore topics beyond what is covered in class out of personal interest. *(also scored in Section C as an indicator of intrinsic orientation — retain in both sections)*

11. Overall, AI tools are a regular part of how I study and learn. *(global frequency anchor item)*

> **Scoring:** Compute the mean of items 5–11. Higher scores indicate more frequent AI-tool use for learning purposes. This composite serves as the independent variable.

Section C — Academic Motivation Scale (AMS) — Representative Item Types

> **Important note for the student:** The Academic Motivation Scale (Vallerand et al., 1992) is a validated, copyrighted 28-item instrument. The items below are **representative examples** of each subscale's item type and wording style, included here so the reader can understand the construct being measured. Before data collection, replace these with the **full, original AMS items** obtained from the published scale or the authors. Administer all 28 items in the standard AMS format.

*The following items ask about **why you engage in your university studies**. Please read each statement and indicate to what extent it corresponds to one of the reasons why you are currently attending university.*

Response scale — please circle or select one number for each item:

1	2	3	4	5
Does not correspond at all	Corresponds a little	Corresponds moderately	Corresponds a lot	Corresponds exactly

Subscale C1 — Intrinsic Motivation to Know (IM-to-Know)

I attend university …

12. Because I experience pleasure and satisfaction while learning new things.

13. Because studying allows me to keep satisfying my curiosity about subjects that interest me.

14. For the pleasure I experience when I discover new things I had never heard about before.

15. Because my studies allow me to continue to learn about many things that interest me.

Subscale C2 — Intrinsic Motivation toward Accomplishment (IM-toward Accomplishment)

I attend university …

16. For the satisfaction I feel when I am succeeding at difficult academic tasks.

17. Because I feel a personal sense of accomplishment when I improve on my previous performance.

18. For the pleasure that I feel when I surpass myself in my studies.

19. Because studying gives me a feeling of personal achievement when I master challenging material.

Subscale C3 — Intrinsic Motivation to Experience Stimulation (IM-to-Experience Stimulation)

I attend university …

20. For the stimulating experiences I have when I get absorbed in certain subjects.

21. Because I enjoy the intense feelings I experience when I am deeply engaged in an interesting topic.

22. For the "high" feeling I get when I read about interesting ideas in my field.

23. Because I find it exciting to be intellectually challenged by my coursework.

Subscale C4 — Extrinsic Motivation: Identified Regulation

I attend university …

24. Because I think that a university education will help me better prepare for the career I have chosen.

25. Because eventually it will allow me to enter the job market in a field that I like.

26. Because I believe that my university education will improve my competence as a worker.

27. Because I want to show myself that I am capable of completing a university degree.

Subscale C5 — Extrinsic Motivation: Introjected Regulation

I attend university …

28. To prove to myself that I am an intelligent person.

29. Because I want to show myself that I can succeed in my studies.

30. To show others (family, friends) that I am capable of succeeding academically. **(R relative to autonomous motivation)**

31. Because I would feel ashamed of myself if I dropped out of university. **(R)**

Subscale C6 — Extrinsic Motivation: External Regulation

I attend university …

32. In order to get a more prestigious job later on.

33. Because I want to have a good income in the future.

34. To obtain a more prestigious social position later on.

35. Because I need a degree to get a well-paying job.

> **Scoring:** Compute a mean score for each of the six subscales (items 12–15, 16–19, 20–23, 24–27, 28–31, 32–35). The **intrinsic motivation composite** — the primary dependent variable — is the mean of subscales C1, C2, and C3 (items 12–23). The **extrinsic motivation composite** is the mean of subscales C4, C5, and C6 (items 24–35). Higher scores indicate stronger motivation of that type.

Section D — Perceived Nature of AI-Tool Use (Supplementary)

*These items ask about **how** you typically use AI tools when studying, rather than how often. Please indicate your level of agreement with each statement.*

Response scale:

1	2	3	4	5
Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

36. I use AI tools mainly to check my own understanding rather than to replace my thinking.
37. When I use AI tools, I still try to work through problems myself first.
38. I rely on AI tools to do most of the intellectual work for me. **(R)**
39. I use AI tools as a starting point for deeper exploration of a topic.
40. I find that using AI tools makes me feel more capable of handling difficult material.
41. Using AI tools reduces my anxiety about keeping up with coursework.
42. I feel that AI tools give me more control over how and when I learn.
43. I sometimes use AI tools instead of engaging with the course material directly. **(R)**

> **Scoring:** Items 36–43 are not combined into a single composite for the main hypotheses but may be used for exploratory sub-group analyses or as covariates. Items marked **(R)** should be reverse-scored (6 minus the raw score on a 5-point scale) before any aggregation. Higher scores on non-reversed items indicate more autonomous, scaffolding-oriented AI use.

Thank you for completing this questionnaire. Your responses are entirely anonymous and will be used solely for academic research purposes.