

Insights into Student Adoption of Generative AI in University Science Coursework

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How to cite: Lam, K. H.; Lo, D.; Huang, X.; Chon, L.; Zhao, A. (2026). Insights into Student Adoption of Generative AI in University Science Coursework. In: 12th International Conference on Higher Education Advances (HEAd'26). Valencia, 15-18 June 2026. <https://doi.org/10.4995/HEAd26.2026.21603>

Abstract

GenAI tools are transforming higher education by offering significant teaching and learning benefits although concerns about academic integrity. This paper reports a pilot study exploring students' perceptions and use of GenAI for their coursework between 59 Programme-Major (PM) science faculty students and 22 Non-Programme-Major (NPM) students from three undergraduate Science subjects. Survey findings revealed that GenAI was widely adopted by both student groups (>90%), particularly over 35% reporting frequent use for brainstorming, information searching, and content summarisation. Both groups perceived GenAI as beneficial for assessment preparation and learning, with generally positive learning gains. Programme major students reported more frequent use of GenAI for translation and project collaboration, while non-programme major students demonstrated higher awareness of potential GenAI misuse. Challenges such as unreliable outputs and ethical concerns highlight the need for AI literacy training and clear academic integrity guidelines. These findings shed light on teaching and assessment practices in GenAI-enabled contexts.

Keywords: GenAI; Assessment; Coursework; Higher Education; Science Education

1. Introduction

The rapid development of Generative Artificial Intelligence (GenAI) has significantly reshaped higher education, especially in the redesign of assessment practices. Scholars increasingly recognize GenAI's capacity to enhance assessment through personalized testing, immediate feedback, and automated grading, thereby supporting self-directed learning and minimizing subjectivity (Alier et al., 2024; Zaibout & Madrane, 2024). Pisica et al. (2025) based on interviews with 18 Romanian academics, identified benefits such as personalization, improved

assessment, and new content development, together with drawbacks including isolation, lack of empathy, and dependency on AI tools.

Beyond assessment, GenAI is transforming education by improving learning outcomes and strengthening teacher preparation. Research on GenAI adoption reveals generally positive student attitudes toward GenAI tools (Khalilova, 2025). Usage patterns vary across contexts, Stranges and MacNutt (2025) observed that only 33% of 310 Canadian health science students used GenAI for reflective writing, mainly for drafting and revision, whereas Freeman (2025) documented widespread adoption among UK undergraduates, with 92% using GenAI for assessments and 18% incorporating AI-generated text. Arbab et al. (2024) noted that 76% of students used AI for idea generation and nearly half viewed AI-generated writing as acceptable.

The growing availability of GenAI tools has raised concerns about plagiarism, academic integrity, and ethical practice (Alier et al., 2024). To address these issues, Moorhouse et al. (2023) recommend more process-oriented assessments that foster critical thinking and AI literacy. Lodge et al. (2023) similarly advocate authentic engagement with AI, emphasizing activities such as prompt design and reflective analysis, while Chan and Colloton (2024) propose prioritizing formative feedback and reflection over traditional grading. Oc and Quamina (2025) warn that overreliance on AI risks eroding essential skills and may increase academic dishonesty.

Empirical findings on the use of AI's impact on student learning outcomes and performance are mixed. Smerdon (2024) reported no significant score differences between students who used AI for topic generation and those who did not, whereas Alimardani (2025) found that law students frequently submitted fabricated citations and inaccurate information generated by AI, underscoring the need for targeted integrity training. In response, Xia et al. (2024) emphasize the need of redesigning tasks that promote creativity, critical reasoning, and problem-solving. Institutions are urged to develop comprehensive AI, data, and digital literacy programs to support ethical usage.

Several scholars propose new pedagogical models. Khlaif et al. (2025) encourage educators to shift beyond traditional assessments and use AI for brainstorming and collaborative problem-solving. However, concerns persist regarding the accuracy of AI outputs and authorship verification (Khlaif et al., 2023). The unreliability of AI-text detectors has been highlighted by Nikiforova and Georgiev (2024), who recommend face-to-face examinations as safeguards. Alternative assessment approaches, such as application-based or project-driven tasks, have also been proposed to reduce integrity risks (Ateeq et al., 2024). Supporting this, Smolansky et al. (2023) and Gamage et al. (2023) stress the importance of institutional policies, educator training, and ethical frameworks for responsible GenAI adoption.

Generative AI (GenAI) offers significant opportunities for innovation in higher education while raising important concerns about academic integrity (Bhuiyan et al., 2025). Although prior

studies reported widespread adoption and generally positive student attitudes, fewer have examined how students from different academic programmes use GenAI within science contexts. This study addresses this gap by examining the perspectives and usage patterns of programme-major and non-programme-major students in science coursework. By comparing their GenAI practices, perceived benefits, ethical awareness, and learning gains, the study provides insights to inform assessment design, instructional strategies, and AI literacy development that balance technological innovation with ethical and educational goals.

2. Methodology

This study adopted a student survey developed by a university-wide project led by the Educational Development Centre. The survey collected perception and experience of programme-major and non-programme-major students in applying Generative AI (GenAI) in learning and completing assessment tasks in science subjects. It explored students' usage of GenAI in assessment, their perceived benefits, learning outcomes and challenges, and their support needs.

The study focused on 2 groups of students who are Programme-Major (PM) and Non-Programme-Major (NPM) who registered the 2025/6 semester one disciplinary-specific subjects (ABCT3625 Chromatographic Analysis Laboratory and ABCT3103 Environmental Science) and elective subjects (ABCT3391 Ecology and Ecosystem and ABCT1D09 Greenhouse Gases and Life) offer by Department of Applied Biology and Chemical Technology (ABCT). All the three subjects were taught by the first author. A total 271 students were invited for this survey, and 81 of them completed (response rate = 30%, 81/271) the online survey using MSForm.

2.1. Data collection and analysis

The survey was set up online in MS Form. The online survey was administered after students had completed their assessment tasks in the subject. Students were invited to answer the survey during a class session in semester one of 2025/6. Participation was voluntary, and students provided their responses using a five-point Likert scale to indicate their opinion. The survey data were first checked for completeness and obvious entry errors; no cases were removed on these grounds. Descriptive statistics, including means, standard deviations, and frequency distribution, were computed to summarise the characteristics of the overall sample and the two subgroups (programme majors and non-programme majors). Group differences between programme majors and non-programme majors were examined using independent-samples t-tests, and effect sizes (Cohen's d) were calculated to complement significance testing. All analyses were performed using IBM SPSS Statistics Version 30.

2.2. Participants

A total of 81 undergraduate students from three subjects completed in the survey (Table 1), including 59 programme-major students (73%) and 22 non-programme major students (27%). The gender distribution was 42 female ($n=34$), 56.8% male ($n=46$) and 1% prefer not to disclose ($n=1$). Most programme-major students in Year 4 or above (85%, $n=50$) while a majority of non-programme majors were in the first or second year of study (82%, $n=18$). As for the cumulative GPA, about 43% students fell in the 2.00–2.99 range, 25% in 3.00–3.69, whereas 22% did not indicate their GPA range. GenAI adoption was high with most students (93% of PM and 91% of NPM) reported using GenAI tools in completing their assessment tasks. Non-Programme-Majors more frequently relied on chatbox-based GenAI tools (95%), whereas programme majors used a wider range of GenAI tools, including chatbox (78.2%), research tools (45%), and coding (18.2%).

Table 1. Characteristics of the Sample Group

Characteristic	Programme major (PM) ($n=59$)		Non-programme major (NPM) ($n=22$)		Overall ($n=81$)	
	n	%	n	%	n	%
Gender						
Female	23	39.0%	11	50.0%	34	42.0%
Male	35	59.3%	11	50.0%	46	56.8%
Prefer not to disclose	1	1.7%	0	0.0%	1	1.2%
Year of Study						
1	0	0.0%	15	68.2%	15	18.5%
2	4	6.8%	3	13.6%	7	8.6%
3	5	8.5%	1	4.5%	6	7.4%
4 or above	50	84.7%	3	13.6%	53	65.4%
Cumulative GPA						
Below 2.00	2	3.4%	0	0.0%	2	2.5%
2.00 – 2.99	29	49.2%	6	27.3%	35	43.2%
3.00 – 3.69	17	28.8%	3	13.6%	20	24.7%
3.70 or above	6	10.2%	0	0.0%	6	7.4%
Not Applicable ^a	5	8.5%	13	59.1%	18	22.2%

Note. Percentages may not sum to 100 due to rounding. ^a “Not applicable” reflects students who did not indicate their cumulative GPA.

3. Results and Discussion

3.1. Use of GenAI in Assessment

For both groups of students, use of GenAI in assessment was high, regardless of their disciplinary background (Table 2). Both groups frequently used GenAI for brainstorming, searching for information, and summarising content (Table 2). On the other hand, programme majors reported more frequent use of GenAI for (i) translating (PM: $M = 3.00$, $SD = 1.22$; NPM:

M = 2.10, SD = 1.17, $t(73) = 2.863$, $p < 0.01$) and (ii) facilitating project collaboration (PM: M = 3.05, SD = 1.13; NPM: M = 2.45, SD = 1.05, $t(73) = 2.088$, $p < 0.05$), with statistically significance at 0.05 level and medium effect sizes.

Table 2. Comparison of GenAI Use in Assessment between Programme and Non-programme Majors

	Programme Major		Non-programme Major		<i>df</i>	<i>t</i>	<i>p</i>	Cohen's <i>d</i>
	M	SD	M	SD				
For brainstorming and generating ideas	3.67	0.96	3.30	0.73	73	1.57	0.12	0.41
For searching information or literature	3.44	0.96	3.35	0.81	73	0.36	0.72	0.09
For summarising information	3.56	1.03	3.40	0.75	73	0.65	0.52	0.17
For writing, proofreading and editing	3.07	1.03	2.65	0.99	73	1.58	0.12	0.41
For translating	3.00	1.22	2.10	1.17	73	2.86	0.01	0.75
For creating digital multimedia and presentations	2.75	1.14	2.30	1.03	73	1.53	0.13	0.40
For analysing data/ solving numerical problems/ coding/ programming	3.18	1.07	2.95	1.10	73	0.82	0.41	0.21
For providing feedback to my work-in-progress	3.15	1.06	2.80	1.11	73	1.23	0.22	0.32
For facilitating project collaboration	3.05	1.13	2.45	1.05	73	2.09	0.04	0.55

Note. Programme Major = students enrolled in the programme; Non-programme Major = students from other disciplines. Values represent group means (M) and standard deviations (SD). *t*, *df*, and *p* are from independent-samples *t*-tests (equal variances assumed). Cohen's *d* reflects the effect size, where 0.20 = small, 0.50 = medium, and 0.80 = large effects.

Generally speaking, non-programme majors reported higher level of agreement for all the items on ethical use of GenAI in assessment. In particular, the non-programme majors were more aware of potential misuse than the programme majors (PM: M = 3.71, SD = 0.69; NPM: M = 4.10, SD = 0.64, $t(73) = -2.22$, $p < 0.01$), with statistical significance at 0.05 level and medium effect size.

Table 3. Comparison of Ethical and Responsible GenAI Use between Programme and Non-programme Majors

	Programme Major		Non-programme Major		<i>df</i>	<i>t</i>	<i>p</i>	Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>				
I cross-check information provided by GenAI tools with other sources.	3.69	0.60	3.85	0.81	73	-0.92	0.36	-0.24
I compare multiple sources of information before forming an opinion based on GenAI recommendations.	3.71	0.66	3.90	0.72	73	-1.09	0.28	-0.28
I question the assumptions and biases underlying the information provided by GenAI tools.	3.73	0.68	3.95	0.76	73	-1.22	0.23	-0.32
I can evaluate the functionality and limitations of GenAI tools or products.	3.69	0.69	3.90	0.72	73	-1.15	0.25	-0.30
I can choose the appropriate solution from the various solutions provided by GenAI tools.	3.78	0.57	3.95	0.69	73	-1.07	0.29	-0.28
I can select the most suitable GenAI tools for various tasks.	3.58	0.66	3.85	0.75	73	-1.51	0.14	-0.39
I always uphold academic integrity/honesty when using GenAI tools.	3.80	0.80	4.15	0.75	73	-1.70	0.09	-0.44
I am always aware of privacy and information security issues when using GenAI tools.	3.67	0.72	3.90	0.79	73	-1.18	0.24	-0.31
I am always aware of the misuse of GenAI technology.	3.71	0.69	4.10	0.64	73	-2.22	0.03	-0.58

3.2. Benefits and Learning Gains of Using GenAI in Assessment

Both groups reported similarly positive views towards the benefits of using GenAI in assessment, with mean ratings ranged from 3.5 to 3.9, out of a five-point Likert scale (Table 4). Both programme-major and non-programme-major students rated ‘understanding assessment requirements and gaining new insights and perspectives’ among the top three benefits. Programme majors showed slightly higher means for ‘saving time when finding information and feeling less stressed/more confident’, whereas non-majors were slightly higher on ‘preparing what/how to do the assessment’. However, no statistically significant difference was found between the two groups of students.

Table 4. Comparison of Perceived Benefits between Programme and Non-programme Majors

	Programme Major		Non-programme Major		<i>df</i>	<i>t</i>	<i>p</i>	Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>				
Understanding the expectations and requirements of the assessment task(s)	3.76	0.71	3.85	0.67	76	-0.50	0.62	-0.13
Preparing for what to include and how to complete my assessment task(s)	3.67	0.71	3.80	0.62	76	-0.72	0.48	-0.19
Helping me save time in finding information	3.86	0.78	3.50	1.01	78	1.70	0.09	0.43
Helping me save time in producing the work (e.g. reports, videos, graphics, PowerPoint slides)	3.53	0.93	3.50	1.10	77	0.11	0.91	0.03
Obtaining immediate and personalised feedback for improving my assessment task(s)	3.65	0.74	3.71	0.90	76	-0.32	0.75	-0.08
Obtaining new and useful insights and perspectives	3.83	0.70	3.86	0.64	78	-0.21	0.83	-0.05
Becoming less stressed in preparing the assessment task(s)	3.74	0.70	3.52	0.75	76	1.18	0.24	0.30
Becoming more confident in preparing the assessment task(s)	3.75	0.74	3.71	0.90	76	0.20	0.84	0.05

Both student groups reported positive learning gains from doing the GenAI-expected assessment task, with all mean ratings above the scale mid-point of 3 (Table 5). The most notable perceived gain was in enhancing understanding subject knowledge, which received the highest mean rating for both programme-major and non-programme majors. With the exception of the item on judging the quality of GenAI output, programme-major students showed higher mean ratings across all other learning gains, e.g., creativity, motivation to learn, and problem-solving skills. Particularly, the difference in creativity between the two groups (PM: $M = 3.63$, $SD = 0.69$; NPM: $M = 3.18$, $SD = 0.91$, $t(79) = 2.36$, $p < 0.05$) was with statistical significance at the 0.05 level.

Table 5. Comparison of Perceived Learning Gains between Programme and Non-programme Majors

	Programme Major		Non-programme Major		<i>df</i>	<i>t</i>	<i>p</i>	Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>				
Enhanced my understanding of subject knowledge and theories	3.76	0.63	3.73	0.55	79	0.23	0.82	0.06
Enhanced my ability in using GenAI tools (AI literacy/competence)	3.73	0.58	3.55	0.74	79	1.17	0.25	0.29
Enhanced my communication skills	3.54	0.70	3.41	0.67	79	0.77	0.44	0.19
Enhanced my skills in judging the quality of GenAI output	3.66	0.66	3.68	0.65	79	0.13	0.90	-0.03
Enhanced my creativity	3.63	0.69	3.18	0.91	79	2.36	0.02	0.59
Enhanced my problem-solving skills	3.71	0.64	3.50	0.60	79	1.34	0.18	0.33
Enhanced my critical thinking skills	3.71	0.62	3.59	0.73	79	0.74	0.46	0.19
Motivated me to learn this subject	3.68	0.65	3.45	0.67	79	1.36	0.18	0.34

3.3. Challenges of Using GenAI in Assessment

Students from both programme-major and non-programme-major groups reported moderate concern across a range of challenges when using GenAI in assessment, with mean ratings ranged from 3.0 to 3.9 (Table 6). Although both groups rated unreliable information or hallucinations as a top three concern for both groups, they showed different patterns of concerns. Programme-major students concerned more on privacy and data security and limited access to the GenAI tools, whereas non-programme-major students were more worried about being falsely accused of plagiarism and the subscription fee for advanced features.

Programme-major students also expressed significantly higher concern about the possibility that GenAI use could increase the time required to complete assessment tasks (PM: $M = 3.42$, $SD = 0.79$; NPM: $M = 3.00$, $SD = 0.76$, $t(79) = 2.17$, $p < 0.05$) and the risk of over-reliance on GenAI (PM: $M = 3.54$, $SD = 0.88$; NPM: $M = 3.09$, $SD = 0.97$; $t(79) = 2.00$, $p < 0.05$), with both differences with statistical significance at 0.05 level. Overall, the findings suggest that while students recognize GenAI's usefulness, they remain cautious about its reliability, integrity risks, and its impact on their learning processes.

Table 6. Comparison of Perceived Challenges between Programme and Non-programme Majors

	Programme Major		Non-programme Major		<i>df</i>	<i>t</i>	<i>p</i>	Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>				
Limited access to the GenAI tools	3.63	0.79	3.41	0.73	79	1.13	0.26	0.28
Subscription fee for accessing advanced features	3.58	0.95	3.64	0.73	79	-0.27	0.79	-0.07
Not familiar with the GenAI tool(s) (required by your teacher(s))	3.37	0.76	3.32	0.78	79	0.29	0.78	0.07
Lack of prompting skills	3.41	0.79	3.27	0.70	79	0.70	0.49	0.17
Worries about being falsely accused of committing plagiarism	3.59	0.85	3.86	0.71	79	-1.32	0.19	-0.33
More time to complete the assessment task	3.42	0.79	3.00	0.76	79	2.17	0.03	0.54
Over relying on GenAI tools	3.54	0.88	3.09	0.97	79	2.00	0.05	0.50
Ethical concerns/academic integrity	3.54	0.73	3.50	0.74	79	0.23	0.82	0.06
Privacy and data security	3.66	0.73	3.45	0.60	79	1.18	0.24	0.30
Unreliable/Inaccurate information/hallucinations	3.80	0.80	3.55	0.67	79	1.30	0.20	0.33

4. Discussion and Limitations

4.1. Discussion

This study examined programme major (PM) and non programme major (NPM) students' use of generative AI (GenAI) in three science subjects. Consistent with prior studies (e.g. Freeman, 2025; Arbab et al., 2024), our findings suggest the widespread adoption of GenAI among both groups, with positive perceptions of its usefulness for assessment preparation and learning. Our findings also extend the literature by highlighting how use patterns and ethical awareness differ according to students' programme affiliation and stage of study within a science context.

Although both groups reported similarly high levels of GenAI adoption, programme major students demonstrated more frequent use of GenAI for translation and project collaboration, whereas non-programme major students consistently expressed higher awareness of potential misuse and academic integrity risks. These differences may be partly explained by the fact that the programme-major students who are science students whose coursework typically prioritises technical content and laboratory-based learning and may offer fewer opportunities for sustained academic writing, resulting in comparatively weaker confidence in academic English, than the non-programme major students who are from other disciplines like humanities and health-related disciplines. The higher ethical awareness expressed by non-programme major students—many of whom were in earlier years—may reflect greater uncertainty about assessment expectations, authorship boundaries, and acceptable uses of GenAI. Their

heightened concern about misuse and plagiarism may also be shaped by limited prior exposure to disciplinary norms and by broader institutional messaging around academic integrity.

Both groups reported broadly positive benefits and learning gains from GenAI use, particularly in understanding assessment requirements, gaining new perspectives, and enhancing subject understanding. The absence of large group differences in perceived benefits may suggest that GenAI can support learning across student populations when appropriately integrated into assessment. The programme major students reported significantly higher gains in creativity. This may be linked to the nature of senior-year science assessments, which often emphasise synthesis, application, and open-ended problem solving. When assessments allow exploratory uses of GenAI, students may experience greater creative support, highlighting the importance of assessment alignment between assessment design and intended learning outcomes.

Despite generally positive views, students in both groups expressed notable concerns about unreliable outputs, over-reliance, and the risk of false plagiarism accusations. These concerns echo wider debates about GenAI limitations and the reliability of detection tools. Students' anxiety about being falsely accused underscores the need for greater clarity and transparency in institutional policies. Rather than relying heavily on surveillance-based approaches, clearer guidance on acceptable GenAI use and explicit assessment criteria may better support responsible GenAI use and reduce student uncertainty.

4.2. Implications for Teaching and Assessment Practices

Several implications for teaching and assessment practice emerge from these findings. First, AI literacy trainings could be differentiated by stage of study. Early-year and NPM students may benefit from explicit guidance on ethical boundaries, citation practices, and the limitations of GenAI outputs, while senior PM students can be supported in developing critical evaluation, reflective use, and discipline-specific applications of GenAI. Second, assessment design could move beyond simple permission or prohibition, by incorporating tasks that require students to document, justify, or critically evaluate their use of GenAI. Such approaches align with calls for process-oriented and authentic assessment in the AI era (Chan & Colloton, 2024; Lodge et al, 2023; Moorhouse et al., 2023). Third, clear assessment and academic integrity guidelines on expectations around GenAI use may also help reduce ambiguity that may lead to student anxiety.

4.3. Limitations and Future Research

This study has several limitations. First, the sample distribution was uneven, with a substantially larger proportion of programme-major students ($n=59$) compared with non-majors ($n=22$). In particular, most non-programme majors were Year 1 or Year 2 students, whereas the majority of programme majors were in their final year. This imbalance in academic maturity and

experience may have influenced students' familiarity with GenAI tools, their views and the ways in which they interpreted assessment expectations. Second, the overall response rate was relatively low, which may limit the generalizability of the findings and increase the possibility of non-response bias. Third, the study was conducted in a single discipline and in a single university. Although data were collected from students in three subjects, all were within science disciplines, and the specific assessment tasks may have shaped students' perceptions of GenAI. Students' usage patterns and attitudes may differ in other subject areas, assessment types, and institutional contexts.

Future studies would benefit from larger, more balanced samples and assessments across a broader range of subject disciplines and study levels, as well as longitudinal designs to trace how GenAI literacy, usage habits, and ethical reasoning evolve over time across multiple semesters. Additionally, examining whether different patterns of GenAI use are associated with actual learning performance (e.g. subject grade), rather than perceived benefits alone, would provide deeper insight into its educational impact.

5. Conclusion

This study examined the GenAI usage in science coursework by a science programme-major students and non-programme major student, highlighting how programme affiliation and stage of study shape students' GenAI usage, ethical awareness, and perceived learning gains. In a time of rapid technological advancement, current student practices largely reflect bounded uses of GenAI, such as summarisation and feedback generation. However, the emergence of more agentic AI systems capable of performing complex, multi-step tasks is likely to further challenge traditional notions of authorship and academic work. Fostering students' capacity to critically supervise, evaluate, and take responsibility for AI-generated outputs will therefore become increasingly important, particularly in science disciplines where judgement and accountability are central to professional practice.

Ethical Declaration Statement

Ethical approval was obtained from the Institutional Review Board (IRB) of The Hong Kong Polytechnic University (Reference Number: HSEARS20240522003).

Acknowledgments

The authors would like to thank the financial support from projects from The Hong Kong Polytechnic University (HKPU): (1) Seed fund from Faculty of Science (FS) Teaching Awards 2024 and Department of Applied Biology and Chemical Technology (ABCT); (2) Fund for Innovative Technology-in-Education (FITE) Grant: "Revolutionizing Higher Education

through Innovative and Emerging Technologies in Flipped Learning” (FITE/01, 89U1) from Department of Health Technology and Informatics (HTI) and Educational Development Centre (EDC); (3) FLTI seed fund project “Developing a Flipped Learning Signature Showcase” (FLSS2025/IN/07, 48BF); (4) Fund for Innovative Technology-in-Education Grant: “To bridge the education needs and career opportunities for STEM graduates (FITE/07/FS, 89V9). This study was part of a larger project titled, Exemplary learning, teaching and assessment practices in UGC-funded institutions in the age of GenAI, supported by the Fund for Innovative Technology-in-Education (FITE) of the University Grants Committee (UGC).

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