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Motivation Map and Typology of College Students' Use of Generative Artificial Intelligence: An Exploratory Interview Study of 52 Undergraduates

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Abstract

We interviewed 52 college students to find out why they use generative AI. Their answers fell into five main types. Most students use AI for practical reasons: to finish assignments, to work faster, to learn new things. Some are just curious. A few only turn to AI when a deadline is close. The three practical reasons—getting work done, finishing assignments, and learning—were reported by most of our respondents. More than two-thirds mentioned them. We call these the core motivations. Curiosity and last-minute coping were much less common. They sit at the margins. We also noticed that students' majors seem to affect which motivations matter most to them. Privacy concerns came up across all groups, but not as a reason to use AI or not to use it. It was more like a background worry. Overall, our findings give a practical picture of why students use GenAI. They also point to ways we might design better tools, teach digital literacy, and help students think more carefully about when and how to use AI.

Keywords

Generative artificial intelligence, Use motivation, College students, Thematic analysis, Motivation map.

1. Introduction

When ChatGPT launched in late 2022, few anticipated how quickly generative AI would weave into everyday academic life. For college students, the uptake has been especially striking. Surveys suggest that a growing number of undergraduates now regularly turn to these tools, not just for quick answers, but for drafting, coding, and even brainstorming [1]. This is hardly surprising. Today's students juggle heavy course loads, competing deadlines, and the constant pressure to acquire new skills. In that context, a tool that retrieves information on demand or generates coherent text on cue can feel less like a luxury and more like a lifeline.

But students don't all use GenAI the same way. Some are drawn by the promise of saving time; others rely on it to slog through difficult assignments or thesis chapters. A smaller group seems motivated by sheer curiosity—wanting to test what the technology can do—while a few admit they only turn to it when a deadline is hours away and panic sets in. These different entry points, we argue, matter. They shape not only how students interact with the tool, but also what they ultimately gain (or lose) from the experience. To understand those outcomes, we first need a clearer picture of the why.

2. Literature Review

2.1. Diffusion and Research Landscape of GenAI in Higher Education

Generative AI tools entered higher education quickly after ChatGPT appeared. They are now common in both classrooms and research [1]. Scholars have examined this shift from different

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angles. Chan and Hu [1] argue that GenAI is breaking down the old line between teaching and independent learning. Others look at the bigger picture. Qu and Wen [2] used bibliometric mapping and found that the literature clusters around three topics: educational transformation, risk governance, and instructional application. But they also note that these categories are still descriptive—we do not yet have strong theories to explain them.

Li et al. [3] took a different approach. They focused on the Chinese context and found that students vary widely in how they adopt these tools. Their work highlights local factors that global surveys often miss. Together, these studies show a field that is growing fast but remains fragmented. Most of the empirical work is still exploratory.

2.2. Theoretical Frameworks for Explaining Use Behavior

Researchers have developed several models to explain why people adopt new technologies. The most influential is the Technology Acceptance Model, or TAM [4]. It centers on two simple ideas: perceived usefulness and perceived ease of use. Later, Venkatesh and colleagues [5] expanded this into the Unified Theory of Acceptance and Use of Technology (UTAUT). They added more factors—performance expectancy, effort expectancy, social influence, and facilitating conditions. A later version, UTAUT2 [6], included hedonic motivation and price value. But these additional dimensions have not been studied much in educational settings.

More recently, researchers have brought in other theories. Ivanov et al. [7] used the Theory of Planned Behavior. They found that behavioral attitude, subjective norm, and perceived behavioral control all shape students' intentions to use GenAI. Shahzad et al. [8] added a different angle. They emphasized trust as a key factor. For them, student adoption is not just about efficiency—it is also about whether students feel confident in the technology.

Several studies have tested these models with students. Zhang [9] used a Chinese sample and found that perceived usefulness, ease of use, and social influence all matter. Qiu et al. [10] looked at something more specific. They distinguished between initial adoption and continued use, and found different drivers for each stage. Strzelecki [11] and Menon and Shilpa [12] both reported similar results: performance expectancy is a strong predictor of usage intention across different cultural settings.

2.3. Dimensionality of Use Motivations and Needs

Prior research has looked at student motivation from several angles. One line of work focuses on instrumental motives—things like improving academic efficiency and completing tasks [13]. A second strand emphasizes the learning experience itself, highlighting personalized support and adaptive feedback [14]. A third perspective brings in affective and social dimensions, such as curiosity, novelty-seeking, and peer influence [13,15].

Most existing studies treat these dimensions as separate or additive. We take a different view. Our typology builds on these insights but treats motivations as potentially overlapping. A single student might have several motivations at once. This approach resonates with Uses and Gratifications theory [16] and with Self-Determination Theory's focus on intrinsic needs [17,18]. We return to both theories in our analytical framework below.

2.4. Impacts, Benefits, and Risks of Use

The growing use of GenAI is not without risks. Fan et al. [19] warn about "metacognitive laziness"—the danger that students outsource their thinking to the machine and lose the habit of critical reflection. There are also broader ethical and security concerns, as Dwivedi et al. [20] have pointed out.

Overall, the literature is rich in theory but thin on empirical evidence about motivation structure. We have good models of technology acceptance and strong measures of usage intention. But we know much less about how different motivations relate to each other—

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whether some are central and others peripheral. That is the gap we aim to fill. We use semi-structured interviews with 52 students and thematic analysis to develop a typology of GenAI use motivations. More importantly, we go beyond listing types. We examine their hierarchical relationships and map them onto a two-dimensional framework—instrumental vs. experiential, planned vs. emergency. Our goal is to move the conversation from a simple list of reasons to a structured understanding of how students' motivations are organized.

3. Research Design

3.1. Conceptual Definition and Theoretical Framework

Before we go further, we need to clarify what we mean by "use motivation" in this study. We draw on Uses and Gratifications theory [16] and take a practical approach. We treat use motivation as the surface-level purposes students report—the specific needs or expectations they mention when they describe why they used GenAI in a particular situation.

Of course, motivation is not just about surface purposes. Self-Determination Theory points to deeper psychological needs—competence, autonomy, and relatedness—that also shape why students engage with technology [17,18]. Our choice to focus on surface-level expressions is not a rejection of these deeper drives. It is a methodological decision. At this early, exploratory stage, interviews are best at capturing the explicit reasons students give. The five motivation types we identify can be understood as the specific forms that motivation takes in everyday learning contexts—the ways students themselves articulate why they use GenAI.

Our analysis draws on three theoretical traditions. The first is the technology acceptance lineage, starting with the Technology Acceptance Model (TAM) [4] and its later development, the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) [5,6]. These frameworks share a basic premise: people adopt technologies because they find them useful and easy to use. For us, this provides a starting point for understanding the more instrumental forms of GenAI use we observed—efficiency, academic support, and knowledge-seeking.

A second lens comes from Self-Determination Theory (SDT) [17,18]. SDT shifts attention from external utility to internal psychological needs—competence, autonomy, and relatedness. This helps us distinguish between motivations that are genuinely curiosity-driven and those triggered by external pressure, like looming deadlines. This distinction is important for understanding why some students use GenAI voluntarily while others only turn to it when they have no other option. Central to SDT is the continuum from autonomous to controlled regulation, anchored in competence, autonomy, and relatedness [17,18].

Third, we look to Rogers' Diffusion of Innovations theory [15]. It offers a useful vocabulary for describing how new technologies spread. The concept of "innovativeness"—people who are naturally curious, experiment willingly, and integrate innovations into their routines—fits well with a subset of our interviewees. These were the students whose curiosity-driven exploration seemed less about immediate task needs and more about general interest in the technology itself. We did not systematically record when each respondent first adopted GenAI, so we use Rogers' framework to describe motivational propensity rather than to certify who counts as an early adopter.

3.2. Research Objectives and Questions

Our review of the literature pointed to a gap. We have two aims in this study. The primary one is empirical: to develop a grounded typology of GenAI use motivations based on what students themselves report. To do this, we conducted semi-structured interviews with 52 undergraduates and analyzed the transcripts using thematic analysis.

Four questions guided our analysis. We started with an open-ended question: what motivational categories emerge from students' accounts? Rather than imposing pre-existing

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frameworks, we let the data guide us. Once we identified the types, we looked at their distinguishing characteristics and how common each one was. We also wanted to know whether students from different disciplinary backgrounds—engineering, economics and management, language studies, and others—tend to emphasize different motivations. This is a question that prior work has largely left unexplored. Most importantly, we wanted to move beyond a simple list of reasons. We wanted to see whether these motivations form a deeper structure—whether some are more central and others more peripheral in students' reported experiences.

By answering these questions, we hope to provide both a descriptive typology and a preliminary framework for future research and educational practice.

3.3. Participants

We used purposive sampling to recruit 52 college students who had used GenAI in the past six months. Interviews were conducted between January and June 2026. Our sampling strategy combined a "core sample" with an "external-school validation sample." Students from our own university made up the main group (46, 88.5%). We used these to refine the core motivation types. The remaining six respondents came from six different external institutions (6, 11.5%). We included them to check whether the typology held across different school contexts. Our inclusion criteria were simple: enrolled college students, any major, with GenAI use experience in the past six months. Table 1 shows the distribution of respondents by major. As noted above, 46 respondents (88.5%) were from our own institution and 6 (11.5%) from six external institutions.

Table 1. Distribution of respondents by major (N=52)

Attribute	Category	Number	Proportion
Major	Engineering	28	53.8%
Major	Economics & Management	16	30.8%
Major	Language	6	11.5%
Major	Other	2	3.8%

3.4. Interview Procedure

We developed a semi-structured interview guide that covered five broad areas: how students first encountered GenAI, how they typically use it, what kinds of tasks they use it for, how they understand the technology, and what concerns they have about risks like misinformation or privacy. The questions were intentionally open-ended. We asked when and why they first tried GenAI, how it affected their efficiency in specific tasks, and whether they ever used it for purposes beyond coursework—exploring new topics or just satisfying curiosity. We also asked about their awareness of potential downsides, including accuracy and data security, and whether these concerns shaped their actual use.

Throughout the interviews, we adapted our follow-up questions based on what each respondent shared, rather than sticking rigidly to the guide. We protected participants' privacy by removing all names and identifying details. We obtained informed consent from every respondent before starting.

Each session lasted about 20 to 30 minutes. With permission, we recorded all interviews and had them transcribed within 24 hours. This gave us about 62,000 Chinese characters of raw text. We then shared the transcripts back with each participant for their review and correction, to make sure our analysis was based on accurate records. Among the tools respondents mentioned spontaneously, Doubao (ByteDance) came up most often, with ChatGPT, Copilot,

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and Wenxin Yiyan (Baidu) mentioned occasionally. Since tool names were volunteered rather than solicited, we do not report frequencies for individual tools.

3.5. Data Analysis

For our analysis, we followed the thematic analysis procedures described by Braun and Clarke [21]. We worked in three main phases. First, we read through each transcript closely and generated initial codes—short labels that captured what seemed important in each interview segment. Then we grouped related codes into broader candidate themes. We refined these by checking them against the raw data to make sure they were grounded in participants' own words. Finally, we reviewed and consolidated these themes into a stable set of five core motivation types. Once we had established these types, we looked at how they related to each other—whether some were more central and others more peripheral in students' accounts. This step led us to the typological framework we present below.

4. Findings

4.1. Motivation Type Identification

We read through each transcript carefully and marked any passage that seemed to reflect a reason for using GenAI. We did this sentence by sentence. This first pass gave us 87 initial codes. We tried to keep them close to participants' own words—phrases like "improve learning efficiency" and "novel experience."

Then we compared these codes across interviews. We looked for patterns and connections. After several rounds of grouping and regrouping, we gradually consolidated the 87 codes into a smaller set of broader categories. This process eventually led us to five core motivation types. We summarize them in Table 2. They are: efficiency enhancement, academic assistance, knowledge expansion, curiosity-driven exploration, and task emergency.

Table 2. Example of the three-level coding process

Initial codes (87 in total, partial examples)	Theme extraction (5)	Theme
"Faster at writing code," "no need to read articles one by one," "help me build the report framework," "saved a lot of time"	Task-completion efficiency	Efficiency enhancement
"Do homework," "assist in translating literature," "brainstorm the English-essay framework," "debug code"	Academic-task assistance	Academic assistance
"Comprehend quickly and deeply," "organize the knowledge framework," "explain concepts I don't understand"	Knowledge acquisition & understanding	Knowledge expansion
"Feels quite novel," "out of curiosity," "want to try"	New-technology exploration	Curiosity-driven exploration
"It's due tomorrow and I'm in a rush," "no time left," "cramming at the last minute"	Time-pressure coping	Task emergency

Note: Initial codes are taken from interviewees' original words.

We wanted to check whether our coding was reliable. So we randomly picked six of the 52 transcripts and had two members of our team—both of us are among the authors—code them separately. Neither knew what the other had coded. When we compared their results, we got

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an initial agreement rate of 89.7% and a Cohen's Kappa of 0.84. Both are above the usual thresholds for acceptable reliability.

But we should be honest about the limits of this check. Six transcripts are only 11.5% of our total. And both coders also helped design the coding scheme. So we treat this as a rough indication, not a definitive test.

We also recognize that we are faculty members studying students at our own institution. That could affect how we see the data. To reduce this risk, we used two independent coders and checked transcripts with participants. We also report themes in participants' own words wherever we can.

We also wanted to know if our sample was big enough. We used a cumulative coding method [22] and tracked when new themes stopped appearing. After the 36th transcript, new themes appeared less often. By the 39th transcript, no new themes came up at all. This gave us confidence that we had reached thematic saturation. The six interviews from other institutions, then, were not meant to generate new categories. They were there to check whether our findings held across different school settings.

Table 3 shows how often each of the five motivation types was mentioned across the full sample.

Table 3. Types and distribution of college students' GenAI use motivations (N=52)

Motivation type	Core feature	Number of mentions	Proportion	Typical disciplinary distribution
Academic assistance	Complete academic tasks such as assignments, theses, programming	41	78.8%	Engineering and Economics & Management
Efficiency enhancement	Improve learning/work efficiency, save time	39	75.0%	Across all majors
Knowledge expansion	Look up information, explain concepts, broaden cognition	36	69.2%	Engineering and Economics & Management
Curiosity-driven exploration	Novelty, trying new technology	3	5.8%	Dispersed (Engineering, Economics & Management)
Task emergency	Rush assignments, temporary needs	3	5.8%	Dispersed

Note: Some respondents mentioned multiple motivations, so the percentages sum to more than 100%; "typical disciplinary distribution" indicates the majors where the motivation is relatively more prominent, not an exclusive attribution.

4.2. Influence of Disciplinary Background on Motivation Types

Fig. 1 displays, for each disciplinary group, the proportion of students who mentioned each motivation type. Because students could report multiple motivations, row percentages do not sum to 100%.

We found some variation across disciplines, though the overall pattern was stable. The three core motivations—academic assistance, efficiency enhancement, and knowledge expansion—were reported consistently across all four disciplinary groups, with academic assistance and efficiency enhancement being the most frequent in most groups.

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The differences showed up in the details. In economics and management, academic assistance stood out (87.5%). In engineering, the three core motivations were reported at similar levels (71%–75%). Language studies students and those in the "other" category reported academic assistance and efficiency enhancement above 80%. They also reported substantial knowledge expansion.

Knowledge expansion appeared across all disciplines. Its mention rates ranged from 56% to 100%. It stayed above the 50% core threshold everywhere. Curiosity-driven exploration and task emergency, on the other hand, remained marginal in every discipline. Their combined share never exceeded about 17%.

The internal ranking of the three core motivations shifted slightly by discipline, even though the overall structure held. Academic assistance was most prominent in economics and management (87.5%). In language studies, efficiency enhancement was equally common (83.3%). Engineering students reported the three at roughly the same rates (71.4%–75.0%). So the core is stable in what it includes, but the relative order of the three motivations varies a little across fields.

A note of caution: the language (n=6) and "other" (n=2) subgroups are very small. The percentages we report for them are only indicative. They should not be treated as stable estimates.

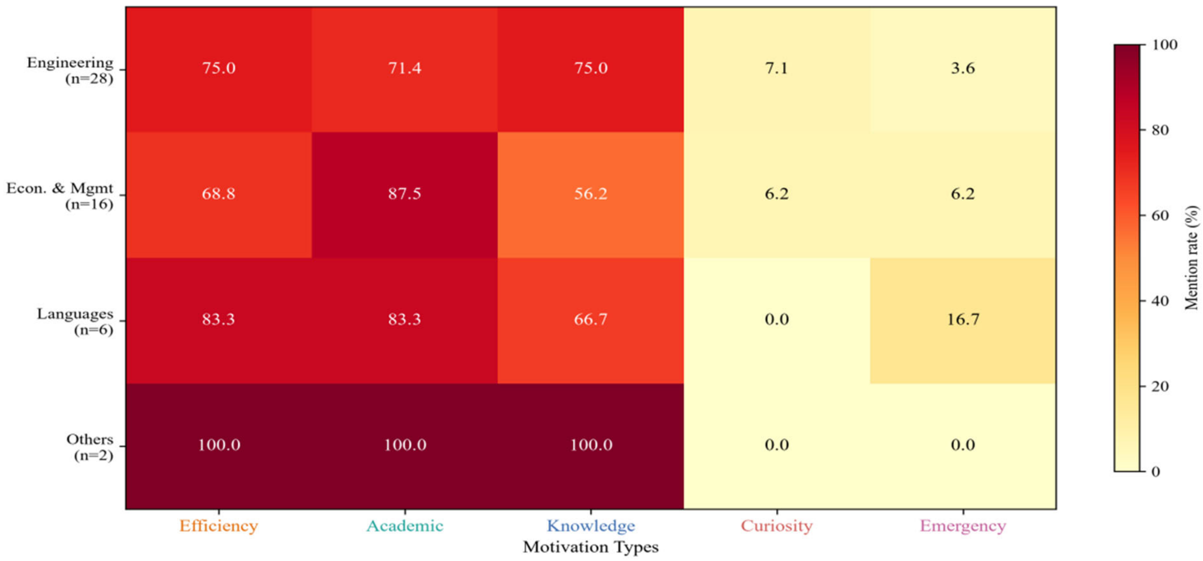

Figure 1. Motivation mention rates by disciplinary category

4.3. Motivation Typology

To better understand how the five motivation types relate to each other, we placed them on two conceptual dimensions (Fig. 2).

The first dimension goes from instrumental to experiential. This reflects the controlled–autonomous continuum in Self-Determination Theory [17,18]. Experiential use comes from intrinsic interest in learning. Instrumental use is about getting tasks done.

The second dimension goes from active planning to passive emergency. It captures whether use is deliberate or triggered by pressure. This echoes Uses and Gratifications research [16], which emphasizes active, gratification-seeking behavior.

These two axes are not based on empirical clustering. They come from the theoretical logic we laid out in Section 3.1. They describe each motivation's character in terms of orientation. This is separate from the prevalence-based core–margin structure.

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When we map the five motivations onto these two dimensions (Fig. 2), a clear pattern emerges. Efficiency enhancement and academic assistance fall on the instrumental and planned side. Both are about deliberate, goal-directed task completion.

Knowledge expansion and curiosity-driven exploration shift toward the experiential end. They reflect more open-ended engagement with GenAI. They are driven by interest or a desire to learn, not by immediate task demands.

Task emergency, by contrast, sits at the passive and reactive edge. It represents a temporary, situation-bound reliance on the tool.

So the five types line up as follows: academic assistance and efficiency enhancement cluster at the instrumental–planned pole. Knowledge expansion and curiosity-driven exploration sit at the experiential–planned pole. Task emergency falls at the instrumental–emergency pole—deadline-driven use is still about completing a task, even though it is reactively triggered.

What is striking is the divergence within the experiential pole. Knowledge expansion and curiosity-driven exploration share the same experiential character. But their prevalence is very different. Knowledge expansion is firmly in the core, reported by 69.2% of respondents. Curiosity-driven exploration is marginal. This is an important reminder: the instrumental–experiential axis captures the nature of engagement, not its frequency. A motivation can be experiential in character and still be core in prevalence. Knowledge expansion is a clear example.

Overall, this two-dimensional positioning suggests that students' motivations are not neatly separable into fixed categories. They seem to lie on a continuum. Different motivations blend instrumental and experiential elements, or planned and reactive impulses, to varying degrees.

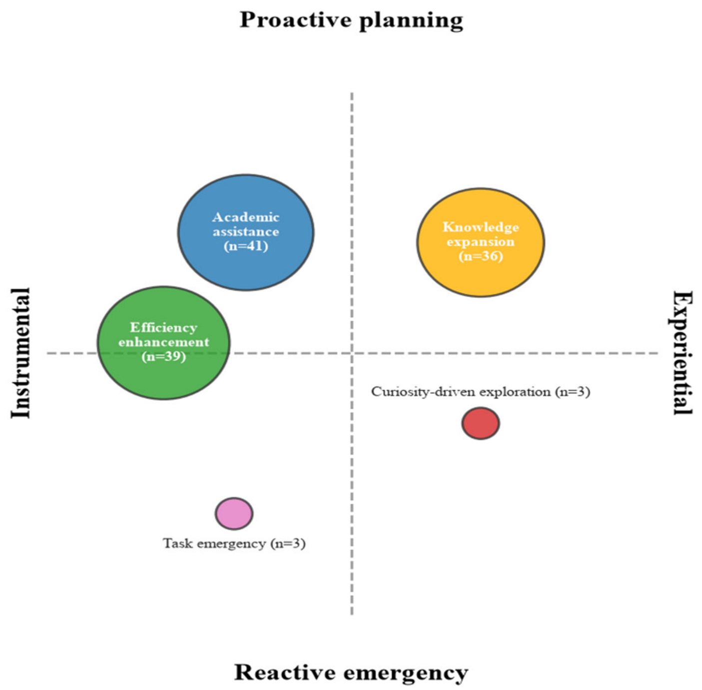

Figure 2. Motivation map of college students' GenAI use

We also created a keyword cloud from the interview transcripts to complement the structured analysis above (Fig. 3). In the cloud, font size shows how often a word appeared across all interviews. Color indicates which of the five motivation categories the word belongs to.

The most frequent words were "data" (81 mentions), "learning" (78), "information" (62), "time" (49), and "assignments" (38).

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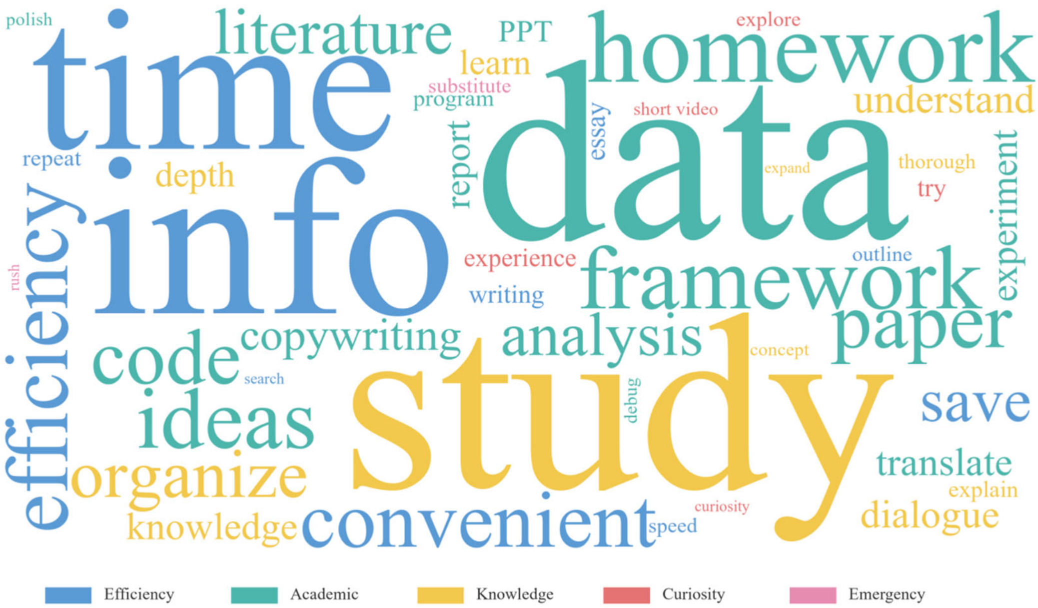
If we look at the cluster of words related to academic work and efficiency—"assignments," "thesis," "code," "efficiency," "saving," and "retrieval"—they point to a core motivational orientation. Students are focused on completing academic tasks and improving efficiency.

A second cluster includes "understanding," "organizing," and "knowledge." This suggests that a meaningful portion of student use is directed toward conceptual learning and cognitive expansion. It is not all about task completion.

At the other end of the spectrum, words like "curiosity," "trying," "urgency," and "substitution" appear much less often. Their smaller size in the cloud confirms what we saw earlier: curiosity-driven exploration and emergency use are relatively uncommon. They are situation-specific, not general patterns..



Note: Font size indicates the frequency of each motivation keyword in the 52-interview text corpus.

Figure 3. Keyword cloud of college students' GenAI use motivations

4.4. The Core–Margin Structure of Motivations

Bringing together Fig. 2, Table 3, and Fig. 3, we identified a clear two-tier structure. Using a >50% core threshold and a <20% margin threshold, three motivations fall in the core—academic assistance (78.8%), efficiency enhancement (75.0%), and knowledge expansion (69.2%)—while curiosity-driven exploration (5.8%) and task emergency (5.8%) fall in the margin, with no motivation in the intermediate range.

The three core motivations are closely matched in their mention rates, suggesting that they anchor the dominant logic of student use: completing academic work efficiently, reliably, and with a genuine desire to deepen understanding. By contrast, the two marginal motivations, curiosity-driven exploration and task emergency, are qualitatively different: they arise not from ongoing academic needs or instrumental planning, but from situational curiosity or time pressure.

To check whether these motivations tend to appear together or separately, we created a co-occurrence matrix (Table 4). The matrix shows that the three core motivations frequently appeared together, whereas the two marginal motivations almost always co-occurred with one or more core motivations, rather than forming separate user profiles. In other words, the core–margin distinction describes the structure of students' motivations, not a classification of students themselves. Most students draw on a combination of motivations, with core types as the common foundation and marginal types as occasional additions.

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Table 4. Motivation co-occurrence matrix (N=52)

Motivation	AA	EE	KE	CE	TE
AA	41	31	30	3	2
EE	31	39	27	3	1
KE	30	27	36	2	2
CE	3	3	2	3	0
TE	2	1	2	0	3

This core–margin distinction should be read as a descriptive summary, not a fixed taxonomy. The thresholds were set by us, and since Fig. 2 and Fig. 3 derive from the same coding scheme and corpus as Table 3, they are not independent confirmations. We nonetheless consider the split meaningful: no motivation falls between the tiers, and across the wide gap between 69.2% and 5.8%, any threshold would yield the same two-group division. Its consistency across disciplinary subsamples is reported in §4.2, but definitive validation will require scale-based measurement.

We chose to keep all five types. We did not collapse the framework to just the three core ones. Curiosity-driven exploration and task emergency capture something different. They represent open-ended experimentation and deadline-driven coping. These are qualitatively distinct use modes. The core types cannot cover them. By presenting them as a margin, we preserve this distinction without overstating how common they are.

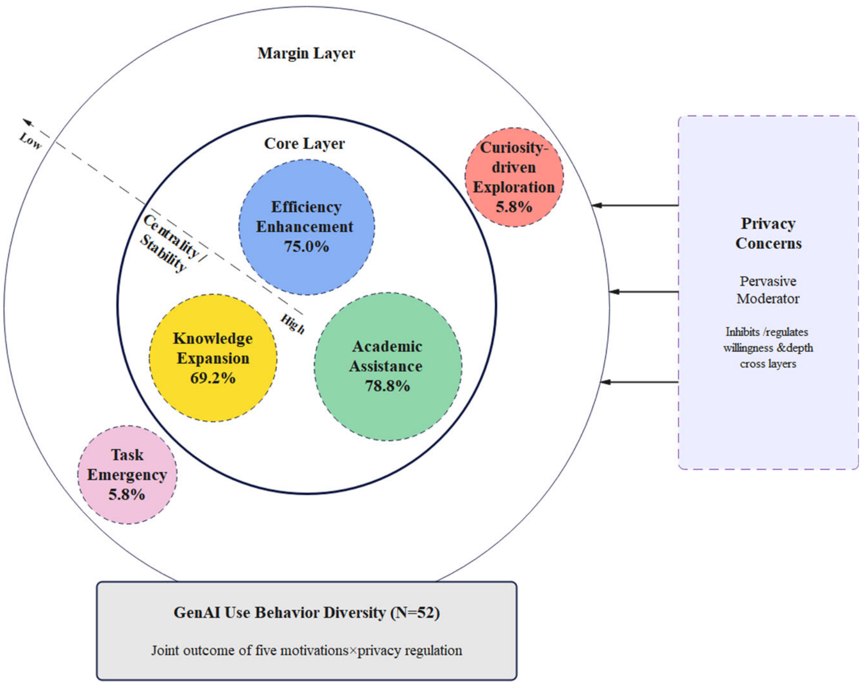

Figure 4. Core–margin structure of the five motivation types

Figure 4 shows the structure. The inner circle stands for the core. The outer circle stands for the margin. As you move outward, the centrality and stability decrease.

The figure also includes privacy concern as a separate element. We did not count it as a motivation type. Why? Because students did not bring it up as a reason to use GenAI. They mentioned it as a concern that cut across different motivations. It was not tied to any one type.

Students voiced this concern across all groups. It seemed to affect how deeply they engaged with the tools. But it did not drive their decision to use them or not.

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5. Discussion

5.1. Major Findings and Theoretical Dialogue

When we look across the five types, three stand out. Academic assistance, efficiency enhancement, and knowledge expansion are the dominant ones.

Knowledge expansion is experiential in orientation. You can see this in Fig. 2. But it still sits firmly in the core (Fig. 4). This suggests that experiential engagement can be almost as common as instrumental task completion.

The dominance of instrumental motivations fits with TAM [4] and UTAUT2 [6]. Students who see GenAI as a way to get things done more efficiently are more likely to use it.

Each motivation type has a theoretical counterpart. In Uses and Gratifications theory [16], the three core motivations line up with needs for task completion, academic support, and cognitive acquisition. Curiosity-driven exploration matches the intrinsic motivation described in Self-Determination Theory [17,18]—it is about interest in the technology itself. Task emergency is different. It is a reactive response to time pressure, driven by external forces rather than internal choice.

Within the core, knowledge expansion deserves a closer look. It is grouped with the other two as a top driver (69.2%). But it is not about task-completion efficiency. It reflects genuine cognitive enrichment. Some respondents saw GenAI as more than a tool for getting work done. They treated it as a cognitive partner for exploration and understanding. This fits with Rogers' idea of "innovativeness" [15].

One important point: "core" here is a frequency-based term. It does not mean "instrumental." Knowledge expansion is in the core because it is common (69.2%), not because it is task-oriented. That is exactly why we treat the instrumental–experiential axis (Fig. 2) and the core–margin structure (Fig. 4) as two separate frameworks. One captures the nature of engagement. The other captures how common it is among students.

We see our findings as contributing to the literature in three ways.

First, we move beyond simple measurement. We offer a more differentiated view of how motivations relate to each other. We identified a core of three dominant motivations and a margin of two situational ones. This is a middle-range framework. It captures both the content and the organization of student motivations. It does not treat them as a flat list.

Second, we provide empirical support for the claim that instrumental and knowledge-seeking motivations are prominent. But we also clarify what "instrumental" means in this context. We specify the concrete task contexts where perceived usefulness matters—assignments, thesis writing, programming, information retrieval. This shows that "usefulness" is not a single thing. It is a bundle of distinct academic and practical needs.

Third, we challenge a common assumption. Many studies treat privacy concern as a separate barrier—something that stands alongside other motivational drivers. Our data suggest a different picture. Privacy concern does not function as an independent driver. It operates as a moderating constraint that cuts across all motivation types.

How do our qualitative findings relate to the quantitative literature? They are complementary. Strzelecki [11] and Menon and Shilpa [12] showed performance expectancy predicts usage intention; our data unpack what this means in practice: manifesting in efficiency enhancement and academic assistance, which operate differently by task type and discipline. Our findings also extend Li et al.'s [3] classification work: rather than listing types, we examined how they relate and mapped them onto a structured framework—the core–margin hierarchy and the two-dimensional motivation map—shifting the focus from "what types exist" to "how types are organized."

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5.2. Disciplinary Background and Privacy Concerns

Our data also showed some disciplinary differences worth noting.

Engineering students were the largest group in our sample (n=28). They reported academic assistance (71.4%), efficiency enhancement (75.0%), and knowledge expansion (75.0%) at similar rates. So no single motivation stood out in engineering.

Economics and management students (n=16) were different. They placed more emphasis on academic assistance (87.5%) than on the other motivations. Language studies students (n=6) and the small "other" group (n=2) reported high levels of academic assistance and efficiency enhancement—above 80%—along with substantial knowledge expansion.

We interpret these patterns as a sign that AI use motivations are not the same across all fields. They seem to be shaped, at least in part, by disciplinary culture, the kinds of tasks students typically do, and the professional socialization they go through in their majors.

A second finding cuts across all groups: privacy.

Regardless of their main reason for using GenAI, most respondents raised some concern about data security and personal privacy. We did not include this in our motivation coding scheme, so we did not quantify it systematically. We report it here as a qualitative observation.

This echoes what Dwivedi et al. [20] discussed about ethical risks in AI adoption. It also supports the view that trust and privacy protection are basic conditions for technology acceptance.

But our data suggest something else too. Privacy concern does not act as a separate driver. It is more like a modulating factor. It may shape how often or how openly students use GenAI in different situations—for example, whether they hesitate to input sensitive academic material. But it does not seem to determine whether they use the tool at all.

5.3. Research Limitations

We recognize several limitations in this study.

First, our sample is larger than many qualitative studies (n=52). But it is still heavily weighted toward one institution. Forty-six of our 52 respondents (88.5%) came from the University of Science and Technology Liaoning. The remaining six came from six different external schools, with only one respondent from each. So we cannot claim to have captured the full diversity of educational contexts. This means our findings—especially the hierarchical structure and the disciplinary patterns—should be interpreted carefully when generalized to other universities or regions.

Second, our data are cross-sectional. They capture students' motivations at one point in time. So we cannot see whether or how these motivations change as students move through their academic careers, gain more experience with GenAI, or face new types of tasks. A longitudinal study would be better suited to answer those questions.

Third, two of the five motivation types—task emergency and curiosity-driven exploration—were each mentioned by only 3 respondents (5.8% of the sample). We think these are meaningful categories conceptually. But their empirical base is thin compared to the three core motivations. More research with larger and more diverse samples is needed to confirm whether these types hold as distinct categories and whether they appear more often in other populations or contexts.

Consistent with the exploratory nature of this study, we see these two margin types as emergent, hypothesis-generating categories. Their low frequency probably reflects our sample, not their absence in other populations.

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6. Conclusion and Recommendations

6.1. Main Conclusions

Our interviews with 52 college students lead us to five main conclusions.

First, we identified five distinct types of GenAI use motivation, varying widely in prevalence: academic assistance was the most commonly reported (78.8%), followed closely by efficiency enhancement (75.0%) and knowledge expansion (69.2%). Curiosity-driven exploration and task emergency were each mentioned by only 3 respondents (5.8%), forming a clearly marginal pair. Three motivations sit in the core (>50%), and two in the margin (<20%).

Second, the core is not defined by instrumentality alone. Academic assistance and efficiency enhancement constitute its clearly instrumental component, but knowledge expansion (experiential in character; see Fig. 2) was comparably prevalent (69.2%). The dominant cluster is therefore a hybrid one, blending instrumental task completion with experiential knowledge-seeking.

Third, the core–margin distinction describes the structure of motivations rather than a classification of students. As the co-occurrence matrix (Table 4) shows, the three core motivations frequently appeared together, whereas the two marginal motivations almost always co-occurred with one or more core motivations rather than forming separate user profiles. Most students thus combine several motivations, with core types as the common foundation and marginal types as occasional additions.

Fourth, we found some disciplinary differences. In economics and management, academic assistance was the most common motivation (87.5% of students). In engineering, the three core motivations—academic assistance, efficiency enhancement, and knowledge expansion—were reported at similar levels (71%–75%). Language studies students and the small “other” group reported very high levels of academic assistance and efficiency enhancement, along with strong knowledge expansion.

Across all groups, the core–margin structure held up. Curiosity and emergency use stayed marginal. The pattern does not support a simple claim like “engineering students gravitate to academic assistance.” Engineering students reported all three core motivations at similar rates. No single one dominated. But the pattern does suggest that disciplinary culture shapes the relative balance among these core motivations.

Fifth, privacy concern came up across all motivation types. It did not act as a separate reason for using or not using GenAI. Instead, it was more like a background factor. It seemed to moderate how openly or how often students engaged with the tools in different contexts.

6.2. Practical Recommendations

Our findings have practical implications for three groups: tool developers, educators, and students.

For tool developers, we see three priorities.

First, make the user experience simple. Students adopt GenAI more easily when it feels intuitive. So simplifying workflows and interfaces is a low-cost change with high impact.

Second, developers should pay attention to disciplinary differences. Our data show that the three core motivations vary by field. Academic assistance is strongest in economics and management. Engineering students report the three at similar levels. We did not cross-tabulate task types with discipline systematically, so we cannot prescribe specific functions for each field. But we think that kind of mapping would be a useful step before building specialized modules.

Third, privacy is a concern that cuts across all groups. Developers need clearer data-use policies. They should also give users more control over what information is stored or shared.

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For educators, the motivation map offers a useful way to think about practice. It is organized around motivation types and use contexts.

For students who use GenAI for efficiency or academic assistance, the priority is helping them collaborate with AI without losing critical thinking. One way is to require process traces and explicit acknowledgment of AI help.

For students focused on knowledge expansion, inquiry-based assignments work well. These train students to question and verify AI-generated outputs.

For curiosity-driven exploration, open experimentation spaces and tool workshops can channel interest productively.

For time-pressure or emergency contexts, institutions should offer just-in-time support. This could include pre-deadline Q&A sessions or extensions on request. That way, AI is not the only option.

Across all contexts, privacy literacy matters. Privacy concern came up regardless of primary motivation. Students should learn how to use GenAI effectively and how to protect their own data.

Finally, educators need clear rules about what counts as acceptable AI assistance and what counts as misconduct. This is especially important in emergency scenarios, where students are most tempted to cut corners.

For students, we offer a few practical takeaways.

Treat GenAI as a tool that helps you think—not one that thinks for you.

Be critical of AI-generated content. These tools are fluent but not always accurate. They also lack human judgment.

Protect your privacy. Avoid putting sensitive personal or institutional information into GenAI platforms, especially when data policies are unclear.

6.3. Future Research Directions

Several directions remain open for future work.

First, we need to move beyond this exploratory, qualitative stage. A larger and more diverse sample would allow us to develop a quantitative scale for measuring GenAI use motivations. This could test how well our five-type typology holds across different populations and settings.

Second, we need to look at change over time. Our cross-sectional design captured students' motivations at one moment. But these motivations may shift as students gain more experience with GenAI, as the technology changes, or as institutional policies evolve. Longitudinal studies could track these dynamics. They could reveal, for example, whether curiosity-driven exploration tends to give way to more instrumental motivations over time—or the reverse.

Third, we need to connect motivations to behavior. Our study focused on why students use GenAI. We did not examine how different motivational profiles translate into actual usage patterns, task performance, or learning outcomes. That would be a natural next step.

Fourth, cross-cultural comparisons would be valuable. Our sample came from one country. Students in other educational systems—with different pedagogical traditions, technological infrastructures, and cultural attitudes toward AI—might show different motivational structures. That remains an open question.

Despite these limitations, we hope the typological framework and the hierarchical model we have developed here offer a useful starting point for future quantitative research. We also hope they provide a practical reference for educators and tool designers who want to support more thoughtful and responsible GenAI use in higher education.

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