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An Exploratory Data Analysis of Agentic System Use on the Chaoxing Platform: Behavioral Correlates, Purposes, and Perceptions

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Abstract: Students increasingly use AI-powered features on learning platforms. We explore AI companion usage patterns on the Chaoxing (Superstar) Learning Platform using survey data from 75 university students. Using a three-tier EDA framework (univariate description, bivariate correlation, and multivariate exploration), we examine usage behaviors (frequency, duration, depth), usage purposes (seven categories), demographic differences, and user perceptions. Key findings reveal a significant positive correlation between usage duration and depth (Spearman $\rho = 0.325$, $p < 0.01$), suggesting a learning curve effect. Usage purposes are significantly associated with behavioral depth: students using AI for assignments ($p = 0.005$), emotional support ($p = 0.011$), and AI Q&A ($p = 0.023$) demonstrate deeper engagement. The strongest purpose co-occurrence is between assignments and instructor requirements (Jaccard = 0.672). In addition, demographic variables (gender, grade, major) show no significant association with usage behavior, with similar usage patterns across groups. User perception analysis reveals 'convenient' as the dominant keyword (n = 22), surpassing 'useful' (n = 10). Overall, usage correlates with depth, purposes differentiate depth, and convenience dominates perceptions; findings are relevant to platform design.

Keywords: Exploratory data analysis (EDA); AI companion; Chaoxing platform; Usage behavior; Learning analytics

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1. Introduction

Generative AI tools are now widely used in higher education, and recent research documents their rapid diffusion amid debate over the opportunities and challenges they bring [1]. In Chinese higher education, empirical studies show that generative AI has become a common component of students' academic work,

with usage patterns evolving from occasional assistance toward deeper integration [2]. Large language models present substantial opportunities for personalized and interactive learning, yet their unreflective use also raises concerns about over-reliance and cognitive outsourcing [3]. These developments motivate a closer empirical look at how students actually use such tools.

Among various AI-enhanced educational platforms, the Chaoxing (Superstar) Learning Platform, widely adopted in Chinese higher education institutions, has integrated a suite of AI companion features, including knowledge graphs, extended learning materials, learning analytics dashboards, AI-powered Q&A agents, and assignment assistance tools. Despite the platform's extensive deployment, systematic empirical research on how students actually use these AI companion functions remains scarce. Existing studies predominantly focus on technology acceptance models or learning outcome assessments, with limited attention to the nuanced behavioral patterns and interrelationships among usage dimensions revealed through exploratory approaches [4,5].

The present study addresses this gap by applying exploratory data analysis (EDA), a methodology that emphasizes letting data reveal patterns before imposing modeling assumptions and remains central to modern statistical practice [6]. EDA is particularly well-suited for early-stage investigations where the phenomenon is not yet fully understood, as it combines descriptive statistics, visualization, and non-parametric testing to uncover structures, anomalies, and relationships in the data. Four research questions guide this study:

RQ1: What are the usage behavior patterns of the Chaoxing AI companion in terms of frequency, duration, and depth?

RQ2: What purposes drive AI companion usage, and how do these purposes co-occur?

RQ3: Are there demographic differences in AI companion usage behavior?

RQ4: How do users subjectively perceive the AI companion features?

2. Methodology

2.1. Data source and cleaning

The data were collected through a structured online questionnaire distributed via the Wenjuanxing platform to students at a Chinese university who had used the Chaoxing Learning Platform. The original dataset contained 109 responses. After removing invalid entries (incomplete responses, straight-lining, or excessively short completion times), 75 valid responses were retained for analysis, yielding an effective response rate of 68.8%.

2.2. Variables

The questionnaire comprised several modules. For this EDA study, we excluded 33 Likert-scale items measuring technology acceptance (PEOU, PU, BI, AC, USE) and higher-order thinking (PS, CT, MN, CR), which are reserved for a separate structural equation modeling study. The retained variables include: (a) usage behavior, comprising three ordinal variables capturing usage frequency (4 levels), usage duration (3 levels), and self-assessed usage depth (3 levels); (b) usage purposes, one multi-select variable with seven options (knowledge graphs, extended materials, learning analytics, AI Q&A, assignment assistance, emotional value, instructor requirement); (c) demographics, including gender, grade level, and major category; (d) daily AI habits, one open-ended item and one binary item on teaching family members to use AI (the binary item was not analyzed in the present study); and (e) open-ended perceptions, keyword evaluation and suggestions for improvement.

2.3. Analytical approach

This study adopts a three-tier EDA framework. The first tier involves univariate descriptive analysis to profile the sample and usage distributions. The second tier employs bivariate analyses: Spearman rank-order correlations for ordinal variable associations, chi-square tests with Cramér's V for categorical cross-tabulations, and Mann-Whitney U tests for comparing usage depth across purpose subgroups. The third tier extends to multivariate exploration through Jaccard similarity coefficients for purpose co-occurrence analysis and network visualization. All analyses were conducted using Python (pandas, scipy, matplotlib, seaborn, and networkx). Statistical significance is reported at three levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

3. Results

3.1. Sample profile

Table 1 presents the demographic profile of the 75 respondents. The sample is relatively balanced by gender (53.3% male, 46.7% female). Sophomores constitute the largest group (n = 40, 53.3%), followed by freshmen (n = 34, 45.3%), with only one junior (1.3%). Business-related majors dominate (n = 36, 48.0%), followed by STEM (n = 17, 22.7%), Other (n = 16, 21.3%), and Humanities & Social Sciences (n = 6, 8.0%) (**Table 1**). **Figure 1** and **Figure 2** provide visual summaries of these distributions.

Table 1. Sample demographic profile (N = 75)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	40	53.3
Gender	Female	35	46.7
Grade	Sophomore	40	53.3
Grade	Freshman	34	45.3
Grade	Junior	1	1.3
Major	Business	36	48
Major	STEM	17	22.7
Major	Other	16	21.3
Major	Humanities & Social Sciences	6	8

Note. N = 75. Percentages may not sum to 100.0% due to rounding.

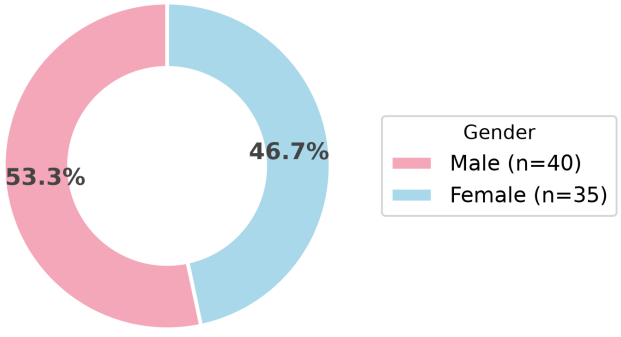


Figure 1. Gender distribution of respondents.

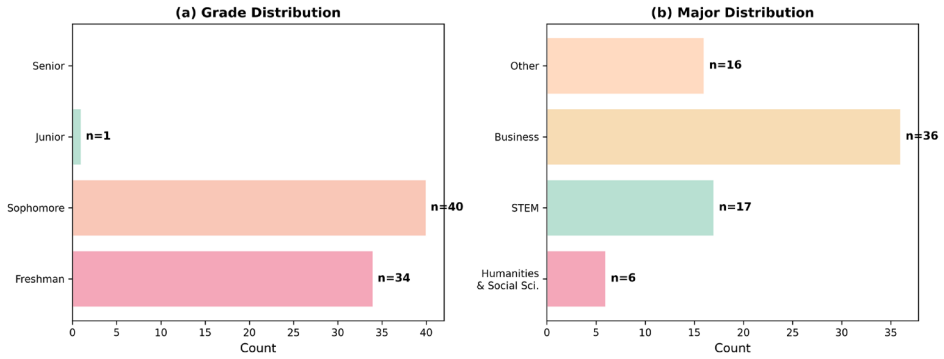


Figure 2. Grade level and major category distribution.

3.2. AI companion usage behavior

Table 2 summarizes the three usage behavior dimensions. Regarding frequency, the largest group uses the AI companion on a weekly basis (n = 26, 34.7%), followed by daily (n = 19, 25.3%) and 1–2 times per semester (n = 19, 25.3%), with monthly users being the smallest group (n = 11, 14.7%). For usage duration, 44.0% have used the features for less than one semester, 30.7% for 1–2 semesters, and 25.3% for more than two semesters. In terms of self-assessed usage depth, nearly half (49.3%) identify as intermediate users, 42.7% as beginners, and only 8.0% as advanced users (**Table 2**). **Figure 3** visualizes these distributions side by side.

Table 2. AI companion usage behavior summary (N = 75)

Variable	Category	Frequency (n)	Percentage (%)
Usage frequency	Weekly	26	34.7
Usage frequency	1–2/semester	19	25.3
Usage frequency	Daily	19	25.3
Usage frequency	Monthly+	11	14.7
Usage duration	< 1 semester	33	44
Usage duration	1–2 semesters	23	30.7
Usage duration	> 2 semesters	19	25.3
Self-rated depth	Intermediate	37	49.3
Self-rated depth	Beginner	32	42.7
Self-rated depth	Advanced	6	8

Note. N = 75. Percentages may not sum to 100.0% due to rounding.

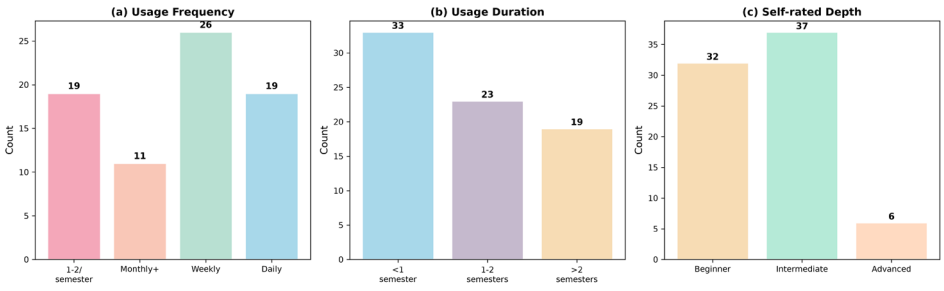


Figure 3. Distribution of usage frequency, duration, and depth.

Table 3 presents the Spearman rank-order correlation matrix among the three usage behavior dimensions. A significant positive correlation emerges between usage duration and depth ($\rho = 0.325$, $p < 0.01$), indicating that students who have used the AI companion for longer periods tend to engage at deeper levels, a pattern consistent with a learning curve effect. A significant positive correlation also appears between usage frequency and duration ($\rho = 0.288$, $p < 0.05$), implying that more frequent users tend to have used the platform for longer periods, consistent with sustained adoption. The correlation between frequency and depth is positive but not statistically significant ($\rho = 0.112$, $p > 0.05$). **Figure 4** provides a visual heatmap of these correlations.

Table 3. Spearman rank-order correlations among usage behavior dimensions

Variable 1	Variable 2	Spearman ρ	*p*-value	Significance
Frequency	Duration	0.2877	0.0123	*
Frequency	Depth	0.1121	0.3384	
Duration	Depth	0.3249	0.0045	**

Note. Spearman rank correlation. N = 75. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

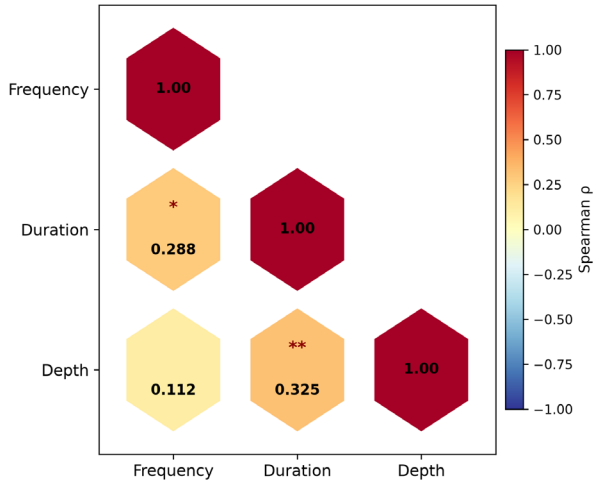


Figure 4. Heatmap of Spearman correlations among usage behavior dimensions.

3.3. Usage purpose analysis

The seven usage purposes were measured as a multi-select item, allowing respondents to choose multiple options. As shown in the radar chart (**Figure 5**), the most frequently selected purposes are assignment assistance (n = 52, 69.3%), access to extended learning materials (n = 45, 60.0%), and instructor requirement (n = 45, 60.0%). Learning analytics (n = 43, 57.3%), knowledge graphs (n = 39, 52.0%), AI Q&A agents (n = 21, 28.0%), and emotional value (n = 10, 13.3%) follow. This distribution reveals a dual motivation structure: task-driven purposes (assignments, instructor requirements) and resource-driven purposes (materials, knowledge graphs) both feature prominently.

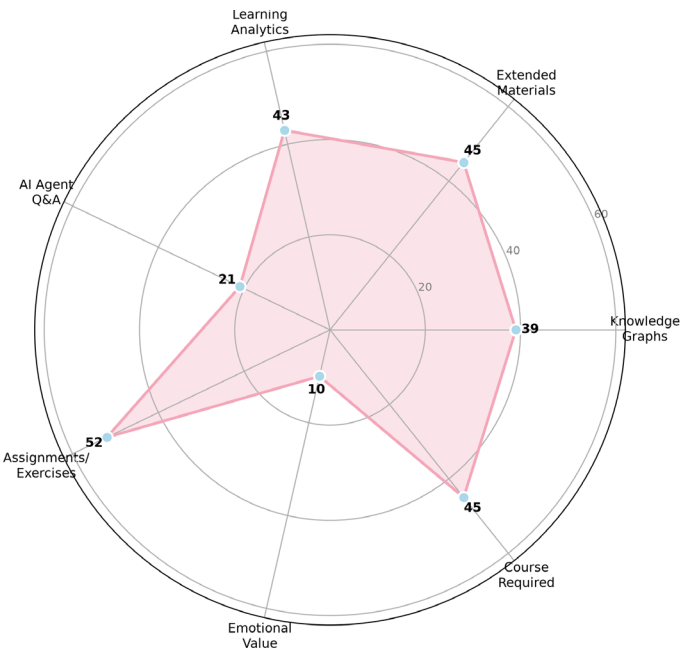


Figure 5. Radar chart of usage purpose selection frequencies.

Table 4 presents the Jaccard similarity coefficient matrix for pairwise purpose co-occurrence. The strongest co-occurrence relationship is between assignment assistance and instructor requirement (Jaccard = 0.672), indicating that these two purposes frequently appear together: students whose instructors require platform usage overwhelmingly also use it for assignments. Other notable co-occurrence pairs include knowledge graphs with learning analytics (Jaccard = 0.547) and extended materials with assignment assistance (Jaccard = 0.540). The network visualization (**Figure 6**) and heatmap (**Figure 7**) summarize these coefficients.

Table 4. Jaccard similarity coefficients for usage purpose co-occurrence

	Know. Graph	Ext. Mater.	Learn. Anal.	AI Q&A	Assign./Ex.	Emot. Value	Course Req.
Know. Graph	1	0.5273	0.5472	0.3953	0.4219	0.225	0.3333
Ext.Mater.	0.5273	1	0.4915	0.375	0.5397	0.1957	0.4516
Learn. Anal.	0.5472	0.4915	1	0.4222	0.4844	0.2045	0.4194
AI Q&A	0.3953	0.375	0.4222	1	0.3273	0.3478	0.2222
Assign./Ex.	0.4219	0.5397	0.4844	0.3273	1	0.1481	0.6724
Emot.Value	0.225	0.1957	0.2045	0.3478	0.1481	1	0.1957
Course Req.	0.3333	0.4516	0.4194	0.2222	0.6724	0.1957	1

Note. Jaccard similarity coefficient. N = 75. Range [0, 1], higher = greater co-occurrence.

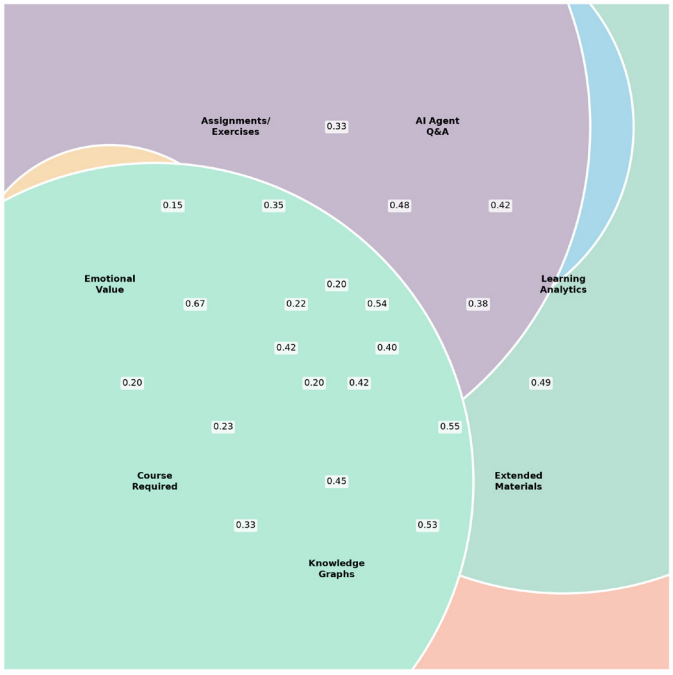


Figure 6. Co-occurrence network of usage purposes (edge width = Jaccard coefficient).

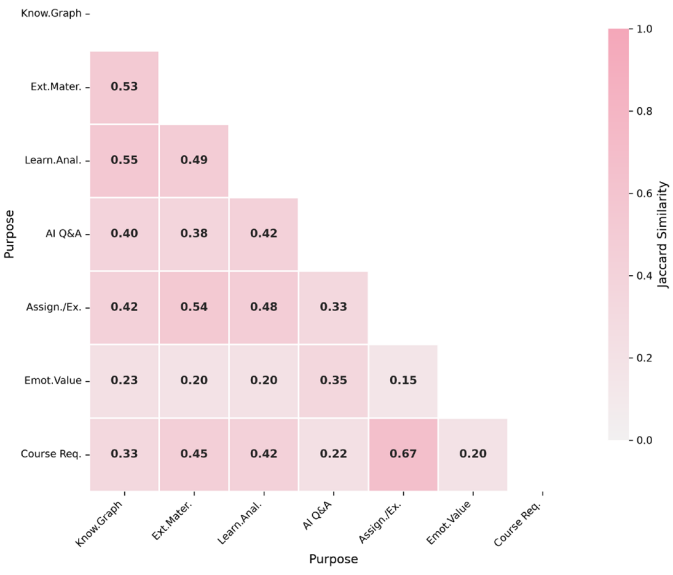


Figure 7. Heatmap of Jaccard similarity coefficients among usage purposes.

Table 5 reports Mann-Whitney U tests examining whether selecting a given purpose is associated with differences in usage depth. Three purposes show statistically significant associations: students who use the AI companion for assignment assistance engage at significantly greater depth (U = 816.5, p = 0.005), as do those using it for emotional value (U = 472.0, p = 0.011) and AI Q&A (U = 740.5, p = 0.023). Course-required usage is significantly associated with higher frequency (p = 0.010) but not depth. In addition, extended-materials users showed marginally higher duration (U = 836, p = 0.063) and depth (U = 837, p = 0.051) than non-users. Figure 8 illustrates the depth contrast between users and non-users for the three significant purposes.

Table 5. Mann-Whitney U tests: Usage purpose × usage behavior

Purpose	Behavior	U statistic	*p*-value	Significance	Selected mean	Not selected mean
Access extended learning materials	Duration	836	0.0627	†	1.956	1.6
Access extended learning materials	Depth	837	0.0511	†	1.778	1.467
Interact with AI agent for Q&A	Depth	740.5	0.0226	*	1.952	1.537
Assist with assignments/exercises	Depth	816.5	0.0052	**	1.788	1.348
Experience emotional value	Depth	472	0.0108	*	2.2	1.569
Required by course instructor	Frequency	903.5	0.0103	*	2.867	2.2

Note. † $0.05 < p < 0.10$. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Usage depth was measured on a 1–3 scale; usage frequency on a 1–4 scale.

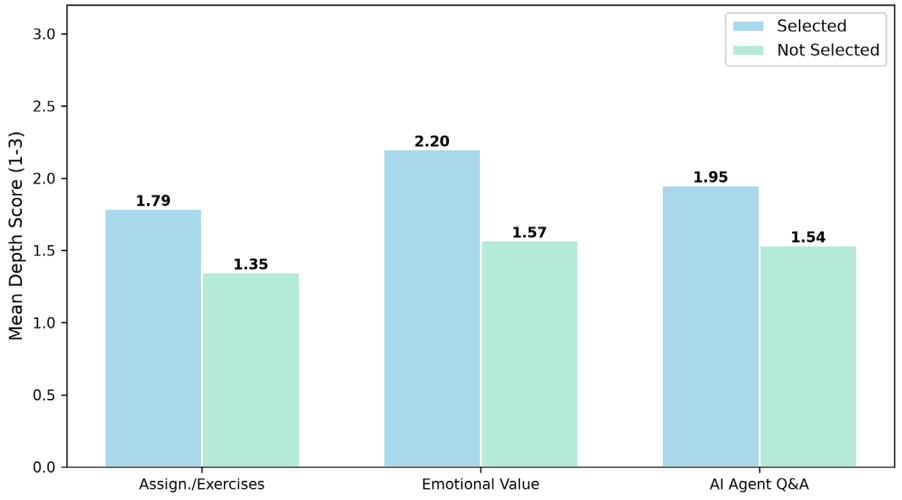


Figure 8. Usage depth comparison by purpose selection status.

3.4. Demographic differences

Table 6 summarizes chi-square tests examining demographic variables against usage behavior. Across all three demographic dimensions, grade × depth, gender × frequency, and major × depth, produced no statistically significant associations (all $p > 0.05$). Grade × depth yielded $\chi^2(4) = 3.74$, $p = 0.443$, Cramér's V = 0.158; gender × frequency: $\chi^2(3) = 1.71$, p = 0.635, Cramér's V = 0.151; and major × depth: $\chi^2(6) = 8.69$, $p = 0.192$, Cramér's V = 0.241. While effect sizes are small to moderate, none reach conventional significance thresholds. **Figure 9** and **Figure 10** provide visual confirmation of these null findings: the distribution of usage depth across grades and majors is remarkably consistent.

Table 6. Chi-square tests: Demographics × usage behavior

Test	Variables	χ^2	df	*p*-value	Cramér's V	Significance
χ^2	Grade × Depth	3.736	4	0.4429	0.1578	
χ^2	Gender × Frequency	1.708	3	0.635	0.1509	
χ^2	Major × Depth	8.694	6	0.1915	0.2408	

Note. Pearson Chi-square test. N = 75. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. All three demographic tests include Cramér's V effect size.

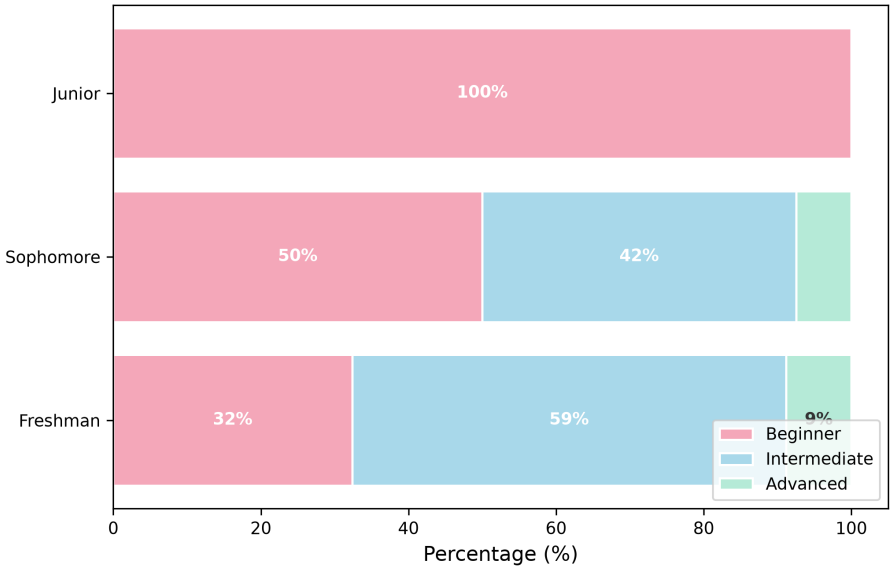


Figure 9. Percentage stacked bar chart of usage depth by grade level.

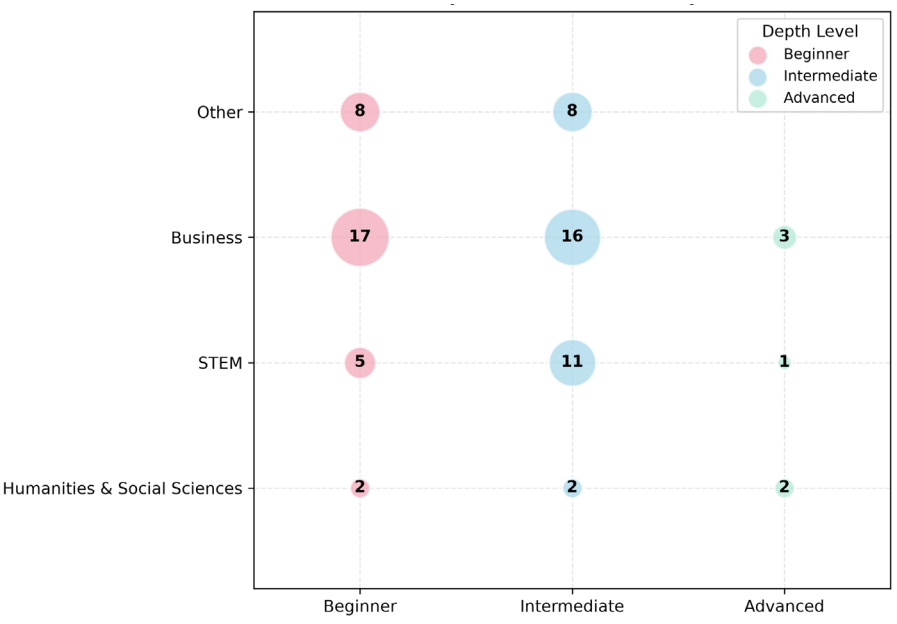


Figure 10. Bubble chart of usage depth by major category (bubble size = number of students).

3.5. Daily AI habits and platform behavior

As an additional exploratory step, we examined whether students' general daily AI habits relate to their platform-specific usage behavior.

Table 7 presents the association between students' daily AI usage habits and their platform behavior. Among the 75 respondents, 63 reported using AI in their daily lives (e.g., for Q&A, content generation, academic tasks), while 12 reported no daily AI use. Chi-square tests reveal no significant association between daily AI habits and either platform usage frequency or depth (all $p > 0.05$), which suggests that platform-specific AI companion usage may not be reducible to general AI literacy; context-specific factors (e.g., course requirements, platform design) may play a role.

Table 7. Chi-square tests: Daily AI habits × platform usage behavior

Test	Variables	χ^2	df	*p*-value	Cramér's V	Significance
χ^2	Daily AI Use × Platform Frequency	0.786	3	0.853	0.102	
χ^2	Daily AI Use × Platform Depth	2.135	2	0.3439	0.1687	

Note. Pearson Chi-square test. N = 75. Daily AI Use coded as binary (any use vs. none); responses indicating no use or non-substantive text (e.g., 'None', 'No', '1') were coded as non-use. Daily AI users n = 63, non-users n = 12.

3.6. User perception: Open-ended responses

The open-ended keyword evaluation item received 62 valid responses containing 38 unique terms. The word cloud (**Figure 11**) and top-15 frequency bar chart (**Figure 12**) reveal that 'convenient' dominates user perceptions with 22 mentions, more than double the second-ranked term 'useful' (n = 10). This gap suggests that for the Chaoxing AI companion, operational convenience outweighs perceived functional utility in shaping user sentiment. Other frequently mentioned terms include 'intelligent' (n = 10), 'good' (n = 9), and 'practical' (n = 5); together these terms portray an evaluation dominated by convenience rather than function. Note that total mentions across the top-15 terms (74) exceed the number of valid responses (62) because each respondent could contribute multiple keywords.

The suggestions for improvement item received 28 valid responses. Thematic analysis identified 'thinking' (n = 7 mentions), 'improve' (n = 5), 'students' (n = 4), and 'knowledge' (n = 4) as the most recurrent themes (**Figure 13**). Students' suggestions centered on fostering independent thinking, improving functionality and accuracy, and expanding knowledge base coverage.



Figure 11. Word cloud of user keyword evaluations (larger font = higher frequency).

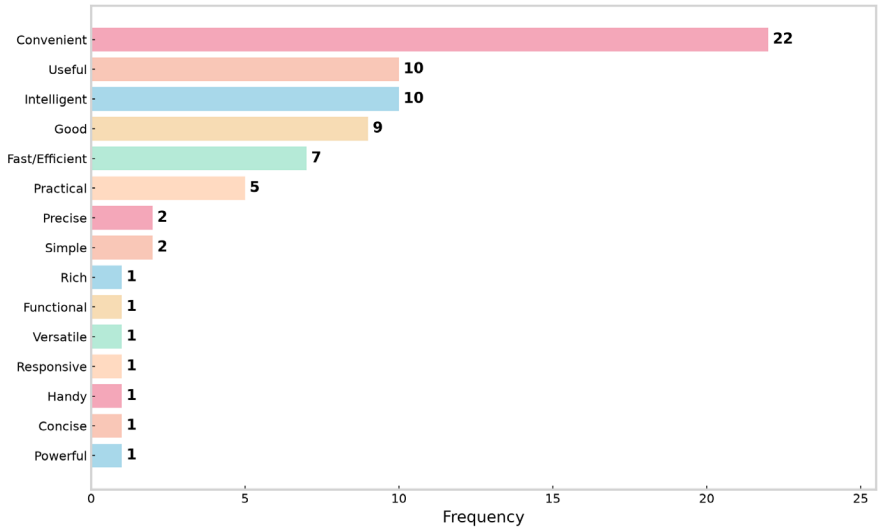


Figure 12. Top 15 most frequent keywords in user evaluations.

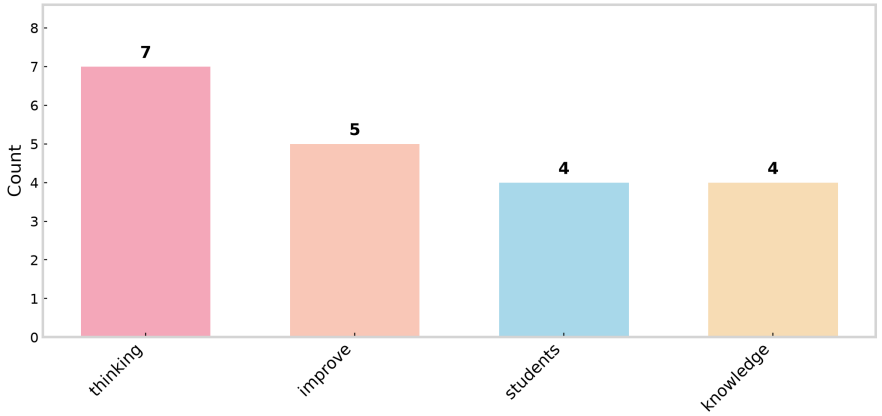


Figure 13. Thematic analysis of user suggestions for improvement.

4. Discussion

4.1. Duration and depth

The significant positive correlation between usage duration and depth ($\rho = 0.325$, $p < 0.01$) constitutes the strongest behavioral association in this study. This pattern is consistent with the learning curve hypothesis: as students accumulate experience with the platform's AI features, they progressively move from surface-level interactions toward more sophisticated engagement. The complementary positive correlation between frequency and duration ($\rho = 0.288$, $p < 0.05$) indicates that more frequent usage accompanies longer platform tenure, reinforcing rather than countering the learning curve pattern. This resembles the technology adoption lifecycle described in Tian et al., in which initial cognitive acceptance and motivational engagement may evolve into sustained, deeper usage for those who persist [7].

4.2. Instructor-driven and self-driven dual pathways

The co-occurrence analysis reveals a dominant instructor-driven pathway: the strongest purpose pair is assignment assistance with instructor requirement (Jaccard = 0.672). This strong co-occurrence suggests that faculty adoption and course integration are strong drivers of student engagement with AI companion tools. However, the significant depth effects for emotionally motivated and AI Q&A users point to a parallel self-driven pathway, where students independently seek deeper AI interaction for personal or cognitive needs. These dual pathways, one externally structured and one internally motivated, mirror the extrinsic–intrinsic motivation distinction in self-determination theory [8,9]. This distinction likewise shapes students' engagement with generative AI tools and has direct implications for platform design: features should support both course-embedded and self-initiated usage modes.

4.3. Convenience dominates user perceptions

The keyword analysis reveals that 'convenient' (n = 22) overwhelmingly dominates 'useful' (n = 10) in user evaluations. This gap contrasts with the technology acceptance literature, where perceived usefulness is typically the strongest predictor of adoption [10]. On the Chaoxing platform, however, the AI companion's integration within the existing learning management system, which eliminates the need for separate logins, context switching, or additional learning curves, may make convenience the primary experiential dimension. This matches the broader trend of embedded AI, where integration into existing learning platforms outweighs standalone capability [11]. For platform designers, this suggests that simplifying access may improve satisfaction more than adding features.

4.4. No significant demographic differences

In this sample, demographic differences in usage behavior are largely absent: unlike many educational technologies that exhibit gender-, grade-, or discipline-based usage gaps, the Chaoxing AI companion is adopted without clear demographic divides. This pattern may reflect the platform's mandatory adoption context: when an AI tool is embedded in required coursework, individual differences in technology propensity may be overridden by institutional expectations. It also suggests that well-integrated AI companions may offer consistent support across student backgrounds [12].

5. Conclusion and limitations

This exploratory analysis of 75 Chaoxing platform users points to four main conclusions. First, platform experience goes hand in hand with engagement: respondents who had used the AI companion longer also reported deeper involvement ($\rho = 0.325$, $p < 0.01$). Second, the purpose behind use shaped how deeply students engaged, with assignment-related, emotion-driven, and Q&A-oriented use linked to greater depth. Third, course integration stood out as a central driver: instructor requirements and assignment assistance co-occurred most strongly of all purpose pairs (Jaccard = 0.672). Fourth, convenience outweighed utility in users' own words, and demographic background barely differentiated behavior, pointing to broad applicability.

This study has several limitations. The sample size (N = 75), though modest, limits statistical power for detecting small to moderate effects in subgroup analyses. The single-institution, single-platform design constrains generalizability. The cross-sectional nature precludes causal inference; the learning curve

interpretation, while plausible, requires longitudinal validation. Usage behavior was also self-reported rather than measured through platform logs, which may introduce recall bias. Because this is an exploratory analysis, no adjustment for multiple comparisons was made; significant results should be interpreted cautiously.

Future work could replicate this analysis with larger samples. Platform log data would allow objective usage measurement, and longitudinal designs could test the learning-curve interpretation; potential links between AI companion usage patterns and academic outcomes also merit investigation. These findings offer a starting point for such work.

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Disclosure statement

The authors declare no conflict of interest.

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