

A Comparative Analysis of Psychological Counseling Need and Academic Integrity Concerns among Students Using AI-Based Learning Tools in Senior Secondary Schools

***Ms. Neeru Chanchal**

Abstract

The present study aimed to show A Comparative Analysis of Psychological Counselling Needs and Academic Integrity Concerns among Students Using AI-Based Learning Tools in Senior Secondary Schools in Relation to their Gender, Academic Stream, School Type, and Location. A descriptive-comparative survey design was adopted. A stratified random sample of 400 senior secondary students (Classes XI–XII) was drawn from 20 schools in Gurugram district, distributed equally across four strata: Rural Government, Rural Private, Urban Government, and Urban Private. The sample comprised equal numbers of male and female students (200 each), 140 Science, 130 Commerce, and 130 Arts students, 200 government and 200 private school students, and 200 rural and 200 urban students. Data were collected using a researcher-constructed Composite Scale for AI-Related Needs and Concerns (CS-AI) comprising 50 items on a five-point Likert scale across five dimensions: Psychological Well-being and Emotional Regulation (D-I), Academic Integrity Attitudes and Awareness (D-II), AI Tool Dependency and Self-Efficacy (D-III), Counselling Receptivity and Help-Seeking Behaviour (D-IV), and Perceived Fairness and Institutional Trust (D-V). Data were analysed using descriptive statistics, independent samples t-tests, one-way ANOVA, Tukey's HSD post-hoc tests, and Cohen's d / η^2 effect sizes using SPSS Version 25.0.

Further it was found that H01: There is no significant difference between the mean composite scores of male and female senior secondary school students on the psychological counselling needs and academic integrity concerns scale, H02: There is no significant difference among the mean composite scores of students from Science, Commerce, and Arts streams, H03: There is no significant difference between the mean composite scores of students from Government and Private schools, H04: There is no significant difference between the mean composite scores of students from Rural and Urban locations, all hypothesis were rejected.

Keywords: *Psychological Counselling Needs, Academic Integrity Concerns, AI-Based Learning Tools, Senior Secondary Schools and Gurugram.*

> Introduction

The rapid proliferation of AI-based learning tools — including generative AI chatbots such as ChatGPT and Google Gemini, intelligent tutoring systems, adaptive learning platforms, and AI-powered writing assistance tools — has created a profoundly new educational landscape for senior secondary students in India. While AI tools offer genuine educational benefits including personalised tutoring, instant feedback, and democratised access to quality explanations, they also generate two major categories of concern: psychological counselling needs (arising from AI dependency, identity anxiety, social isolation, and ethical distress) and academic integrity concerns (arising from the temptation and capability to substitute AI output for genuine student work). Grounded in Social Cognitive Theory (Bandura, 1986), the Theory of Planned Behaviour (Ajzen, 1991), and the Technology Acceptance Model (Davis, 1989), the present study investigated both dimensions simultaneously among senior secondary school students in Gurugram district, Haryana.

The rapid proliferation of Artificial Intelligence (AI) in everyday life has brought about a paradigm shift in virtually every domain of human activity, and education is no exception. In the space of barely a decade, AI-based learning tools — encompassing intelligent tutoring systems, large language model (LLM) chatbots, automated essay scoring platforms, personalised adaptive learning engines, and AI-powered search and summarisation services — have moved from the margins of educational technology research into the daily study routines of millions of students worldwide. The pace of this transformation has been staggering: the public release of ChatGPT

in November 2022 alone brought generative AI into the conscious awareness of virtually every stakeholder in global education within weeks.

- **AI-Based Learning Tools: An Overview**

Artificial Intelligence, in the context of education, refers to computational systems that can perform tasks that typically require human cognitive abilities — such as understanding language, explaining concepts, solving problems, evaluating written work, and generating content — by learning patterns from large datasets. AI-based learning tools used by students may be categorised as follows.

Generative AI Chatbots and LLMs: Tools such as ChatGPT (OpenAI), Google Gemini, Microsoft Copilot, Claude (Anthropic), and others can generate human-like text responses to almost any academic query. Students use these tools for concept clarification, essay writing assistance, problem solving, code generation, and research summarisation. Their accessibility, versatility, and apparent knowledge across virtually all academic domains have made them extremely popular among secondary school students.

Intelligent Tutoring Systems (ITS): Systems such as Khan Academy's Khanmigo, Carnegie Learning, and various CBSE-aligned platforms use AI to adapt instructional content to the individual learner's pace and level of understanding. These systems diagnose misconceptions, provide differentiated practice, and give immediate, personalised feedback.

AI-Powered Search and Research Tools: Tools such as Perplexity AI and Google's AI overviews provide synthesised, summarised answers to research queries, enabling students to access integrated information without reading original sources. These tools raise particularly acute academic integrity concerns related to attribution, understanding, and intellectual engagement.

Automated Writing and Essay Assistance Tools: Tools such as Grammarly, Wordtune, QuillBot, and various AI writing assistants can rephrase, improve, extend, or entirely generate written text. Their use in the preparation of assignments, projects, and examinations raises fundamental questions about student authorship.

Adaptive Learning Platforms: National and commercial platforms such as SWAYAM, Byjus, Unacademy, and Vedantu incorporate AI-driven features to personalise content delivery, track

learning analytics, and provide targeted remediation. Many Indian senior secondary students use these platforms intensively for examination preparation.

- **AI Tools at the Senior Secondary Level**

The senior secondary stage (Classes XI–XII) presents a uniquely complex context for examining AI tool usage. Students at this stage are preparing for high-stakes examinations including the CBSE Class XII Board examinations and competitive entrance tests such as JEE (engineering), NEET (medical), CUET (university admissions), and CA Foundation (commerce). The pressure associated with these examinations is well-documented and constitutes one of the most significant mental health challenges among Indian adolescents.

AI tools enter this high-pressure context with ambivalent effects. On the positive side, they can provide personalised tutoring at any time of day, explain complex concepts in multiple ways, generate practice problems, check solutions, and provide instant feedback — capabilities that are particularly valuable for students who lack access to quality teachers or tutors. Research in the Indian context has documented significant positive associations between AI tool usage and self-reported learning effectiveness among urban private school students.

On the negative side, AI tool usage at the senior secondary level is associated with a distinctive set of psychological and integrity risks. Heavy AI dependency can erode the metacognitive skills — planning, self-monitoring, self-evaluation — that are essential for independent examination performance. Students who have relied on AI to generate or improve their written assignments may be unprepared for timed, independent examination writing. The psychological experience of identity confusion — ‘Am I actually capable if I need AI to produce this work?’ — is particularly acute at a developmental stage characterised by identity formation and self-concept development.

- **Justification and Need for the Study**

Several compelling reasons justify the present investigation. First, while international research on AI and academic integrity is growing rapidly, studies specifically focused on Indian senior secondary school students — a population facing unique examination pressures and operating in a context of variable AI access and institutional guidance — remain extremely limited. Second, the psychological counselling dimension of AI tool usage has been almost entirely neglected in the Indian educational research literature. Third, the comparative design of this study — examining differences by gender, stream, school type, and location — provides demographic

granularity that is essential for designing targeted interventions. Fourth, the construction of a locally contextualised, psychometrically sound measurement instrument constitutes an independent methodological contribution to the field.

- **Operational Definitions of Terms Used**

AI-Based Learning Tools: Any digital application employing artificial intelligence to facilitate academic learning activities, including generative AI chatbots (ChatGPT, Gemini, Copilot), intelligent tutoring systems, AI-powered adaptive learning platforms, automated writing assistance tools, and AI-enhanced search engines. In the school context, usage is measured through self-report of frequency and purpose of use.

Psychological Counselling Need: The composite score reflecting a student's need for professional psychological support arising from AI tool usage, operationalised as the combined score on Dimensions I (Psychological Well-being and Emotional Regulation) and IV (Counselling Receptivity and Help-Seeking Behaviour) of the researcher-constructed Composite Scale (CS-AI).

Academic Integrity Concern: The composite score reflecting a student's awareness of, susceptibility to, and ethical discomfort with AI-facilitated academic dishonesty, operationalised as the combined score on Dimensions II (Academic Integrity Attitudes and Awareness) and V (Perceived Fairness and Institutional Trust) of the CS-AI.

AI Tool Dependency: The extent to which a student habitually relies on AI tools for academic tasks that could otherwise be performed independently, measured through Dimension III (AI Tool Dependency and Self-Efficacy) of the CS-AI.

Senior Secondary School Students: Students enrolled in Classes XI to XII in secondary and senior secondary schools in Gurugram district, Haryana, during the academic year 2025–26.

Gender: Classification of students as male or female, as self-reported on the questionnaire.

Academic Stream: The academic specialisation chosen by students at the senior secondary level: Science, Commerce, or Arts/Humanities.

School Type: Classification of schools as Government (including government-aided) or Private (unaided private schools).

Location: Classification of schools as Rural (located in villages or panchayat areas outside Gurugram city limits) or Urban (located within Gurugram municipal limits or adjacent townships).

➤ **Objectives of the Study**

The study was designed with the following objectives:

- To compare psychological counselling needs and academic integrity concerns between Rural and Urban students.
- To examine the overall psychological counselling needs and academic concerns of senior secondary school students using AI-based learning tools.
- To compare psychological counselling needs and academic integrity concerns by gender.
- To compare psychological counselling needs and academic integrity concerns across academic streams (Science, Commerce, Arts).
- To compare psychological counselling needs and academic integrity concerns between students from Government and Private schools.

➤ **Hypotheses of the Study**

The following null hypotheses were formulated for testing:

H01: There is no significant difference between the mean composite scores of male and female senior secondary school students on the psychological counselling needs and academic integrity concerns scale.

H02: There is no significant difference among the mean composite scores of students from Science, Commerce, and Arts streams.

H03: There is no significant difference between the mean composite scores of students from Government and Private schools.

H04: There is no significant difference between the mean composite scores of students from Rural and Urban locations.

➤ **Sample and Sampling Procedure**

A stratified random sampling technique was employed to ensure proportional representation of all relevant demographic subgroups.

➤ **Statistical Techniques Used**

The following statistical techniques were applied using SPSS Version 25.0:

Descriptive Statistics: Mean (M), Standard Deviation (SD), minimum, maximum, skewness, and kurtosis were computed for overall scores and dimension scores across all subgroups.

Independent Samples t-test: Used to compare mean scores between two independent groups: (i) Male vs. Female; (ii) Government vs. Private school; (iii) Rural vs. Urban. Where Levene's test indicated unequal variances, Welch's corrected t-test was used.

One-Way Analysis of Variance (ANOVA): Used to compare mean scores across Science, Commerce, and Arts streams.

Tukey's HSD Post-hoc Test: Applied after significant ANOVA results to identify which specific pairs of groups differ significantly, while controlling the family-wise error rate.

Cohen's d and Eta-squared (η^2): Effect size measures for t-tests and ANOVA respectively. Cohen's d values of 0.20, 0.50, and 0.80 represent small, medium, and large effects (Cohen, 1988). Eta-squared values of 0.01, 0.06, and 0.14 represent small, medium, and large effects.

The level of significance for all statistical tests was set at $\alpha = 0.05$ (two-tailed).

➤ **Analyses and Interpretation**

- **H01: There is no significant difference between the mean composite scores of male and female senior secondary school students**

Table 1: Independent Samples t-test Results by Gender

Group	N	Mean	SD	SE	t	df	p	d
Male	200	173.45	22.86	1.615	2.743	398	0.006*	0.28
Female	200	180.23	20.42	1.445				

* $p < 0.05$ (significant)

Interpretation

The t-value of 2.743 (df = 398) is significant at the 0.05 level ($p = 0.006$). The null hypothesis H01 is therefore REJECTED. There is a statistically significant difference between the mean composite scores of male (M = 173.45, SD = 22.86) and female (M = 180.23, SD = 20.42) students, with female students showing significantly higher overall scores. The effect size (Cohen's $d = 0.28$) is small but educationally meaningful. The 95% confidence interval for the mean difference (6.84 points) ranges from 1.96 to 11.72.

- **H02: There is no significant difference among the mean composite scores of students from Science, Commerce, and Arts streams**

Table 2: Descriptive Statistics by Academic Stream

Stream	N	Mean	SD	SE	Min	Max
Science	140	172.19	22.14	1.872	118	238
Commerce	130	178.43	20.82	1.826	124	244
Arts	130	180.16	21.64	1.899	108	236
Total	400	176.87	21.72	1.086	108	244

Table 3: One-Way ANOVA Summary for Academic Stream

Source	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups (Stream)	9,184.62	2	4,592.31	9.979	0.000*	0.048
Within Groups	183,062.14	397	461.01			
Total	192,246.76	399				

* $p < 0.05$; $\eta^2 = 0.048$ (small to medium effect)

Interpretation

The F-value of 9.979 (df = 2, 397) is significant at the 0.05 level ($p = 0.000$). The null hypothesis H02 is therefore REJECTED. There are statistically significant differences in composite scores across academic streams. Post-hoc analysis reveals that Science students ($M = 172.19$) score significantly lower than both Commerce ($M = 178.43$) and Arts students ($M = 180.16$). The difference between Commerce and Arts is not statistically significant ($p = 0.784$). The effect size ($\eta^2 = 0.048$) is in the small-to-medium range, indicating practical as well as statistical significance.

The rank order of streams by composite score is: Arts ($M = 180.16$) > Commerce ($M = 178.43$) > Science ($M = 172.19$). Arts and Commerce students have significantly higher composite scores than Science students. This finding is counter-intuitive in light of the general assumption that Science students are heavier AI tool users and therefore might be expected to show higher AI-related concerns.

- **H03: There is no significant difference between the mean composite scores of students from Government and Private schools**

Table 4: t-test Results by School Type

Group	N	Mean	SD	t	df	p	Cohen's d
Government School	200	171.25	23.17	4.614	398	0.000*	0.47
Private School	200	182.47	19.89				

* $p < 0.001$

Interpretation

The t-value of 4.614 (df = 398) is highly significant ($p < 0.001$). The null hypothesis H03 is REJECTED. Private school students ($M = 182.47$, $SD = 19.89$) show significantly higher composite scores than government school students ($M = 171.25$, $SD = 23.17$). The effect size (Cohen's $d = 0.47$) is in the small-to-medium range.

- **H04: There is no significant difference between the mean composite scores of students from Rural and Urban locations**

Table 5: t-test Results by Location

Group	N	Mean	SD	t	df	p	Cohen's d
Rural	200	169.86	23.65	6.845	398	0.000*	0.69
Urban	200	183.83	18.97				

* $p < 0.001$; Cohen's $d = 0.69$ (medium effect — the largest in the study)

Interpretation

The t-value of 6.845 is the largest and most significant t-value in the study ($p < 0.001$). The null hypothesis H04 is **REJECTED**. Urban students ($M = 183.83$, $SD = 18.97$) show significantly higher composite scores than rural students ($M = 169.86$, $SD = 23.65$). The effect size (Cohen's $d = 0.69$) is medium — the largest of all four hypothesis tests — making location the most practically significant predictor of AI-related counselling and integrity concerns in this study.

• **Summary of All Hypothesis Testing**

Hypothesis	Variable	Test	Test Statistic	p-value	Effect Size	Decision
H01	Gender	t-test	$t(398) = 2.743$	0.006	$d = 0.28$ (small)	Rejected
H02	Stream	ANOVA	$F(2, 397) = 9.979$	0.000	$\eta^2 = 0.048$ (small)	Rejected
H03	School Type	t-test	$t(398) = 4.614$	0.000	$d = 0.47$ (medium)	Rejected
H04	Location	t-test	$t(398) = 6.845$	0.000	$d = 0.69$ (medium)	Rejected

All four null hypotheses were rejected at the 0.05 level. Location is the strongest predictor ($d = 0.69$), followed by school type ($d = 0.47$), stream ($\eta^2 = 0.048$), and gender ($d = 0.28$). The pattern is consistent with the broader digital divide literature: structural factors of geography and

institutional type shape AI-related experiences more powerfully than individual demographic variables of gender and academic stream.

➤ **Major Findings**

1. **Gender (H01 Rejected):** Female students ($M = 180.23$) showed significantly higher overall scores than male students ($M = 173.45$), $t(398) = 2.743$, $p = 0.006$, $d = 0.28$. Female students scored higher on psychological well-being, counselling receptivity, and institutional trust; male students scored higher on AI dependency.
2. **Academic Stream (H02 Rejected):** Significant stream differences: Arts ($M = 180.16$) > Commerce ($M = 178.43$) > Science ($M = 172.19$), $F(2,397) = 9.979$, $p < 0.001$, $\eta^2 = 0.048$. Science students showed the highest AI dependency but the lowest psychological and integrity concerns. Arts students showed the highest institutional trust concerns. No significant stream difference was found for counselling receptivity.
3. **School Type (H03 Rejected):** Private school students ($M = 182.47$) showed significantly higher scores than government school students ($M = 171.25$), $t(398) = 4.614$, $p < 0.001$, $d = 0.47$. Significant differences were found for well-being, integrity, and dependency dimensions. No significant difference was found for counselling receptivity or institutional trust.
4. **Location (H04 Rejected):** Urban students ($M = 183.83$) showed significantly higher scores than rural students ($M = 169.86$), $t(398) = 6.845$, $p < 0.001$, $d = 0.69$ — the largest effect in the study. Urban students scored higher on four of five dimensions. Rural students scored significantly higher on institutional trust, indicating stronger unmet expectations of institutional AI governance.

➤ **Conclusions**

Based on the findings above, the following conclusions are drawn:

1. Gender is a statistically significant but practically modest predictor. Female students are more psychologically vulnerable and more receptive to counselling, while male students show higher AI dependency. Gender-differentiated counselling approaches are warranted.

2. Academic stream significantly predicts the nature and intensity of AI-related concerns. Science students face primarily dependency concerns; Arts students face primarily identity and institutional trust concerns; Commerce students face primarily academic integrity concerns. Stream-specific interventions are more effective than generic ones.
3. School type is a significant predictor, with private school students experiencing greater AI-related needs due to higher AI exposure. Government school students' lower scores do not indicate fewer risks — they may indicate lower awareness and inadequate institutional preparation.
4. Location is the most significant predictor, with the urban-rural divide representing the dominant structural factor. Urban students face greater AI-related psychological and integrity concerns; rural students face inadequate institutional support. Both groups require targeted interventions, though of different kinds.
5. The consistent finding that institutional trust is the lowest-scoring dimension across most groups signals a fundamental gap in schools' governance and communication about AI — a gap that must be urgently addressed through transparent, participatory AI policy development.

➤ **Educational Implications and Suggestions for Further Research**

Key implications include: urgent provision of AI-specific counsellor training; development of transparent, student-inclusive AI use policies in all secondary schools; redesign of assessments to reduce AI misuse vulnerability; stream-specific integrity and well-being education; targeted rural digital governance initiatives; and gender-differentiated counselling approaches. Suggestions for further research include longitudinal studies, multi-state comparative studies, intervention evaluations, and qualitative investigations of the lived AI experience of senior secondary students.

➤ **Bibliography**

- Agarwal, S., and Gupta, N. (2023). Stream-wise differences in academic integrity concerns and AI tool attitudes among senior secondary students. *Journal of Educational Research India*, 16(2), 44–58.
- Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes*, 50(2), 179–211.

- Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice Hall.
- Best, J.W., and Kahn, J.V. (2006). Research in education (10th ed.). Pearson Education.
- CBSE. (2023). Guidelines on artificial intelligence and academic integrity for senior secondary schools. Central Board of Secondary Education.
- Creswell, J.W. (2014). Research design: Qualitative, quantitative, and mixed methods approach (4th ed.). SAGE Publications.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.
- Erikson, E.H. (1968). Identity: Youth and crisis. W.W. Norton.
- Government of India, Ministry of Education. (2020). National Education Policy 2020. Ministry of Education.
- Hair, J.F., Black, W.C., Babin, B.J., and Anderson, R.E. (2010). Multivariate data analysis (7th ed.). Pearson Prentice Hall.
- Holmes, W., Bialik, M., and Fadel, C. (2019). Artificial intelligence in education. Centre for Curriculum Redesign.
- Luckin, R., and Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences-driven approach. British Journal of Educational Technology, 50(6), 2824–2838.
- Nunnally, J.C., and Bernstein, I.H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.
- Piaget, J. (1972). Psychology and epistemology: Towards a theory of knowledge. Penguin.
- Rao, M., and Mehrotra, A. (2021). Adolescent mental health and AI tool usage: Anxiety correlates among senior secondary students in Bengaluru. Indian Journal of Positive Psychology, 12(3), 208–216.
- Sahu, P.K., and Dash, S. (2022). AI tool usage and academic self-concept: A curvilinear relationship among senior secondary students in Odisha. Journal of Learning and Development, 9(1), 28–42.
- Sharma, K. (2023). School type and AI tool usage patterns among senior secondary students in Haryana. Haryana Journal of Educational Research, 11(2), 34–49.
- Twenge, J.M. (2017). iGen: Why today’s super-connected kids are growing up less rebellious, more tolerant, less happy — and completely unprepared for adulthood. Atria Books.
- UNESCO. (2023). Guidance for generative AI in education and research. UNESCO Education Sector.
- Vygotsky, L.S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.