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

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1. Background and Rationale

The integration of AI tools into undergraduate learning has accelerated rapidly, shifting from an optional supplement to a structurally significant feature of how students study and seek feedback. This transformation raises questions that extend beyond adoption patterns: at stake is whether growing engagement with AI-assisted learning reshapes the motivational orientations that underpin sustained academic effort. Yet despite proliferating 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 study will address is the absence of systematic empirical evidence on the relationship between AI tool use frequency and intrinsic motivation among undergraduates, and on the variables that moderate this relationship. Existing studies have examined learner perceptions of AI tools (Molla, 2025), language-learning applications (Alkandari, 2025), and vocabulary acquisition (Kheder, 2025), but none has tested whether more frequent AI tool use predicts higher intrinsic motivation, nor whether this relationship varies across stages of undergraduate study. The proposed study will address these gaps by applying a quantitative, cross-sectional survey design to a planned sample of approximately 200 undergraduate students, combining the Academic Motivation Scale (Vallerand et al., 1992) with researcher-developed items measuring AI tool use frequency, and testing year of study as a moderator — generating a theoretically grounded empirical account that currently does not exist in the literature.

2. Research Questions and Hypotheses

The proposed study is organised around a central question: is the frequency with which undergraduate students use AI tools for learning positively associated with their level of intrinsic motivation? A secondary question follows: does year of study moderate this relationship, such that the association is stronger among first-year students than among those in more advanced years?

Two directional hypotheses will be tested:

H1 (alternative): There is a statistically significant positive relationship between AI tool use frequency and intrinsic learning motivation among undergraduate students.

H1 (null): There is no statistically significant relationship between AI tool use frequency and intrinsic learning motivation.

H2 (alternative): The positive relationship between AI tool use frequency and intrinsic motivation is significantly stronger among first-year students than among advanced students — year of study moderates the relationship.

H2 (null): Year of study does not moderate the relationship; the association does not differ between first-year and advanced students.

Both hypotheses will be tested within a cross-sectional regression framework, with year of study, gender, and GPA entered as control variables.

3. Literature Review and Theoretical Background

The proposed study is grounded in Self-Determination Theory (SDT) (Deci & Ryan, 1985), which holds that intrinsic motivation is sustained by the satisfaction of three basic psychological needs: autonomy, competence, and relatedness. Learning environments that support perceived competence and autonomous engagement are expected to nurture intrinsic motivation, while those that undermine these needs tend to produce extrinsic or amotivated orientations. The Academic Motivation Scale (AMS) (Vallerand et al., 1992), planned for this study, was developed within the SDT tradition and operationalises intrinsic and extrinsic motivational subtypes, permitting differentiated analysis rather than a single composite.

The empirical literature on AI-assisted learning and motivation has expanded rapidly, though it remains methodologically uneven. The most consistent finding is that AI tools are associated with improved affective and motivational experiences. Alsswey (2025) found that an AI-tool intervention produced significant improvements in hedonic benefits and user experience, suggesting AI may make learning feel more rewarding. A complementary account invokes control-value theory to argue that AI tools reduce negative appraisals — particularly anxiety — that suppress intrinsic motivation, while amplifying positive achievement emotions such as enjoyment (Shao, 2025). (Molla, 2025) similarly observed that AI-assisted tools relate to increased learner autonomy and motivation through personalised feedback environments.

A significant counterpoint comes from qualitative evidence suggesting technology-enhanced learning may carry motivational costs. Khanduri and Teotia (2023) found that technology use correlates with decreased creativity and reduced cognitive functioning — findings that reinforce the importance of distinguishing AI-assisted learning from undifferentiated digital consumption.

Ongoing institutional uncertainty about legitimate AI use, compounded by the variable accuracy of AI-detection tools ("An Empirical Study Of," 2023), may itself function as a motivational inhibitor.

The literature also points to meaningful variation in AI engagement across the undergraduate trajectory. Dong (2025) demonstrated that motivations for AI use vary significantly by year of study and discipline, with accumulated domain knowledge shaping adoption patterns. Much existing evidence is concentrated in EFL contexts (Alkandari, 2025; Kheder, 2025), limiting generalisability. The proposed study will test whether motivational effects obtain across a broader undergraduate population and whether year of study functions as a systematic moderator — a question no existing study has directly addressed using a validated psychometric instrument.

4. Methodology

The proposed study will adopt a quantitative, cross-sectional survey design, suited to the research questions because it permits simultaneous measurement of the independent variable, dependent variable, and moderator within a single data-collection wave. A structured online self-report questionnaire will be administered to undergraduate students who use AI tools for learning.

The target population will consist of undergraduate students enrolled at higher-education institutions who use large-language-model-based chatbots, summarisation tools, or AI-assisted learning platforms. Participants will be recruited through convenience sampling via institutional email lists, course announcement boards, and student social-media channels — appropriate because no comprehensive sampling frame of AI-using undergraduates exists.

The planned analytic sample is approximately 200 undergraduate students. This figure is determined by an a-priori power analysis calibrated to the most demanding planned analysis — the moderation model tested via Hayes PROCESS. Using G*Power, with a target medium effect size ($f^2 \approx 0.15$), $\alpha = .05$, and target power = .80, the minimum required N for the moderation model is comfortably met by the planned sample of ~200. This N also provides adequate power for the primary Pearson correlation test of H1 at the same parameters for a medium effect ($r \approx .30$). The sample will include students across multiple academic years; year of study will be dichotomised into first-year versus advanced (second year and above) to operationalise the H2 moderator. Gender and cumulative GPA will be collected as control variables.

The **independent variable — AI tool use frequency** (continuous) will be measured via a researcher-developed composite scale assessing how often participants use AI tools (e.g., ChatGPT, Microsoft Copilot) for learning, rated on a five-point Likert-type frequency scale (1 = never, 5 = daily); a composite mean will be computed. Researchers have noted that undergraduates vary considerably in AI engagement patterns (Prandner, 2025), reinforcing the need for a sensitive multi-item measure. The **dependent variable — intrinsic motivation** (continuous) will be measured using the AMS (Vallerand et al., 1992), developed within the SDT framework (Deci & Ryan, 1985), which operationalises three intrinsic motivation subscales (IM-to-Know, IM-toward Accomplishment, IM-to-Experience Stimulation). The intrinsic motivation composite will be formed by averaging these three subscale scores. The AMS will be administered on a five-point response scale (1–5) rather than the original seven-point scale, to maintain consistency with the questionnaire format throughout. This adaptation preserves the ordinal structure while reducing response options; internal consistency will be assessed via Cronbach's alpha (target $\alpha \geq .70$ per subscale) prior to hypothesis testing, and the adaptation and its validity implications will be reported transparently. The **moderator — year of study** (categorical) will be dichotomised into first-year (coded 1) versus advanced (coded 0). **Control variables** — gender and cumulative GPA — will be entered as covariates in the moderation model.

Participants will complete the questionnaire via an anonymous online link over a planned four-week data-collection period. The survey will open with an informed-consent screen; only participants providing active consent will proceed. Estimated completion time is approximately twelve minutes. Responses will be stored on a password-protected server with no personally identifying information recorded beyond the required demographic variables.

All analyses will be conducted in SPSS version 29. Descriptive statistics and reliability coefficients will be computed for all scales; normality will be assessed via Shapiro-Wilk tests and visual inspection. H1 will be tested using Pearson's r ($df = 198$), with Spearman's rho as a non-parametric fallback, and a 95% confidence interval reported. H2 will be tested using Hayes' PROCESS macro (Model 1), with AI tool use frequency as the IV, intrinsic motivation as the outcome, year of study as the moderator, and gender and GPA as covariates. Effect size will be reported as ΔR^2 and Cohen's f^2 for the overall model; multicollinearity will be assessed via variance inflation factors.

5. Ethical Considerations

Data collection will not begin until institutional ethics-committee approval has been obtained. All procedures will comply with applicable institutional ethical standards. Informed consent will be obtained via a consent screen before participants access any items; participation will be entirely voluntary, and students may withdraw at any point without consequence or explanation. No incentive constituting undue inducement will be offered.

Anonymity will be preserved throughout: no names, student identification numbers, email addresses, or IP addresses will be recorded. Demographic variables will be used solely for statistical grouping. Data will be stored on a password-protected server accessible only to the research team and deleted or anonymised at the project's conclusion in accordance with institutional data-retention guidelines. The study involves no deception, no sensitive clinical populations, and no foreseeable risk of physical or psychological harm; participants may skip any item or withdraw entirely at will.

6. Anticipated Outcomes

Regarding H1, it is anticipated that a statistically significant positive association will be found between AI tool use frequency and intrinsic motivation. Students who report more frequent AI tool use are expected to score higher on AMS intrinsic motivation subscales — reflecting greater curiosity, autonomous engagement, and perceived competence — consistent with SDT's account that AI scaffolding may support the psychological conditions under which intrinsic motivation flourishes (Deci & Ryan, 1985). The effect size is expected to fall within the medium range ($r \approx .30$), in line with motivational associations reported in related empirical work (Alsswey, 2025).

Regarding H2, year of study is expected to function as a significant moderator, with the positive association stronger among first-year students than among advanced students. This prediction rests on the argument that AI scaffolding addresses the acute convergence of cognitive load and affective uncertainty characteristic of early undergraduate formation; as students develop greater domain knowledge and self-regulatory capacity, the marginal motivational contribution of AI scaffolding is expected to diminish — consistent with evidence that AI use motivations vary by year of study (Dong, 2025). It is also anticipated that the positive association will be specific to intrinsic motivation subscales rather than equally pronounced for extrinsic composites, providing theoretically informative differentiation.

7. Anticipated Limitations and Risks

Cross-sectional design. The single time-point design will preclude causal inference: it will not be possible to determine whether AI use cultivates intrinsic motivation, whether motivated students are more inclined to adopt AI tools, or whether both directions operate simultaneously. The study will be framed explicitly as associational, and future longitudinal work will be recommended.

Recruitment and self-selection. Convenience sampling may attract students already positively disposed toward AI tools, likely inflating the observed association. Attrition over the four-week window may further skew the sample. The sampling strategy and its limitations will be reported transparently; the planned N of ~200 provides a buffer against moderate attrition.

Self-report bias. AI tool use frequency will rely on participant recall rather than objective logs, and social desirability pressures may inflate reported use. The anonymous online format will be used to reduce this effect; the validated multi-item AMS (Vallerand et al., 1992) provides greater construct reliability than single-item measures.

Residual confounding. Despite entering year of study, gender, and GPA as controls, unmeasured factors — such as prior digital literacy or discipline-specific norms — may confound results. The discussion will explicitly acknowledge these as boundary conditions.

Generalisability. The convenience sample will be drawn from a restricted institutional context and will include only students who already use AI tools. Much prior literature is similarly concentrated in EFL contexts (Alkandari, 2025; Kheder, 2025), limiting cross-study comparability. The scope of generalisation will be stated explicitly, and comparative future work will be recommended.

Scale adaptation. Administering the AMS on a five-point rather than the original seven-point scale may affect distributional properties and limit comparability with published norms. Internal consistency will be assessed prior to hypothesis testing and the adaptation reported transparently.

8. Proposed Timeline

The study is planned across approximately five months in six phases.

Phase 1 — Literature review and theoretical framework (Weeks 1–4). Relevant databases (ERIC, PsycINFO, Google Scholar) will be searched using terms related to AI-assisted learning, intrinsic motivation, SDT, and undergraduate education. A core subset of approximately 30–40 studies will be deep-coded for theoretical and methodological detail; the remainder will be mapped at abstract level. The theoretical framework and hypotheses will be finalised.

Phase 2 — Instrument preparation and piloting (Weeks 5–7). The full questionnaire will be assembled and piloted with approximately 15–20 students to assess item clarity, completion time, and preliminary internal consistency (target $\alpha \geq .70$ per subscale). Revisions will be made before full deployment.

Phase 3 — Ethics approval (Weeks 6–8, overlapping with Phase 2). The ethics application will be submitted to the institutional review body. Data collection will not begin until written approval is received.

Phase 4 — Data collection (Weeks 9–12). The anonymous online survey will be distributed over a four-week window targeting approximately 200 students, with a reminder message sent at the midpoint.

Phase 5 — Data analysis (Weeks 13–15). Data will be cleaned, reliability coefficients computed, and normality assessed. Pearson correlation (H1) and Hayes PROCESS moderation analysis (H2) will be conducted in SPSS version 29.

Phase 6 — Writing and submission (Weeks 16–20). The full project report will be drafted and revised in response to supervisor feedback before final submission.

9. Expected Contribution and Significance

The proposed study will make three interconnected contributions. **Empirically**, it will provide direct evidence — using a validated psychometric instrument — on the association between AI tool use frequency and intrinsic motivation in a general undergraduate population. No existing study directly measures intrinsic motivation using the AMS (Vallerand et al., 1992) in a non-language-specific undergraduate sample, nor examines year of study as a systematic moderator of the AI–motivation relationship. **Theoretically**, by grounding the analysis in SDT (Deci & Ryan, 1985) and applying the AMS's subscale structure, the study will advance a scaffolding-based account of AI's pedagogical function — reframing AI integration as a motivational question rather than a digital-skills question, extending concerns that prior work has raised but not yet resolved empirically (Dong, 2025). **Practically**, if the hypotheses are supported, the findings will carry implications for instructional designers and institutional policymakers: evidence that motivational benefits are concentrated among first-year students would invite more targeted deployment of AI-assisted resources at the transition into higher education. The quantitative design will yield effect-size estimates that descriptive studies cannot provide, offering an actionable evidence base for curriculum and policy decisions and a replicable methodological framework for future longitudinal and cross-institutional research.

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