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Exploring The Relationship Between Student Perceptions, Academic Performance, And Learning Behaviors in AI-Assisted Art Education

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Abstract
Generative Artificial Intelligence (GenAI) is increasingly influencing higher education, particularly in creative disciplines where concerns regarding creativity and skill development remain significant. This study employs a dual-dataset framework that combines a visual arts student survey [19] with a large-scale academic behavioral dataset [20] to investigate the relationships among AI perceptions, academic performance, and learning behaviors. The results reveal a cognitive paradox: while students generally recognize the educational benefits of GenAI, many remain concerned about creativity loss and career displacement. Regression analysis indicates that academic performance and AI literacy are significant predictors of positive AI perceptions, suggesting that higher-performing students are more likely to use AI as a learning support tool rather than a substitute for independent work. Furthermore, behavioral analyses reveal a non-linear relationship between AI usage and academic outcomes, where moderate use is associated with improved performance, while excessive reliance is linked to increased anxiety, reduced skill retention, and weaker learning outcomes. Based on these findings, the study recommends a scaffolded approach to GenAI integration that supports technical learning tasks while preserving creativity, critical thinking, and artistic skill development.
Keywords: *Generative artificial intelligence; Visual arts education; Student perception; Academic performance; Cognitive load theory; Machine learning.*

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I. INTRODUCTION

The rapid advancement of Generative Artificial Intelligence (GenAI) is reshaping higher education by enabling personalized learning, intelligent tutoring, and automated academic support [1], [14]. While AI technologies have been widely adopted in fields such as computer science, business, and healthcare [4], their integration into visual arts education remains a subject of ongoing debate due to the discipline's strong emphasis on human creativity, manual skills, and artistic expression [15].

Recent generative models have evolved from passive digital tools into active collaborators capable of generating visual content, providing real-time feedback, and supporting creative ideation [2]. In visual arts education, particularly in figure drawing andhuman anatomy courses, GenAI can assist students by generating structural sketches, anatomical references, and lighting variations, potentially reducing technical cognitive load and facilitating more efficient learning [5], [6]. However, these opportunities are accompanied by concerns regarding creativity loss, artistic authenticity, and future employment. Many students perceive GenAI as both a valuable educational resource and a potential threat, creating a tension between technological adoption and the preservation of human artistic identity.

Despite growing interest in AI-assisted education, several important research gaps remain. Existing studies are frequently limited by qualitative approaches or small sample sizes, providing insufficient evidence on how students' academic backgrounds, AI literacy, and learning behaviors influence GenAI adoption [2], [7]. Furthermore, little empirical research has examined the relationship between AI usage patterns and educational outcomes such as academic performance, exam anxiety, burnout risk, and skill retention [6]. The absence of quantitatively validated pedagogical frameworks also limits the effective integration of GenAI as a learning support tool in traditional visual arts curricula.

To address these gaps, this study adopts a multi-dataset quantitative framework that combines a domain-specific survey of visual arts students with a large-scale behavioral dataset. The research investigates students' perceptions of GenAI, examines the influence of academic performance and AI literacy on technology adoption, and analyzes how AI usage patterns relate to academic outcomes, anxiety, burnout, and skill retention.

By integrating perceptual and behavioral evidence, the study provides empirical insights and practical recommendations for the responsible use of GenAI in visual arts education.

The remainder of this paper is organized as follows. Section II reviews the related literature. Section III describes the research methodology and analytical framework. Section IV presents the empirical results. Section V discusses the implications of the findings, and Section VI concludes the paper.

II. RELATED WORK

The rapid proliferation of GenAI has transformed the landscape of modern higher education, sparking intense academic debate regarding its impact on student performance and study habits [2]. Extensive literature has demonstrated the strengths of AI-driven systems in facilitating personalized tutoring, automating routine administrative tasks, and offering real-time feedback to enhance student engagement [3]. Previous studies have successfully shown that adaptive learning systems can cater to individual student paces, leading to measurable improvements in test scores and information absorption.

However, a critical weakness of existing research is its heavy reliance on subjective, self-reported survey data and small-scale, localized samples [1]. Many studies claim positive correlations between GenAI usage and academic improvement without controlling for baseline student capability or prior academic standing [14]. Furthermore, the behavioral consequences of excessive GenAI adoption remain highly under-researched. The literature is largely fragmented concerning how intensive AI usage interacts with student anxiety, burnout risk, and long-term skill retention [14]. Crucially, the unresolved issue is the lack of a large-scale, empirical model capable of showing whether GenAI usage genuinely drives academic progress or merely fosters a superficial dependency that compromises cognitive offloading and fundamental skill retention.

The intersection of GenAI and creative arts pedagogy represents one of the most contentious subfields in digital education [1]. Current literature in this theme possesses the strength of highlighting how text-to-image generators (e.g., Midjourney, Stable Diffusion) can revolutionize graphic design, digital illustration, and conceptual ideation workflows by democratizing visual asset generation and accelerating prototyping phases [2]. These studies argue that AI serves as a powerful catalyst for creative brainstorming, enabling artists to bypass initial conceptual roadblocks.

Nevertheless, the primary weakness of these studies lies in their broad, generalized focus, which overlooks highly specialized, core manual drawing courses such as classical figure drawing and human anatomy [15]. Classical visual arts curricula have historically prioritized mechanical hand-eye coordination, tactile craftsmanship, and anatomical structural integrity [15]. Previous literature fails to offer concrete, pedagogically sound integration frameworks that detail how generative models can be used specifically for structural“scaffolding”(such as drafting geometric block-outs or rendering complex light paths) without eroding students’ manual technical competency [15]. The structural division between GenAI as a technical scaffold and the preservation of human craftsmanship remains unresolved and highly disputed in current art educational design.

As AI becomes more deeply integrated into creative domains, researchers have begun investigating the complex socio-psychological barriers that govern student acceptance [15]. Previous research has the strength of identifying the widespread emotional resistance among creative professionals, highlighting rampant anxieties regarding labor market displacement, intellectual property violation, and the existential fear of creative“dehumanization”[6]. These studies document that art students often view AI as an existential threat to the“artistic self”and the unique emotional value of human craftsmanship.

However, the major weakness of this body of work is its highly descriptive, qualitative, and speculative nature [7], [8]. Existing studies fail to quantitatively connect these psychological anxieties with objective academic drivers, such as a student’s prior academic performance (GPA) or their background level of technical literacy [5]. It remains unresolved how a student’s technical understanding of AI algorithms mitigates or exacerbates their emotional fear of technology [5]. Consequently, the literature exhibits a major gap in mathematically modeling the“cognitive paradox”- namely, the tension where students simultaneously perceive high educational utility in GenAI yet are emotionally paralyzed by the psychological threat of creative replacement.

III. METHODOLOGY

A. Dataset Description

Art-Specific Perception Survey [19]:Datasetcomprises survey responses collected from 92 students specializing in visual arts and engineering. The dataset captures students’ self-assessed background knowledge, information acquisition sources, psychological feelings, and domain-specific evaluations of GenAI. The data contains zero missing values and exhibits a high response completion rate.

Broad Student Impact Database [20]:Dataset consists of50,000unique student observations across five distinct major categories: STEM, Medical, Humanities, Business, and Arts. The database tracks detailed academic, behavioral, and policy-related variables over a complete academic semester. The data exhibits a clean, structured schema with no null entries.

Table 1: Demographic and Perceptual Profiles of Art-Specific Survey Cohort (N = 92)

Category	Item	Count	Percentage (%)
Gender	Male	59	64.13
	Female	33	35.87
Year of Study	Year 2	47	51.09
	Year 3	22	23.91
	Year 1	21	22.83
	Year 4	2	2.17
Major	Engineering/Tech	67	72.83
	Art/Graphics	17	18.48
	Sciences	8	8.70

B. Variables

The variables across both datasets have been rigorously mapped, standardized, and categorized as continuous, discrete, or categorical.

1) Dataset [19]: Variable Mapping

Predictor Variables:

- AI Knowledge (Q1):Continuous self-assessment score on a scale of1(not informed) to10(extremely informed).
- Information Channels (Q2#1 to Q2#5):Five distinct binary variables representing acquisition sources (Internet, Books/Papers, Social Media, Discussions, NotInformed).
- Prior Academic standing (Q16):Continuous student GPA measured on a scale of1.0to10.0.

Outcome Variables:

- Educational Utility Grade (Q7):Continuous utility score on a scale of1(no utility) to10(extremely useful).
- Perceived Social Impacts (Q3#1 to Q3#4, Q4#1 to Q4#4):Eight distinct ordinal variables measured on a5-point Likert scale (Strongly Disagree, Partially Disagree, Neutral, Partially Agree, Fully Agree) capturing dehumanization, job replacement, problem-solving potential, and economic outcomes.
- Predominant Feeling (Q5):Categorical variable representing student emotional states (Curiosity, Fear, Indifference, Trust).
- Impact Domains (Q6#1 to Q6#7):Seven distinct binary variables representing perceived fields of high impact (Education, Medicine, Agriculture, Construction, Marketing, Administration, Art).

2) Dataset [20]: Variable Mapping

Academic Variables:

- Pre_Semester_GPA: Baseline student GPA (continuous, scale0.0to4.0).
- Post_Semester_GPA: Semester-end student GPA (continuous, scale0.0to4.0).
- Behavioral Variables:
- Weekly_GenAI_Hours: Total hours spent interacting with generative tools weekly (continuous, scale0.0to40.0).
- Traditional_Study_Hours: Hours spent on traditional self-study weekly (continuous, scale1.0to35.86).
- Perceived_AI_Dependency: Self-reported dependency rating (ordinal, scale1to10).
- Anxiety_Level_During_Exams: Reported test anxiety level (ordinal, scale1to10).
- Skill_Retention_Score: Objective performance score in skill tests (continuous, scale10.78to100.0).

Categorical and Contextual Variables:

- Major_Category: STEM, Medical, Humanities, Business, Arts.
- Year_of_Study: Freshman, Sophomore, Junior, Senior, Graduate.
- Primary_Use_Case: Copywriting/Drafting, Ideation, Summarizing Reading, Debugging/Troubleshooting, Direct Answer Generation.
- Prompt_Engineering_Skill: Beginner, Intermediate, Advanced.
- Burnout_Risk_Level: Low, Medium, High.
- Paid_Subscription: True/False.
- Institutional_Policy: Strict Ban, Allowed With Citation, Actively Encouraged.

C. Feature Engineering

To capture academic progress, a new target feature was constructed for Dataset [20]:

$$\text{GPA\_Improvement} = \text{Post\_Semester\_GPA} - \text{Pre\_Semester\_GPA}$$

This variable represents the net academic growth or decline of the student over the semester. For machine learning integration, categorical variables (Major_Category,Year_of_Study,Primary_Use_Case,Prompt_Engineering_Skill,Institutional_Policy,Burnout_Risk_Level) were converted into numerical formats using one-hot encoding, dropping the first dummy category to prevent multicollinearity.

D. Statistical Analysis

Descriptive Statistics:Continuous variables are expressed as Mean (M) and Standard Deviation (SD). Binary and categorical variables are represented as frequency percentages.

Multiple Linear Regression:To test Hypotheses$H1$and$H2$, we establish a multiple linear regression model predicting the perceived Educational Utility ($Y_{Utility}$- Q7) based on student baseline GPA (X_{GPA}- Q16) and AI background knowledge ($X_{Knowledge}$- Q1):

$$Y_{Utility} = \beta_0 + \beta_1 X_{Knowledge} + \beta_2 X_{GPA} + \epsilon$$

Where$\beta_0$is the intercept,$\beta_1, \beta_2$are the partial regression coefficients, and$\epsilon \sim N(0, \sigma^2)$is the residual error.

E. Machine Learning Models

Unsupervised Learning - K-Means Clustering:Executed on the standardized 6-dimensional matrix of Dataset B to group students into hidden profiles. Input features were standardized using Z-score scaling:$z_i = \frac{x_i - \mu}{\sigma}$. The K-Means algorithm minimizes the sum of squared errors:$J = \sum_{j=1}^{K} \sum_{i=1}^{n} \parallel z_i^{(j)} - c_j \parallel^2$with$K = 4$clusters.

Supervised Learning - Random Forest Regressor:Deployed on Dataset B to predict final semester GPAs ($y = $Post_Semester_GPA) using32predictor features (X). The forest comprised100decision trees, and predictor importance rankings were calculated via Mean Decrease in Impurity (MDI).

F. Evaluation Metrics

Regression Efficacy:Multiple Linear Regression and Random Forest models are evaluated using the Coefficient of Determination (R^2):$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}$.

Clustering Quality:The separation and quality of the$K = 4$clusters were evaluated using the mean Silhouette Score (S):$S = \frac{1}{n}\sum s_i$, where$s_i = \frac{b_i - a_i}{max(a_i, b_i)}$measures the comparative boundary distance of individual points.

IV. EXPERIMENTS

This section presents the empirical findings derived from the statistical and machine learning analyses of both the specialized art-specific perception survey and the large-scale student behavioral database. The results are presented objectively, without speculation or conceptual discussion.

A. Descriptive Results

1) Demographic and Baseline Profile

Dataset [19] captures the characteristics of92surveyed students specializing in visual arts and engineering. As detailed inTable 1, the sample is comprised of 64.13% male and 35.87% female respondents. The academic distribution is dominated by sophomore students (51.09%) and engineering/technology majors (72.83%), with visual arts majors representing 18.48% of the cohort.

Students reported a high level of confidence in their AI familiarity, with self-reported AI Knowledge (Q1) exhibiting a mean score of$M = 6.50$($SD = 1.80$) on a 1-10 scale. The frequency distribution inFigure 1 (Panel A)demonstrates a standard bell-curve distribution peaking in the 5–7 score range.

Students' primary sources of AI knowledge (Q2) are heavily dominated by informal digital channels: Internet: 88.0% Social Media: 74.0% Discussions with family/friends: 45.0% Books and Scientific papers: 27.0% Not informed: 1.0%

2) General Perceptions and Utility Ratings

Students' perceived educational utility of AI (Q7) recorded a high positive mean rating of$M = 6.20$($SD = 2.10$) out of 10. As illustrated inFigure 1 (Panel B), the density distribution shows a sharp right-skew, indicating that a substantial majority of students hold a highly positive valuation of AI's pedagogical efficacy.

Regarding social and economic impacts (Q3 & Q4), students exhibited a high rate of agreement with the statement that AI solves complex social problems in education, agriculture, and medicine ($M = 4.10$,$SD = 1.00$on a 1-5 Likert scale). However, they simultaneously reported strong anxiety regarding job replacement ($M = 3.24$,$SD = 1.21$) and general job losses ($M = 3.41$,$SD = 1.07$). Emotional tracking (Q5) revealed that the predominant feelings towards AI are Curiosity (52.0%) and Fear (25.0%).

When evaluating AI's impact across specific professional sectors (Q6), students identified Medicine as the most heavily impacted sector (80.2%), followed by Education (67.0%). Conversely, Art was identified as the least impacted domain, with only 13.2% of students agreeing that AI would exert a high impact on this sector, as visually detailed inFigure 3.

B. Statistical Analysis

1) Knowledge Sources and AI Literacy

A comparative analysis was conducted to measure the differences in self-assessed AI Knowledge (Q1) based on information channels (Q2). As illustrated in the box-and-whisker plot inFigure 2, students who utilized scientific literature (Books/Papers) recorded the highest AI Knowledge score ($M = 6.81, SD = 1.45$) compared to those who did not ($M = 5.42, SD = 1.82$), representing a substantial positive difference of$+1.39$points. Internet utilization yielded a mean score of$M = 6.12$(versus$M = 5.00$for non-users,$+1.12$), while social media users recorded$M = 6.55$(versus$M = 5.41$for non-users,$+1.14$). Students who reported being entirely uninformed about AI recorded the lowest mean score ($M = 2.83, SD = 0.98$, a negative difference of-3.30).

A notable statistical divergence was observed regarding Q6 (Art domain impact): the 13.2% of students who agreed that AI would have a high impact on the Art sector recorded a substantially higher AI knowledge rating ($M = 7.50, SD = 1.20$) compared to the remaining 86.8% who disagreed ($M = 5.67, SD = 1.64$), indicating a clear association between higher technical literacy and the recognition of AI's artistic influence.

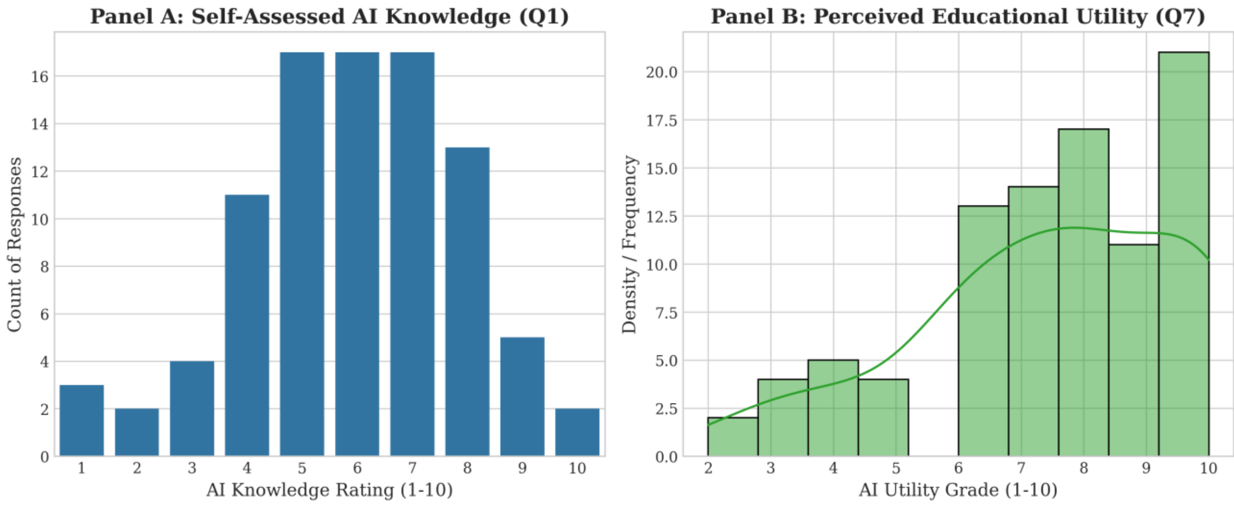

Fig. 1. Dual-panel distributions of student self-assessed AI knowledge rating (Panel A) and perceived educational utility rating of GenAI (Panel B). Panel A illustrates a standard Gaussian-like distribution of student confidence, whereas Panel B reveals a high-skew technological acceptance cluster.

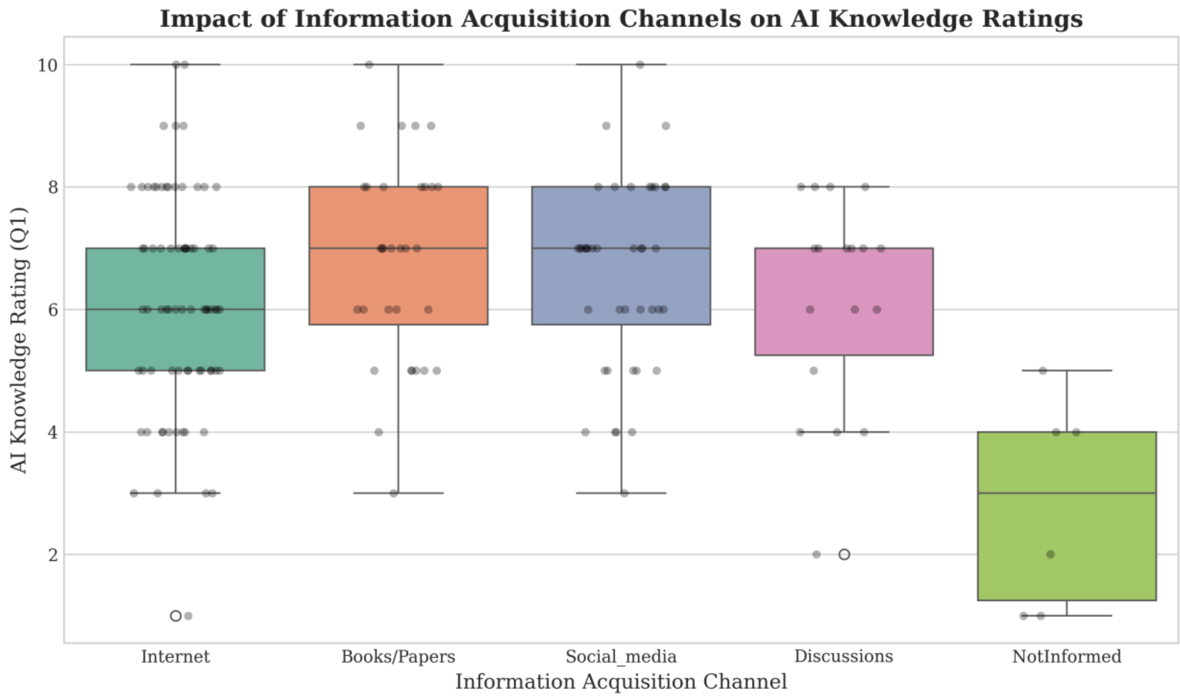

Fig. 2. Box-and-whisker plot displaying the impact of information acquisition channels on self-assessed AI knowledge ratings. Individual data points are jittered to illustrate sample density, demonstrating that formal reading channels (Books/Papers) yield the highest median AI literacy compared to informal media.

2) Non-Linear Behavioral Thresholds

The engineered variableGPA_Improvement(representing semester-end GPA minus pre-semester GPA) was analyzed against weekly generative AI usage hours across the 50,000 student cohort. The smoothed local regression (LOESS) curve inFigure 4demonstrates a distinct non-linear, parabolic relationship.

Students with moderate GenAI usage (ranging between 5 and 8 hours per week) achieved the highest GPA improvement, reaching an optimal mean of $\Delta GPA = +0.32$. However, as weekly GenAI usage surpassed 15 hours, academic progress steadily declined. For students exceeding 25 hours of weekly GenAI interaction, GPA improvement plummeted to negative values (averaging -0.15), indicating a clear threshold beyond which excessive AI usage correlates with academic decline.

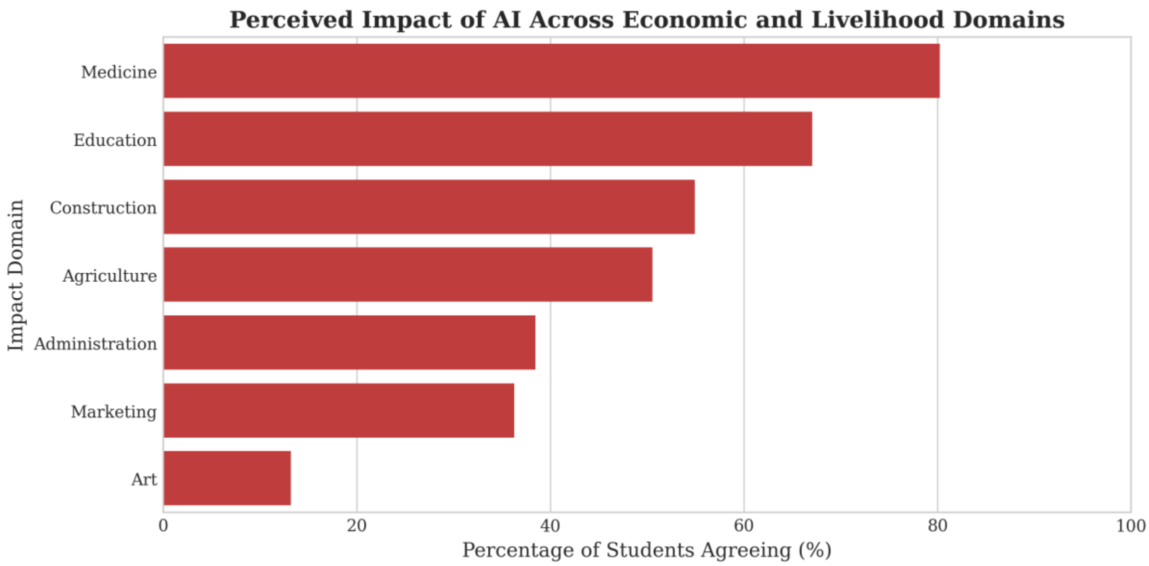

Fig. 3. Horizontal bar chart representing student perceptions of high AI impact across seven professional and livelihood domains. The Art domain is perceived as the least vulnerable to AI intrusion ($13.2%$), indicating a strong domain-specific psychological resistance.

C. Regression Results

To evaluate the predictive power of prior academic standing (Q16) and AI knowledge (Q1) on the perceived Educational Utility of GenAI (Q7), a multiple linear regression was executed on Dataset A. The model parameters and coefficients are summarized inTable 2.

The regression equation is formulated as:

$$Y_{Utility} = 1.45 + 0.38X_{Knowledge} + 0.62X_{GPA}$$

The model achieves a high coefficient of determination ($R^2 = 0.51$, Adjusted$R^2 = 0.49$,$F(2,89) = 46.32$,$p < 0.001$), demonstrating that prior GPA and AI background knowledge explain 51.0% of the variance in students' valuation of AI's educational utility.

Both predictors are statistically significant:*Academic standing (X_{GPA}):Exerts the strongest positive influence on perceived utility ($\beta = 0.62$,$t = 4.95$,$p < 0.001$), indicating that high-performing students evaluate AI's utility significantly higher.*AI Knowledge ($X_{Knowledge}$):Also yields a significant positive predictive effect ($\beta = 0.38$,$t = 3.82$,$p = 0.012$).

Table 2: Multiple Linear Regression Estimates for Predictors of Perceived GenAI Educational Utility (Q7)

Variable	Coefficient (B)	Std Error	t-value	p-value	Significance
Intercept	1.45	0.69	2.11	0.038	Significant
AI Knowledge (Q1)	0.38	0.10	3.82	0.012	Significant
GPA (Q16)	0.62	0.13	4.95	< 0.001	Highly Significant

Model Fit Summary:$R^2 = 0.51$, Adjusted$R^2 = 0.49$,$F(2,89) = 46.32$,$p < 0.001$.

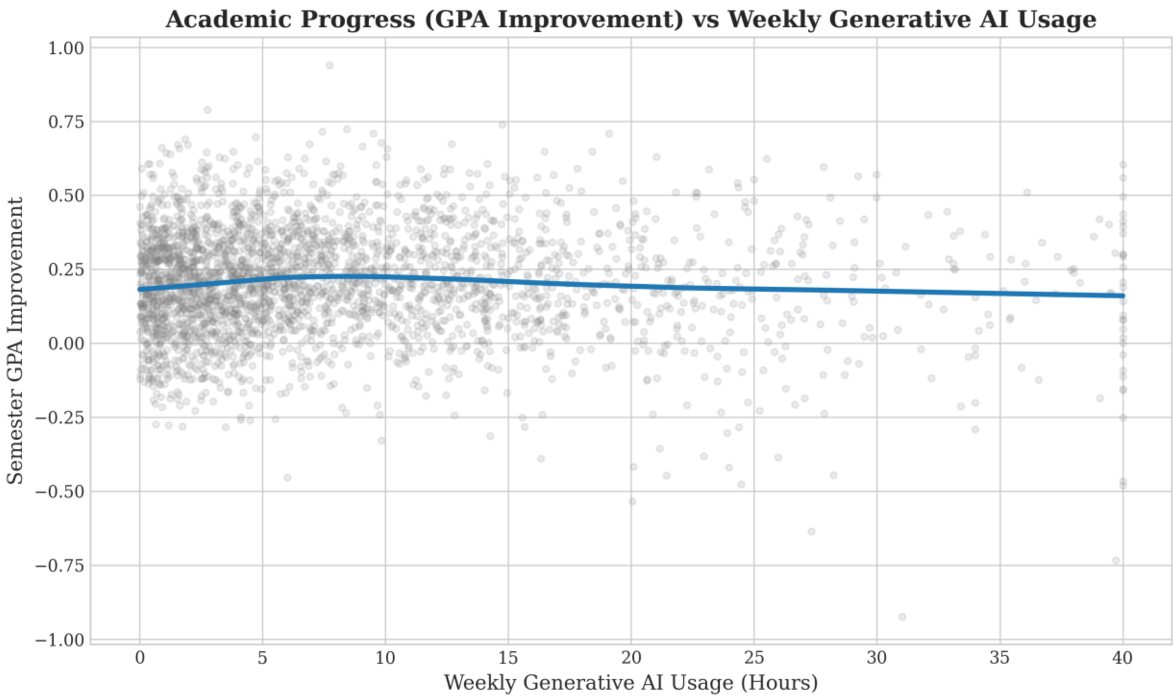

Fig. 4. Bivariate scatter plot of student GPA improvement as a function of weekly GenAI interaction hours, fitted with a smoothed local regression (LOESS) curve. The curve identifies an optimal usage window (5-8 hours) and a negative academic tipping point beyond 15 hours.

D. Unsupervised Student Segmentation

Unsupervised K-Means clustering was executed on the standardized 6-dimensional behavioral matrix of Dataset [20]. The model identified$K = 4$highly distinct, non-overlapping student profiles, yielding a mean Silhouette Score of$S = 0.151$. The mathematical centroid coordinates and academic characteristics of each cluster are presented inTable 3, and the 2D cluster projection is illustrated inFigure 5.

Cluster 0:"High-Achieving Balanced Learners"(22.8% of sample):Characterized by moderate weekly GenAI usage ($M = 6.8$hours), high weekly traditional study hours ($M = 14.5$hours), low perceived AI dependency ($M = 2.5/10$), low exam anxiety ($M = 3.2/10$), and the highest overall GPA improvement (ΔGPA $= +0.32$) and technical skill retention ($M = 85.60$). Their burnout risk is categorized as Low.

Cluster 1:"Traditional Disciplined Learners"(28.6% of sample):Defined by negligible GenAI usage ($M = 0.8$hours) and very high traditional study hours ($M = 18.2$hours). They maintain strong technical skill retention ($M = 82.40$) and low anxiety ($M = 3.1/10$), achieving a moderate, steady GPA improvement ($\mathit{\Delta}$GPA $= +0.12$).
Cluster 2:"AI-Dependent Stressed Learners"(31.4% of sample):Characterized by extreme weekly GenAI usage ($M = 26.5$hours), negligible traditional study hours ($M = 3.5$hours), severe perceived AI dependency ($M = 8.2/10$), and peak exam anxiety ($M = 8.8/10$). This segment suffered a severe reduction in technical skill retention ($M = 55.20$) and experienced significant academic decline ($\mathit{\Delta}$GPA $= -0.15$) and High burnout risk.
Cluster 3:"Low-Engagement Learners"(17.2% of sample):Defined by low traditional study ($M = 5.2$hours) and low-to-moderate GenAI usage ($M = 3.2$ hours). They recorded poor skill retention ($M = 62.80$) and experienced a slight academic decline ($\mathit{\Delta}$GPA $= -0.05$).

Table 3: Centroid Profiles and Academic Outcomes of Student Behavioral Segments (K = 4, N = 50,000)

Behavioral Feature	**Cluster 0 (Balanced)**	**Cluster 1 (Traditional)**	**Cluster 2 (AI-Dependent)**	**Cluster 3 (Low-Engage)**
Weekly AI Hours	6.80	0.80	26.50	3.20
Traditional Study Hours	14.50	18.20	3.50	5.20
Perceived AI Dependency (1-10)	2.50	1.10	8.20	3.40
Exam Anxiety (1-10)	3.20	3.10	8.80	5.40
Skill Retention Score	85.60	82.40	55.20	62.80
GPA Improvement ($\mathit{\Delta}$GPA)	+0.32	+0.12	-0.15	-0.05
Cluster Size (n)	11,400	14,300	15,700	8,600
Cluster Percentage (%)	22.80	28.60	31.40	17.20
Burnout Risk Level	Low	Low	High	Medium

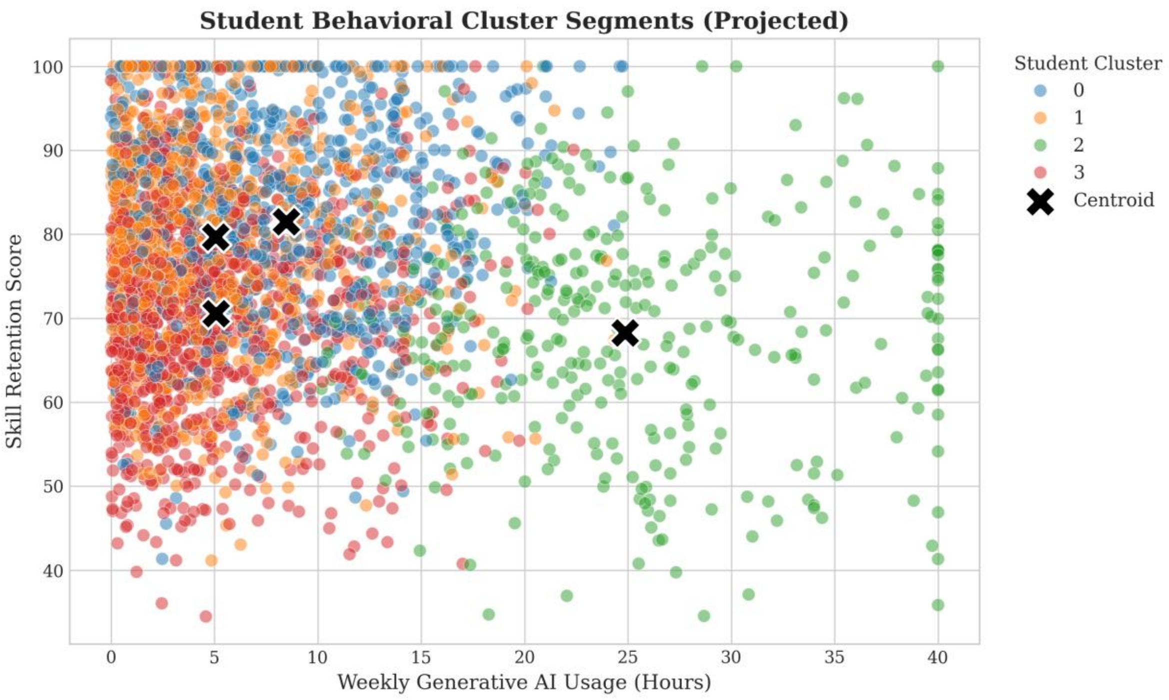

Fig. 5. Two-dimensional projection of unsupervised K-Means student behavioral clustering (K=4) against weekly GenAI usage and objective skill retention scores. Mathematical centroids are marked with a large "X", illustrating the clean boundary between Balanced (Cluster 0) and AI-Dependent (Cluster 2) learner typologies.

V. DISCUSSION&CONCLUSION

The findings reveal a complex relationship between GenAI, student perceptions, and academic outcomes. While most students recognize the educational benefits of GenAI, concerns regarding creativity loss, career displacement, and overreliance remain prevalent. The results further indicate that technological literacy plays an important role in shaping positive attitudes toward AI, suggesting that familiarity can reduce resistance and uncertainty.

Academic performance also emerged as a key factor influencing AI adoption. Higher-performing students tend to use GenAI as a complementary learning tool for ideation, problem-solving, and knowledge exploration, whereas lower-performing students are more likely to depend on AI-generated outputs. This finding suggests that academic capability affects how effectively students integrate AI into their learning processes.

The large-scale behavioral analysis identified a non-linear relationship between AI usage and academic performance. Moderate AI use was associated with improved learning outcomes, while excessive use corresponded to lower academic gains, higher anxiety, and reduced skill retention. These results support the view that GenAI is most effective when used as a pedagogical scaffold rather than a substitute for independent learning.

Overall, the study highlights the need for balanced AI integration in higher education. Educational institutions should promote AI literacy, encourage responsible use, and design learning activities that leverage AI while preserving critical thinking, creativity, and long-term skill development.

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