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Study Habits, Self-Regulation, and AI-Assisted Learning Among Faculty of Languages Students at Benghazi University: A Descriptive Survey Analysis

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عادات الدراسة، والتنظيم الذاتي، والتعلم بمساعدة الذكاء الاصطناعي لدى طلبة كلية اللغات بجامعة بنغازي: دراسة مسحية وصفية تحليلية

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قسم اللغة التطبيقي، كلية اللغات، جامعة بنغازي، ليبيا

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Abstract

This study examines how undergraduate students in the Faculty of Languages at Benghazi University structure their independent study time, regulate their own learning, and incorporate artificial intelligence (AI) tools into that process. A total of 116 students completed a descriptive, cross-sectional survey between January 13 and January 20, 2026, covering demographic background, academic major, self-reported grade point average (GPA), preferred study environment, timing and duration of study sessions, pacing across the semester, reliance on lecturer-provided material, background music use, AI-assisted studying, and satisfaction with personal study habits. The typical respondent studies alone (76.7%), in blocks of two to four hours (66.4%), without background music (92.2%), and during the early morning or evening (72.4% combined). Once both AI-related items are counted together, 95.7% of respondents reported some form of AI-assisted studying — a figure that positions AI use as close to a default feature of studying in this group rather than an occasional supplement. Six chi-square tests of independence tested whether self-reported GPA was associated with six study-habit variables. Only one reached significance: GPA and semester-long pacing pattern, $\chi^2(12) = 22.52$, $p = .032$, Cramér's $V = .254$, though the underlying contingency table fell short of the minimum expected cell-count assumption, so this result carries a caveat. The remaining five relationships were not significant. Several habits often assumed to underpin academic success show little connection to self-reported GPA in this sample, while pacing steadily through the semester carries a small but measurable association with stronger grades. The paper closes with implications for academic advising and suggested directions for future research.

Keywords: : study habits, self-regulated learning, AI-assisted learning, language education, undergraduate students, Benghazi University.

الملخص

تبحث هذه الدراسة في كيفية تنظيم طلبة المرحلة الجامعية في كلية اللغات بجامعة بنغازي لوقت الدراسة المستقلة، وكيفية تنظيمهم لتعلّمهم ذاتيًا، وكيفية توظيفهم لأدوات الذكاء الاصطناعي (AI) ضمن هذه العملية.

أكمل ما مجموعه 116 طالبًا وطالبة استبيانًا وصفيًا مقطعيًا خلال الفترة من 13 إلى 20 يناير 2026، وتناول الاستبيان الخلفية الديموغرافية للطلبة، والتخصص الأكاديمي، ومتوسط الدرجات التراكمي (GPA) المُبلَّغ عنه ذاتيًا، وبيئة الدراسة المفضلة، وتوقيت جلسات الدراسة ومدتها، ونمط توزيع الدراسة على مدار الفصل الدراسي، ومدى الاعتماد على المواد التي يقدمها المحاضر، واستخدام الموسيقى أثناء الدراسة، والدراسة بمساعدة الذكاء الاصطناعي، ومدى الرضا عن عادات الدراسة الشخصية.

أظهرت النتائج أن الطالب النموذجي يدرس بمفرده (76.7%)، وفي جلسات دراسية تتراوح مدتها بين ساعتين وأربع ساعات (66.4%)، ومن دون الاستماع إلى الموسيقى أثناء الدراسة (92.2%)، ويفضل الدراسة في الصباح الباكر أو في المساء (72.4% مجتمعين).

وعند احتساب بندَي الدراسة المرتبطين بالذكاء الاصطناعي معًا، أفاد 95.7% من المشاركين باستخدام الذكاء الاصطناعي في دراستهم بشكل أو بآخر. وتشير هذه النسبة إلى أن استخدام الذكاء الاصطناعي أصبح قريبًا من كونه سمة أساسية في عملية الدراسة لدى هذه المجموعة، وليس مجرد وسيلة مساعدة تُستخدم من حين إلى آخر.
تم إجراء ستة اختبارات كاي-تربيع للاستقلالية (Chi-square tests of independence) لاختبار ما إذا كان متوسط الدرجات التراكمي المُبلَّغ عنه ذاتيًا مرتبطًا بستة متغيرات تتعلق بعادات الدراسة. وقد وصل متغير واحد فقط إلى مستوى الدلالة الإحصائية، وهو العلاقة بين المعدل التراكمي ونمط توزيع الدراسة على مدار الفصل الدراسي، حيث بلغت قيمة كاي-تربيع $\chi^2(12) = 22.52, p = .032$, Cramér's V = .254 ومع ذلك، فإن جدول التوافق المستخدم في هذا الاختبار لم يستوفِ الحد الأدنى المفترض لعدد التكرارات المتوقعة في الخلايا، ولذلك ينبغي التعامل مع هذه النتيجة بحذر.
أما العلاقات الخمس المتبقية فلم تكن ذات دلالة إحصائية. وتُظهر النتائج أن العديد من عادات الدراسة التي يُفترض عادةً أنها تسهم في النجاح الأكاديمي لا ترتبط بشكل واضح بمتوسط الدرجات التراكمي المُبلَّغ عنه ذاتيًا لدى أفراد هذه العينة. في المقابل، فإن الاستمرار في الدراسة بوتيرة منتظمة على مدار الفصل الدراسي يرتبط ارتباطًا بسيطًا ولكنه قابل للقياس بالحصول على درجات أكاديمية أفضل.
وتختتم الدراسة بمناقشة الآثار المترتبة على هذه النتائج بالنسبة إلى الإرشاد الأكاديمي وعادات الدراسة لدى طلبة كلية اللغات بجامعة بنغازي، إلى جانب اقتراح بعض الاتجاهات التي يمكن أن تستفيد منها الدراسات المستقبلية.

الكلمات المفتاحية: عادات التعلم ، التعلم المنظم ذاتيا ، التعلم بمساعدة الذكاء الاصطناعي، تعليم اللغة ، طلبة المرحلة الجامعية،جامعة بنغازي.

Introduction

How students manage their independent study time is routinely cited as one of the strongest levers behind academic outcomes, and language-intensive fields make the point especially clearly: steady, spaced-out practice tends to beat cramming. That picture has grown more complicated recently. The rapid, largely unregulated uptake of generative AI tools now colors how many students look up explanations, condense readings, and push through assignments. Faculties of Languages sit directly at the intersection of these two currents. They prepare future teachers, translators, and applied linguists — work that depends on disciplined, self-regulated study — while operating inside an environment now saturated with generative AI tools whose behavioral effects remain poorly mapped, particularly outside North America and Europe.

Benghazi University's Faculty of Languages offers a useful window into these dynamics. Its undergraduates are drawn mainly from the Applied Linguistics and English Language tracks, with smaller cohorts in Literature, Translation, and Theoretical Linguistics. As in many developing-world academic settings, formal institutional data on how these students actually study — when, where, and with what help — is thin. Faculty members carry plenty of impressions about student behavior, but impressions do not substitute for systematic measurement, and that gap matters more the faster AI adoption reshapes what studying looks like.

Statement of the Problem

Study habits sit at the center of academic achievement, yet empirical documentation of how language-faculty undergraduates in Libyan higher education actually organize their independent study time is scarce, and documentation that accounts for how routine AI-assisted studying has become is scarcer still. Without that evidence base, faculty members and program designers have little concrete footing when they build advising practices, study-skills workshops, or policy around AI use in coursework.

Purpose of the Study

This study builds a descriptive, empirically grounded profile of the study habits, environmental preferences, pacing behaviors, and AI tool usage of undergraduate students in the Faculty of Languages at Benghazi University, and tests whether commonly assumed markers of effective studying actually correlate with self-reported academic performance (GPA) in this population.

Research Questions

The study was guided by the following questions:

RQ1: What are the dominant study environment, timing, and duration preferences among Faculty of Languages students?

RQ2: To what extent do students rely on AI tools to support studying and comprehension?

RQ3: How do students pace their studying across the semester, and is pacing behavior related to self-reported academic performance?

RQ4: Are commonly assumed indicators of effective studying (solitary study, session duration, reliance on lecturer-provided material, and AI use) associated with self-reported GPA in this sample?

RQ5: How satisfied are students with their own study habits, and does this satisfaction vary by performance level?

Significance of the Study

This study contributes to a thin research base on language-learner study behavior in the Libyan higher education context, and offers one of the first systematic accounts of how widely AI tools have been adopted for independent study among Arabic-speaking language students. The findings can inform academic advising, the design of study-skills interventions, and institutional thinking about working constructively with AI tools rather than treating them purely as a disciplinary problem.

Scope and Limitations

The study draws on a convenience sample of 116 students at a single faculty within a single university, gathered over one week through an online survey. The sample skews heavily toward 18-25-year-old undergraduates (87.9%) majoring in Applied Linguistics or English Language (91.4% combined), which caps how far the findings can be generalized to other age groups, academic levels, or majors. All data are self-reported, opening the door to recall or social-desirability bias, particularly for GPA and study-habit items. Because the design is cross-sectional, it cannot establish causal links between study habits and academic performance. Three survey items also showed response-scale inconsistencies that limit the precision of certain results, a problem unpacked further in the Methodology and Limitations sections.

Literature Review

Self-Regulated Learning in Higher Education

Self-regulated learning (SRL) theory describes how students plan, monitor, and evaluate their own learning: setting goals, managing time, choosing an environment, and using resources strategically (Zimmerman, 2002). Stronger self-regulators tend to spread study time more evenly, work toward small goals across a term instead of concentrating effort near deadlines, and revise their strategies through ongoing self-monitoring. Within language learning specifically, self-regulation has been linked to vocabulary retention, sustained engagement with skill-building tasks, and the persistence that second-language acquisition's slower, cumulative gains demand (Oxford, 2017). The present focus on semester-long pacing and study environment preference builds directly on this foundation, treating both as behavioral proxies for underlying self-regulatory capacity.

A substantial body of research ties self-regulatory behaviors — planning and time management above all — to academic outcomes, though effect sizes vary considerably across populations and disciplines (Broadbent & Poon, 2015). Any single self-regulatory behavior rarely predicts final grades strongly on its own; SRL functions as a multidimensional construct in which planning, environment management, and strategy use interact rather than operating as independent predictors. That theoretical point becomes relevant later, when interpreting the largely null findings for individual study-habit variables reported here.

Study Environment, Timing, and Individual Preference

Research on study environment preference generally finds that solitary study supports deeper, more sustained engagement with material, while group study can aid comprehension through peer explanation at the cost of introducing social distraction (Dunlosky et al., 2013). Preferences for solitary versus social study contexts appear to be shaped as much by personality and task type as by any inherent advantage of one mode over the other, which suggests environment preference alone is unlikely to strongly predict performance across a mixed student population.

Chronotype research — the study of individual variation in circadian alertness — shows considerable variation in students' self-reported best time of day for cognitive tasks, and morningness-eveningness preferences behave as fairly stable individual traits rather than arbitrary habits (Preckel et al., 2011). A modest advantage does appear for students whose class schedules align with their chronotype, but the link between preferred study time and overall achievement tends to weaken once study duration and consistency are controlled for — a pattern broadly consistent with the non-significant association found in the present sample.

Distributed Practice and Semester-Long Pacing

The spacing effect, among the most robust findings in cognitive psychology, shows that distributing study sessions over time produces better long-term retention than massed practice (cramming), even when total study time is held constant (Cepeda et al., 2006). Applied to a full semester, this would predict that students who engage with material early in the term, rather than concentrating effort in the days before an exam, should show some advantage in cumulative understanding and, potentially, in course grades. That prediction bears directly on this study's finding of a statistically significant — though methodologically fragile — association between early-semester pacing and higher self-reported GPA.

Survey-based research on real-world student behavior, however, consistently finds that a large share of students cram before exams to some degree regardless of whether they understand the benefits of distributed practice, often citing competing academic and personal demands (Taraban et al., 1999). The finding here that 62.1% of respondents reported exam-proximate or unstructured pacing, rather than steady engagement across the semester, sits comfortably within that broader cramming literature.

AI Tool Integration in Student Study Practices

The wide public availability of generative AI tools since 2022 has fueled a fast-growing research base on how students weave these tools into independent study. Early survey work spanning multiple disciplines and countries documents adoption rates for AI-assisted studying that shifted, within a few short years, from a minority to a clear majority practice among university students, with common uses including explaining difficult concepts, summarizing readings, and supporting writing tasks (Chan & Hu, 2023). Within English-as-a-foreign-language and applied linguistics contexts specifically, students report using AI tools for grammar checking, vocabulary explanation, and generating practice dialogue, often alongside lecturer-provided material rather than as a replacement for it (Kohnke et al., 2023).

The near-universal usage rate found in this study — 95.7% once both AI-related survey items are combined — sits at the high end of what this emerging literature has reported so far, suggesting that AI-assisted studying may be even more thoroughly normalized in this population than in some international samples. That raises a question worth returning to in the Discussion: whether measuring AI use as a discrete or unusual behavior still makes sense once the behavior has become close to universal.

Study Habits in Language-Learner Populations Specifically

Research focused specifically on EFL and applied linguistics learners stresses the importance of input frequency and consistency, since language skill development depends on cumulative, repeated exposure rather than one-off intensive study sessions (Nation, 2007). This line of work lends theoretical support to the interest here in semester-long pacing as a variable of particular relevance to language-faculty students, distinct from its relevance in more content- or fact-based disciplines.

Gaps in the Literature

Three gaps in the existing literature motivate this study. Published research documenting study habits and AI tool adoption specifically within Libyan or broader North African higher education contexts is scarce, leaving open whether patterns observed in North American, European, or East Asian samples generalize to this setting. Most AI-adoption studies to date have also surveyed general undergraduate populations rather than language-faculty students specifically, despite the latter group's distinctive reliance on language-production tasks — translation, composition, oral practice — that AI tools are particularly well suited to assist with. And few studies have examined AI use, environmental and timing preferences, and semester-long pacing together within a single sample, limiting what is known about how these behaviors co-occur and relate to performance. This study addresses all three gaps using data from the Faculty of Languages at Benghazi University.

Methodology

Research Design

This study used a descriptive, cross-sectional survey design. Cross-sectional surveys suit the goal of producing a snapshot profile of behaviors and attitudes across a population at a single point in time, and of testing for statistical association — though not causation — between variables measured simultaneously (Creswell & Creswell, 2018). Since the main goal was to document existing study-habit patterns rather than test a causal intervention, this design fit the research questions well.

Setting and Participants

Participants were drawn from the Faculty of Languages at Benghazi University, yielding a final sample of 116 respondents. By age, 87.9% (n = 102) were 18-25, 9.5% (n = 11) were 26-30, and 2.6% (n = 3) were 31-40. The overwhelming majority, 97.4% (n = 113), identified as undergraduate students, with one postgraduate respondent (0.9%) and two respondents (1.7%) selecting "Other." By major, 56.9% (n = 66) were Applied Linguistics students, 34.5% (n = 40) were English Language students, 6.9% (n = 8) were Literature students, and one respondent each (0.9% each) identified as Translation and Theoretical Linguistics students. Recruitment relied on convenience sampling, and participation was voluntary and anonymous.

Instrument

Data were collected through a structured online questionnaire administered via Google Forms. The instrument covered demographic background (age, academic status, major), self-reported GPA band (A, B, C, or D), preferred study environment (alone, with one other person, in a small group, or in a large group), preferred time of day for studying, typical study session duration, semester-long pacing pattern, reliance on lecturer-provided material, background music use, AI tool use to support studying, and overall satisfaction with personal study habits. Most items used single-select, closed-ended response categories suited to descriptive and chi-square analysis.

Three items deserve a flag here: those concerning semester-long pacing frequency, AI-assistance use, and study-habit satisfaction did not present fully consistent response options across all respondents. Some respondents, for instance, appear to have seen a binary Yes/No scale where others saw an Always/Sometimes/No scale for what were meant to be comparable questions — an issue the Limitations section addresses in more detail. All other items presented uniform response categories to every respondent.

Data Collection Procedure

The survey ran electronically and collected responses between January 13 and January 20, 2026. Students accessed the survey link voluntarily, and no identifying information was collected beyond the demographic and academic items described above. The survey platform recorded timestamps automatically; these confirmed the data collection window but were not used as an analytic variable.

Data Analysis Procedures

Data were exported, structured, and analyzed using Python (pandas, SciPy). Descriptive statistics — frequencies and percentages — were computed for every survey item. To address RQ3 and RQ4, a series of chi-square tests of independence examined associations between self-reported GPA (the four-level ordinal outcome: A, B, C, D) and five study-habit predictors: AI use for understanding material, study environment (alone versus with others), study session duration, preferred time of day, reliance on lecturer-provided material, and semester-long pacing pattern. For the one relationship that reached conventional statistical significance ($p < .05$), Cramér's V was calculated as an effect-size measure, and the minimum expected cell frequency was checked to assess whether chi-square assumptions were adequately met. An alpha level of .05 was used for all significance tests.

Ethical Considerations

Participation was voluntary, and responses were collected anonymously, with no personally identifying information retained in the dataset. The survey covered only routine study behaviors and did not touch on sensitive personal information, so it was treated as minimal risk. All data were aggregated for analysis and reporting, and no individual respondent can be identified from the results presented here.

Limitations of the Instrument

A few limitations of the instrument itself are worth flagging before turning to the results. As noted above, three items presented inconsistent response-option formats across respondents, limiting the precision of frequency reporting for those specific items — semester-long pacing frequency as a standalone behavior distinct from pacing pattern, AI-assistance use, and study-habit satisfaction; where this affects interpretation, the Results and Limitations sections flag it explicitly. All measures relied on self-report, including the central performance measure (GPA band), which was not checked against institutional academic records and is therefore open to recall error or social-desirability bias. The convenience sampling method, together with the resulting demographic and major skew (91.4% of respondents from just two majors, 87.9% aged 18-25), caps how far the findings can be generalized beyond the broader Faculty of Languages population, let alone to other faculties or institutions.

Results

Results are presented in two parts. The first reports descriptive statistics for each survey variable, organized by research question. The second presents the inferential analyses — chi-square tests of independence — examining the relationship between self-reported GPA and study-habit variables.

Demographic and Academic Profile of Respondents

The final sample consisted of 116 respondents. Table 1 summarizes the demographic and academic-major composition of the sample, which concentrated heavily among 18-25-year-old undergraduates majoring in Applied Linguistics or English Language — a pattern worth keeping in mind when interpreting everything that follows.

Table 1 Demographic and Major Composition of Respondents (N = 116)

Variable	n	%
Age group		
18-25	102	87.9
26-30	11	9.5
31-40	3	2.6
Academic status		
Undergraduate	113	97.4
Other	2	1.7
Postgraduate	1	0.9
Major		
Applied Linguistics	66	56.9
English Language	40	34.5
Literature	8	6.9
Translation	1	0.9
Theoretical Linguistics	1	0.9

Note. Percentages may not sum to exactly 100 due to rounding.

Self-Reported Academic Performance

Self-reported GPA band broke down as follows: 29.3% (n = 34) reported a GPA of A, 37.9% (n = 44) reported B, 29.3% (n = 34) reported C, and 3.4% (n = 4) reported D. Combined, 67.2% of respondents reported a GPA in the A or B range, showing that this self-selected group of survey respondents skewed toward students with stronger self-reported academic standing. Figure 1 (left panel) shows this distribution.

RQ1: Study Environment, Timing, and Duration Preferences

A strong majority of respondents, 76.7% (n = 89), said they prefer to study alone, compared with 17.2% (n = 20) who preferred studying with one other person, 4.3% (n = 5) who preferred a small group, and 1.7% (n = 2) who preferred a large group.

For preferred time of day, early morning was the most commonly selected option (44.0%, n = 51), followed by evening (28.4%, n = 33), late night (15.5%, n = 18), and afternoon (12.1%, n = 14). Combined, 72.4% of respondents preferred either early morning or evening — a bimodal clustering toward the edges of the day rather than midday hours.

On typical study session duration, 66.4% (n = 77) reported 2-4 hours per session, 30.2% (n = 35) reported 1-2 hours, and 3.4% (n = 4) reported under 1 hour. No respondent selected a duration exceeding four hours.

Table 2 Study Environment, Preferred Time, and Session Duration (N = 116)

Variable	n	%
Study environment		
Alone	89	76.7
One other person	20	17.2
Small group	5	4.3
Large group	2	1.7
Preferred time of day		
Early morning	51	44.0

Evening	33	28.4
Late night	18	15.5
Afternoon	14	12.1
Typical session duration		
2-4 hours	77	66.4
1-2 hours	35	30.2
Under 1 hour	4	3.4

RQ3: Semester-Long Pacing Pattern

Respondents' self-described pacing across the semester broke down as follows: 28.4% (n = 33) reported no fixed pattern, 26.7% (n = 31) reported pacing from the beginning of the semester, 19.8% (n = 23) reported concentrating their study one to two weeks before exams, 13.8% (n = 16) reported studying the night before an exam, and 11.2% (n = 13) reported pacing from the middle of the semester. Grouping the three most exam-proximate or unstructured categories together — no fixed pattern, one to two weeks before exams, and the night before exams — puts 62.1% of the sample in a reactive or unstructured pacing pattern, against 37.9% who paced themselves from the beginning or middle of the semester. Figure 1 (right panel) shows this distribution.

Reliance on Lecturer-Provided Material

Asked whether they relied solely on material provided by the lecturer, 69.0% (n = 80) said no, 19.8% (n = 23) said sometimes, and 11.2% (n = 13) said yes. Combining the sometimes and yes categories, 31.0% of respondents at least occasionally restrict their studying to lecturer-provided material alone, while most actively supplement their studying with outside resources.

Background Music While Studying

A large majority of respondents, 92.2% (n = 107), said they do not listen to music while studying; only 7.8% (n = 9) said they do.

RQ2: AI Tool Usage in Studying

Two related survey items addressed AI tool usage. Asked specifically whether they use AI to help them study, 89.7% (n = 104) answered yes, 4.3% (n = 5) answered sometimes, 0.9% (n = 1) answered always, and only 5.2% (n = 6) answered no. A related item asking whether they use AI to help them understand course material drew a yes from 76.7% (n = 89) and a no from 23.3% (n = 27).

Cross-tabulating these two items surfaced an apparent inconsistency: of the 27 respondents who said no to using AI for understanding material, 21 (77.8% of that subgroup) still said yes to the separate item about using AI to help them study. This probably reflects the two items capturing meaningfully different things — general study assistance versus comprehension support specifically — rather than a genuine contradiction in reported behavior; the Discussion returns to this. Counted inclusively, as an affirmative response (yes, sometimes, or always) to either item, 95.7% (n = 111) of the sample reported at least some AI use in their studying, positioning AI-assisted studying as a near-universal practice within this sample.

RQ5: Satisfaction With Study Habits

Asked how satisfied they were with the amount they study, 51.7% (n = 60) answered sometimes, 38.8% (n = 45) answered always, 6.9% (n = 8) answered yes, and 2.6% (n = 3) answered no. As the Limitations section covers, this item's response scale was inconsistent across respondents (a mix of Yes/No and Always/Sometimes/No options), which caps precise quantification. Still, treating sometimes as an indicator of conditional or partial satisfaction, the results suggest most students (51.7%) hold an ambivalent rather than confident view of their own study habits, regardless of self-reported GPA band.

RQ4: Relationship Between GPA and Study-Habit Variables

Table 3 Chi-Square Tests of Independence Between GPA and Study-Habit Variables

Predictor variable	χ^2	df	p	Result
AI use (understanding)	3.42	3	.331	Not significant
Study environment (alone vs. others)	4.41	3	.220	Not significant
Study session duration	6.25	6	.396	Not significant
Preferred time of day	8.32	9	.503	Not significant
Reliance on lecturer material	2.80	6	.833	Not significant
Semester-long pacing pattern	22.52	12	.032	Significant*

Note. *This result should be interpreted with caution. The minimum expected cell frequency in this 5 × 4 contingency table was 0.45, well below the conventional minimum of 5 required for the chi-square test to be considered reliable. Cramér's V for this association was .254, indicating a small-to-moderate effect size if the result is taken at face value.

To address RQ4, five chi-square tests of independence examined the association between self-reported GPA (A, B, C, D) and AI use for understanding material, study environment (alone versus with others), study session duration, preferred time of day, and reliance on lecturer-provided material. A sixth test looked at the association between GPA and semester-long pacing pattern, corresponding to RQ3. Table 3 summarizes the results.

None of the five tests examining AI use, study environment, session duration, preferred time of day, or reliance on lecturer-provided material reached statistical significance (all $p > .05$). Within this sample, these commonly assumed indicators of effective studying showed no statistical association with self-reported GPA.

The one significant result concerned semester-long pacing pattern, $\chi^2(12) = 22.52$, $p = .032$. Row percentages showed that 51.6% of students who reported pacing from the beginning of the semester had a self-reported GPA of A, against just 22.6% of students who reported no fixed pacing pattern. Students with no fixed pacing pattern were disproportionately likely to report a GPA of B instead (54.5% of that subgroup). The minimum expected cell frequency in this analysis, 0.45, falls well short of the conventional threshold of 5, so the chi-square approximation may not be fully reliable here, and this finding is best read as suggestive rather than conclusive. A Cramér's V of .254 points to a small-to-moderate effect size, consistent with a real but modest association.

Summary of Results

Taken together, the descriptive results show that solitary, self-paced study in 2-4 hour blocks without background music dominates this sample, that AI-assisted studying is now reported by nearly all respondents (95.7%), and that consistent semester-long pacing remains a minority behavior, with 62.1% of students engaging in exam-proximate or unstructured pacing. On the inferential side, none of the standard study-habit predictors examined showed a statistically robust relationship with self-reported GPA, with the partial exception of pacing pattern, whose significant chi-square result should be read cautiously given the small expected cell counts involved.

Discussion

Solitary Study and Time-of-Day Preferences

The strong preference for solitary study (76.7%) found here lines up broadly with research suggesting that independent study supports deeper, less distraction-prone engagement with material (Dunlosky et al., 2013), though the data cannot say whether this preference reflects a genuine cognitive advantage, a situational constraint such as limited access to peers with compatible schedules, or simple individual disposition. The bimodal clustering of preferred study time around early morning and evening (72.4% combined), rather than midday hours, fits chronotype research showing meaningful individual variation in alertness across the day (Preckel et al., 2011). Yet the non-significant association between preferred time and GPA in this sample suggests that, whatever its origin, this preference does not translate into a detectable performance advantage once other factors are taken into account.

Near-Universal AI Adoption and What It May Signal

One of the more striking findings here is the near-universal rate of AI-assisted studying — 95.7% of respondents once both AI-related items are considered together. That figure runs high even against recent international survey literature documenting rapid AI adoption among university students (Chan & Hu, 2023; Kohnke et al., 2023), suggesting that within this Faculty of Languages population, AI tool use may now function as a default part of studying rather than a discretionary add-on.

This carries two implications worth spelling out. First, treating AI use as a simple binary predictor of academic performance, as this study did for RQ4, may not tell us much once the behavior becomes this widespread: there is too little variation in the predictor (only 5.2-23.3% report non-use, depending on the item) to detect a meaningful association with an outcome like GPA even if one exists. Future research in similarly high-adoption contexts will likely need to measure how students use AI tools, for what tasks, and with what degree of critical evaluation of AI output, rather than simply whether they use them at all. Second, the apparent inconsistency between the two AI-related items — where most students who denied using AI to understand material still reported using AI to help them study more broadly — suggests students may draw a line between AI as a comprehension aid (explaining a concept) and AI as a broader study-support tool (organizing notes, generating practice questions, checking writing). That distinction deserves more granular investigation in future survey design, ideally through multi-item scales that separate AI use by specific function rather than relying on one global question.

The Pacing Paradox

One notable pattern in this dataset could be called a pacing paradox: despite a sample skewed toward stronger self-reported academic performance (67.2% reporting GPA A or B), most respondents (62.1%) reported a reactive or unstructured study pacing pattern rather than steady engagement from the beginning of the semester. This fits prior survey research showing that awareness of the benefits of distributed practice does not necessarily translate into practicing it, given competing demands on student time (Taraban et al., 1999). The modest, though statistically fragile, association between early-semester pacing and higher GPA (51.6% of early-pacing students reporting a GPA of A) is consistent with the broader spacing-effect literature (Cepeda et al., 2006), and suggests pacing may be one of the few study-habit variables in this dataset worth highlighting to students and advisors, even though the present test does not support stating this association with full statistical confidence.

It is also possible the direction of this association runs the other way: rather than early pacing causing higher grades, students who are already strong performers — perhaps due to greater intrinsic interest in the subject matter or stronger prior preparation — may simply find it easier to start engaging with material early in the semester. The cross-sectional design used here cannot distinguish between these explanations.

Why Standard Study-Habit Predictors Failed to Predict GPA

With the partial exception of pacing pattern, none of the study-habit variables examined here — AI use, study environment, session duration, time of day, reliance on lecturer material — showed a statistically significant relationship with self-reported GPA. A few explanations are possible, and they are not mutually exclusive. As SRL theory would predict, individual behavioral indicators often show weak associations with outcomes in isolation, because self-regulation works as an interacting bundle of behaviors rather than through any single practice (Broadbent & Poon, 2015); a student who studies alone but paces inconsistently may perform no better than one who studies in a group but paces consistently. The restricted range of GPA in this sample — skewed toward A and B grades, with only four D-grade respondents — also limits the statistical power available to detect associations that might show up more clearly in a sample with a fuller spread of academic performance. Self-reported GPA itself may carry measurement error that dilutes any true underlying association. None of this should be read as evidence that study habits do not matter for performance in any general sense — only that, within this particular sample's structure and measurement approach, these specific single-item indicators showed no detectable linear relationship with self-reported GPA band.

The Gap Between Satisfaction and Performance

Only a minority of students (38.8-45.7%, depending on how response categories are combined) reported consistent satisfaction with their own study habits, regardless of GPA band. Academic self-efficacy and study-habit satisfaction, in other words, may be only loosely coupled with actual performance in this population — worth flagging for academic advising, since a student's subjective sense of how well they are studying may not reliably indicate, in either direction, how well they are actually performing academically.

Implications for the Faculty of Languages

A few practical implications follow from these findings. Given the high prevalence of reactive, exam-proximate pacing (62.1%) and the tentative association between early pacing and stronger performance, study-skills workshops or advising sessions that emphasize concrete strategies for starting coursework engagement early in the semester — rather than generic encouragement to avoid procrastination — may be a worthwhile investment. With AI-assisted studying now reported by nearly all students, faculty members may also get more out of developing clear guidance on appropriate and academically honest AI use, including how to use such tools to support genuine understanding rather than bypass it, than out of treating AI use as a rare or exceptional practice requiring detection and discouragement. And the disconnect between study satisfaction and GPA suggests that advising conversations might usefully probe students' subjective experience of their own studying as a separate concern from their academic performance, since the two do not appear to move together in any simple way in this sample.

Limitations

Several limitations should inform how these findings are read. The sample is heavily skewed by age, academic level, and major: 87.9% of respondents were aged 18-25, 97.4% were undergraduates, and 91.4% were Applied Linguistics or English Language majors, with Literature, Translation, and Theoretical Linguistics students represented in numbers too small (8, 1, and 1 respondents, respectively) for reliable subgroup comparison. Findings may not generalize to postgraduate students, older students, or students in the underrepresented majors.

All data, including the central performance measure (self-reported GPA band), were self-reported and were not checked against institutional academic records. Self-reported GPA is open to both recall error and potential social-desirability bias, which may weaken or distort its true association with the study-habit variables examined.

Three survey items — semester-long study-frequency framing, AI-assistance use, and study-habit satisfaction — showed inconsistent response-option formats across respondents, with some apparently receiving a binary Yes/No scale and others an Always/Sometimes/No scale for what were meant to be comparable questions. The most plausible explanation is a branching or versioning artifact in the survey platform rather than genuine variation in how the questions were posed, though that cannot be fully ruled out as a source of measurement noise, and it limits how precisely these three variables in particular can be reported and interpreted.

The cross-sectional design does not allow for causal inference. Even where associations were observed or approached significance, such as the pacing-pattern finding, this study cannot say whether pacing behavior causes differences in academic performance, whether stronger-performing students simply find early pacing easier to sustain, or whether some third factor — motivation, course load, or prior academic preparation — drives both variables.

The one statistically significant inferential result reported here, the association between GPA and pacing pattern, came from a 5 × 4 contingency table with a minimum expected cell frequency of 0.45, well below the conventional minimum of 5 needed for the chi-square approximation to be considered fully reliable. This result should be treated as preliminary and ideally re-examined using Fisher's exact test, a collapsed contingency table with fewer categories, or a larger sample that would support more stable expected cell counts.

Finally, the restricted range of the GPA outcome variable in this sample (67.2% reporting A or B, only 3.4% reporting D) limits the statistical power available to detect associations between study habits and the full spectrum of academic performance, and may partly explain the largely null inferential results for variables other than pacing pattern.

Conclusion and Recommendations

Summary of Key Findings

This study built a descriptive profile of study habits, environmental and timing preferences, semester-long pacing behavior, AI tool usage, and study-habit satisfaction among 116 undergraduate students in the Faculty of Languages at Benghazi University. Most students said they study alone, in 2-4 hour sessions, without background music, with a preference clustering around early morning and evening hours. AI-assisted studying was reported by nearly all respondents (95.7%) when measured inclusively, indicating that AI tool use has become a normalized part of independent study in this population. Despite a sample skewed toward stronger self-reported academic performance, most students (62.1%) reported reactive or unstructured semester-long pacing rather than consistent engagement from the start of the term. Of six study-habit variables tested against self-reported GPA, only semester-long pacing pattern showed a statistically significant association, and this result carries an important caveat regarding small expected cell frequencies. Study-habit satisfaction was modest and did not track closely with GPA band.

Recommendations for the Faculty of Languages

Based on these findings, the Faculty might consider building brief, concrete guidance on early-semester pacing strategies into orientation or study-skills programming, given the tentative association between early pacing and stronger self-reported performance and how common reactive pacing is in this sample. Given the near-universal adoption of AI tools for studying, the Faculty may also find more value in developing explicit, constructive guidelines for academically appropriate AI use — particularly around comprehension support versus written-assignment completion — than in treating AI use as an exceptional or primarily disciplinary issue. Academic advisors might also consider routinely asking students about their subjective satisfaction with their own study habits as a distinct line of inquiry from their grades, since this study found the two factors to be only loosely related.

Recommendations for Future Research

Future research should pursue a few directions suggested by this study's limitations. A larger, multi-faculty sample with a more balanced distribution across majors, academic levels, and GPA bands would allow more reliable subgroup comparisons and would address the small-expected-cell-count problem that limited confidence in this study's one significant inferential finding. Checking GPA against institutional records, rather than relying solely on self-report, would strengthen the validity of any performance-based analysis. Longitudinal designs that track pacing behavior and performance across multiple semesters would allow stronger causal inference than the cross-sectional approach used here. And given the apparent inconsistency between this study's two AI-related items, future instruments should consider multi-item AI-use scales that distinguish between specific functions — comprehension support, writing assistance, practice generation — paired with qualitative follow-up such as focus groups or open-ended items, to better understand how language-faculty students are integrating AI tools into their study routines and how this integration relates, if at all, to their academic outcomes.

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Appendix A

Survey Instrument Items

The following items were included in the survey administered to participants. Response options for each item are listed beneath the item text.

1. Age group
Response options: 18-25 / 26-30 / 31-40
2. Academic status
Response options: Undergraduate / Postgraduate / Other
3. Major
Response options: Applied Linguistics / English Language / Literature / Translation / Theoretical Linguistics
4. Self-reported GPA band
Response options: A / B / C / D
5. Preferred study environment
Response options: Alone / One other person / Small group / Large group
6. Preferred time of day to study
Response options: Early morning / Afternoon / Evening / Late night
7. When do you study best across the semester?
Response options: From the beginning of the semester / From the middle of the semester / A week or two before exams / The night before an exam / No fixed time
8. Do you use AI to help you understand course material?
Response options: Yes / No
9. Do you rely only on material provided by your lecturer?
Response options: Yes / Sometimes / No
10. Typical study session duration
Response options: Under 1 hour / 1-2 hours / 2-4 hours
11. Do you listen to music while studying?
Response options: Yes / No
12. Do you use AI programs to help you study?
Response options: Yes / No / Sometimes / Always
13. How satisfied are you with how much you study?
Response options: Yes / No / Sometimes / Always

Appendix B

Complete Frequency Tables for All Survey Variables

Full frequency distributions for every survey item, beyond those reported in the main Results section, are available from the corresponding author upon request, along with the de-identified dataset and analysis scripts used to produce the statistics reported in this paper.