Digital Competence in Generative AI Contexts Through a Second-Level Digital Divide Lens

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Abstract: As generative artificial intelligence (GenAI) becomes part of university study, students may differ in how they evaluate its outputs, incorporate generated content, manage personal data and direct their interactions with AI tools. Drawing on the second-level digital divide, this study considers differences in the judgements students bring to GenAI use. It examines whether students' general perceptions of higher-order digital competence are associated with their responses to related GenAI-specific indicators, and explores how students describe these practices. Using an explanatory sequential mixed-methods design, questionnaire responses from 95 university students in China were analysed alongside follow-up interviews with three respondents. Four competences from DigComp 2.2 guided the study: information evaluation, content integration, protection of personal data and privacy, and creative use of digital technologies. The questionnaire included four general self-reported proficiency indicators and eight GenAI-contextualised self-report items. Eight theoretically matched associations were examined using Spearman correlations, with confidence intervals estimated by bootstrapping and p-values adjusted for multiple testing. Interview accounts were analysed thematically and considered alongside the quantitative findings. Most matched associations were small and uncertain; seven of the eight correlation confidence intervals included zero. The only association that remained significant after adjustment linked general privacy competence with awareness of personal-data risks in AI systems ($\rho = .284$, adjusted $p = .043$). The same general indicator showed little association with knowledge of data-protection regulation. Interviews suggested that verification depended on prior knowledge, perceived uncertainty and task demands; participants also differed in how actively they guided AI interactions. Awareness of privacy risks did not consistently translate into understanding or protective action. These findings suggest that general competence self-reports and GenAI-contextualised indicators should be examined separately, even when they address the same DigComp competence. Differences in item specificity and response format may also explain the limited associations. The study therefore does not establish whether competence transfers across contexts, but identifies decisions and conditions that merit closer attention when assessing students' GenAI use.

Keywords: Generative AI, Higher-order digital competence, Second-level digital divide, Contextualised self-report, Higher education

1. Introduction

Generative artificial intelligence (GenAI) is becoming part of university students' academic work, from searching for information to producing content and developing ideas (Chan and Hu, 2023). Using these tools effectively requires more than access or basic technical skills. Students need to evaluate inaccurate or biased outputs, decide how AI-generated content should be used, make informed choices about personal data, and use AI strategically and creatively. These activities rely on higher-order digital competences that are becoming more relevant as GenAI enters everyday academic practice.

These differences can be understood through the second-level digital divide. While the first-level divide concerns access to digital technologies, the second-level divide focuses on differences in how people use them and the skills they bring to that use (van Deursen and van Dijk, 2011). This distinction matters for GenAI because access to the same tools does not mean that students use them in the same way. Some may be better able to evaluate AI-generated information, adapt it to their needs, or decide when and how AI should be used. Looking only at access or frequency of use may therefore miss important differences in students' digital competence.

The European Digital Competence Framework for Citizens (DigComp 2.2) provides a basis for examining these differences. It describes digital competence across five areas and 21 individual competences and includes examples of knowledge, skills and attitudes related to artificial intelligence (Vuorikari, Kluzer and Punie, 2022). This study focuses on four competences that are closely related to GenAI use: evaluating data, information and digital content (1.2), integrating and re-elaborating digital content (3.2), protecting personal data and privacy (4.2), and creatively using digital technologies (5.3). These competences cover how students evaluate information, work with digital content, manage privacy, and make purposeful use of digital technologies.

One question is whether students view these competences in the same way when they are placed in a GenAI context. Students who feel confident about evaluating digital information or protecting personal data in general may respond differently to AI-specific statements. Research on systems-thinking assessment and self-regulated learning illustrates the importance of distinguishing assessment approaches (Davis et al., 2023; Cleary and Russo, 2024). More directly relevant to GenAI, Beckman et al. (2025) identify distinct combinations of self-reported

digital and AI literacy among university students. Their findings provide a basis for examining how general competence self-reports relate to GenAI-contextualised indicators.

This study examines these relationships through a sequential explanatory mixed-methods design with university students in China. The quantitative phase compares students' general self-perceptions across four DigComp competences with their responses to theoretically matched GenAI-specific items. The qualitative phase then explores students' experiences with GenAI to contextualise the patterns found in the quantitative data. The study addresses the following research questions:

RQ1. To what extent are students' general perceptions of higher-order digital competence associated with theoretically matched GenAI-contextualised self-report indicators?

RQ2. How do students' accounts of GenAI use contextualise the quantitative findings?

2. Conceptual Background

2.1 Digital Competence and the Second-level Digital Divide

The second-level digital divide concerns differences in the skills and uses of digital technologies that can persist beyond access. Van Deursen and van Dijk (2011) distinguish operational and formal internet skills from information and strategic skills, showing why the ability to operate a technology should be considered separately from the ability to evaluate information and use it purposefully. This perspective directs attention to the resources students bring to GenAI use, including how they judge outputs and decide how to incorporate them into their work.

DigComp 2.2 provides the conceptual framework for specifying the competences examined here. It identifies 21 competences across five areas and includes AI-related examples of knowledge, skills and attitudes (Vuorikari, Kluzer and Punie, 2022). This study selects four: evaluating data, information and digital content (1.2); integrating and re-elaborating digital content (3.2); protecting personal data and privacy (4.2); and creatively using digital technologies (5.3). They were selected to examine evaluative, integrative, privacy-related and creative judgements relevant to GenAI use. The term higher-order digital competence refers here to these selected aspects of judgement and purposeful use; it does not designate a separate DigComp subscale or imply that participants have attained advanced proficiency.

Recent research connects digital inequality with students' engagement with GenAI. In a survey of 194 university students during early GenAI adoption, Beckman et al. (2025) identified distinct self-reported digital and AI literacy profiles, including students reporting high digital literacy alongside low AI literacy. Their findings suggest that general and AI-related self-reports need to be distinguished. These broad profiles motivate a closer examination of how students' general competence self-reports relate to specific GenAI-contextualised indicators.

2.2 GenAI Literacy and the Selected Digital Competences

GenAI refers to AI systems that generate content, including text, images and code, in response to prompts (Miao and Holmes, 2023). In this study, the focus is on students' reported judgements and practices when interacting with such tools and using their outputs. The study examines content generation and its associated decisions, rather than AI technologies in general.

AI literacy concerns the competences needed to evaluate AI critically, communicate and collaborate with it, and use it effectively (Long and Magerko, 2020). Within this broader field, GenAI literacy addresses understanding, assessing and working responsibly with content-generating systems. Annapureddy, Fornaroli and Gatica-Perez (2025) propose twelve competencies that include understanding tool limitations, assessing outputs, prompting, and recognising ethical and legal implications. Their model offers a conceptual account of relevant capabilities rather than evidence that these capabilities necessarily develop or operate together.

Recent empirical work also treats GenAI literacy as multidimensional. Gümüş and Kara's (2025) learning-focused scale covers needs analysis, prompt and language skills, autonomous learning and critical thinking. Yan et al. (2026) identify awareness, usage, evaluation and ethics/risks, and report associations between literacy dimensions and self-reported privacy protection and information verification. These studies extend attention from operating tools to the judgements involved in their use, while operationalising literacy differently.

The four DigComp competences examined here overlap with selected concerns in this literature: judging bias and reliability, integrating generated content and considering authorship, managing personal-data risks, and

using and evaluating AI tools purposefully. DigComp supplies the organising framework for the questionnaire, while GenAI literacy research helps specify the demands of this technological context. The resulting indicators address selected aspects relevant to GenAI literacy; they do not constitute a comprehensive assessment of it.

2.3 Comparing General and GenAI-contextualised Self-reports

The distinction between perceived and demonstrated competence matters when interpreting these measures. Jin et al. (2025) developed GLAT, a multiple-choice GenAI literacy test validated with 355 higher education students. Its scores predicted performance in GenAI-supported tasks better than self-reported measures such as perceived ChatGPT proficiency. This provides evidence that a knowledge test and a self-report can yield different information. It does not establish how two self-report formats should relate to each other.

The present study examines that narrower relationship. General proficiency descriptions ask students to judge their capabilities across digital activities, whereas the GenAI-contextualised items ask about specific knowledge, awareness and practices involving AI. Theoretical alignment within a DigComp competence provides a reason to compare these responses, but does not establish that they measure identical constructs. For example, general privacy self-perception, awareness of AI-related data risks and reported knowledge of regulation address related but distinct aspects of privacy.

Comparing matched indicators can therefore establish whether students reporting higher general competence also tend to endorse related GenAI-specific statements more strongly. Differences in item content, specificity and response format must inform interpretation. Limited associations cannot by themselves demonstrate failure of competence transfer or a discrepancy between perceived and actual ability. Follow-up interviews provide contextual accounts of students' decisions and experiences that can help interpret these patterns. This approach examines the relationship between two forms of self-report and explores how students describe the practices to which they refer.

3. Methodology

3.1 Research Design

An explanatory sequential mixed-methods design (QUAN → qual) (Creswell and Creswell, 2018) examined associations between general competence self-perceptions and matched GenAI-contextualised indicators. Questionnaire analysis was followed by interviews with three respondents. Integration related the quantitative patterns to participants' reported judgements, strategies and experiences with GenAI.

3.2 Participants and Data Collection

A total of 103 students from two classes within the same academic programme and year of study at a university in China were invited to participate. Of these, 95 submitted the questionnaire. The remaining eight opened the questionnaire but did not submit it, so no questionnaire responses from them were available for analysis. These classes were accessible through a teacher, who distributed the questionnaire invitation through the class group chats. Selecting students who shared a programme, year of study and curriculum was intended to reduce variation in educational background. Participation was voluntary, and eligibility required prior experience of using generative AI. The questionnaire examined four competences selected from DigComp 2.2 (Vuorikari, Kluzer and Punie, 2022): evaluating data, information and digital content (1.2); integrating and re-elaborating digital content (3.2); protecting personal data and privacy (4.2); and creatively using digital technologies (5.3).

Part 1 assessed general self-perceptions of the four competences. For each competence, participants selected one of four ordered proficiency descriptions representing progressively more complex engagement with digital tasks. The four indicators were analysed separately, reflecting the distinct DigComp competences (Vuorikari, Kluzer and Punie, 2022).

Part 2 contained eight five-point Likert items (1 = strongly disagree; 5 = strongly agree) examining the four competences in GenAI-specific contexts. The items were developed by contextualising selected AI-related examples of knowledge, skills and attitudes provided in DigComp 2.2 into self-report statements concerning GenAI. Two items were associated with each competence. Competence 1.2 concerned awareness and judgement of bias and potential unreliability in AI-generated information; 3.2 addressed the integration of AI-generated content and issues of authorship and originality; 4.2 concerned personal-data risks and knowledge of data-protection regulation; and 5.3 concerned the creative use and evaluation of AI tools. These items were treated as GenAI-contextualised self-reports.

For the qualitative phase, stratified purposive sampling was used. Aggregate scores from the eight GenAI-contextualised items in Part 2 were used for interview recruitment. Students at or below the 25th percentile formed the lower-scoring group, those at or above the 75th percentile formed the higher-scoring group, and those between these cut-offs formed the middle-scoring group. One student from each group was recruited for a semi-structured interview, taking into account willingness to participate and availability for contact. This approach sought to include accounts from different levels of self-reported endorsement of the GenAI-contextualised items. The interviews lasted between 30 and 60 minutes and explored participants' experiences, strategies and decisions when using GenAI. They were audio-recorded with consent and transcribed verbatim. Participants are identified as H, M and L, corresponding to the higher-, middle- and lower-scoring recruitment groups.

3.3 Quantitative Analysis

Quantitative analysis was conducted in R (version 4.5.3). Initial data screening examined missingness, response ranges and duplicate records. Across the 12 variables included in the analysis, three responses were missing; no values fell outside the expected response ranges, and no complete duplicate records were identified. Descriptive analyses used all available responses for each item, while pairwise-complete observations were used for correlation analyses.

For the four Part 1 indicators, response frequencies and percentages, medians and interquartile ranges (IQRs) were calculated to describe students' general self-perceptions across the four ordered proficiency levels. For the eight Part 2 items, response distributions, means, standard deviations, medians and IQRs were examined to identify patterns and variation in GenAI-contextualised self-reports. Aggregate scores for Part 2 were used for interview sampling only. Quantitative analyses examined the individual indicators separately, without using composite competence scores.

Eight theoretically specified associations were tested, matching each Part 1 indicator with the two Part 2 items addressing the same competence: 1.2 with Q13_1 and Q13_2; 3.2 with Q13_3 and Q13_4; 4.2 with Q13_5 and Q13_6; and 5.3 with Q13_7 and Q13_8. Spearman correlations accommodated the ordered proficiency categories and individual Likert responses without assuming interval-level measurement. Ninety-five per cent confidence intervals were estimated using 10,000 non-parametric percentile bootstrap resamples with a fixed random seed. P-values were adjusted across the eight pre-specified associations using the Benjamini–Hochberg false discovery rate procedure (Benjamini and Hochberg, 1995). Interpretation considered effect magnitude, confidence intervals and adjusted p-values.

3.4 Qualitative Analysis and Mixed-methods Integration

The three transcripts were analysed using reflexive thematic analysis (Braun and Clarke, 2021), involving familiarisation, initial coding, theme development and refinement, and interpretation in relation to the research questions. Analysis attended to participants' reasoning and reported practices in evaluation, content integration, privacy and creative GenAI use.

Quantitative findings informed areas for qualitative exploration, while analysis remained open to themes emerging from participants' accounts.

Integration used narrative weaving and a joint display, considering quantitative patterns alongside interview evidence for convergence, elaboration and divergence.

4. Findings

4.1 Quantitative Patterns in General and GenAI-contextualised Competence

Students' general self-perceptions varied across the four higher-order digital competences. Responses were concentrated in Levels 1 and 2 for all four competences, although the distributions differed across areas. For evaluating data, information and digital content (1.2), 36.8% of participants selected Level 1 and 47.4% Level 2 (median = 2, IQR = 1). A similar pattern was observed for protecting personal data and privacy (4.2), where 45.3% selected Level 1 and 39.0% Level 2 (median = 2, IQR = 1). Responses for integrating and re-elaborating digital content (3.2) were more dispersed across the four levels (median = 2, IQR = 2). Creative use of digital technologies (5.3) showed the strongest concentration at the first two levels, selected by 51.6% and 44.2% of participants respectively (median = 1, IQR = 1).

In the GenAI-contextualised items, students generally reported moderate-to-positive endorsement, but responses varied across specific GenAI-contextualised indicators. Understanding the potential risks associated

with the use of personal data in AI systems received the highest endorsement (M = 3.95, SD = 0.76), with 77.9% of participants agreeing or strongly agreeing. Awareness of authorship and originality issues and the ability to use AI creatively both had means of 3.77. In contrast, appropriate integration and acknowledgement of AI-generated content received the lowest mean rating (M = 3.53, SD = 0.70; median = 3). Knowledge of data-protection regulation was also more variable across participants (M = 3.66, SD = 0.81) than awareness of personal-data risks.

4.2 Associations Between General and GenAI-contextualised Indicators

Seven of the eight matched correlations were small, with confidence intervals including zero (Table 1). This pattern occurred across information evaluation, content integration and creative technology use.

Table 1: Associations Between General Digital Competence Perceptions and Matched GenAI-Contextualised Indicators

Competence	GenAI indicator	N	ρ	95% CI	BH-adjusted p
1.2	Bias awareness	95	-.086	[-.293, .131]	.671
1.2	Unreliability recognition	94	-.182	[-.381, .030]	.315
3.2	AI-content integration	95	.152	[-.046, .349]	.379
3.2	Authorship/originality	95	.035	[-.174, .243]	.841
4.2	Personal-data risk	95	.284	[.070, .481]	.043
4.2	Data-protection regulation	95	.045	[-.164, .252]	.841
5.3	Creative AI use	95	.019	[-.177, .215]	.858
5.3	AI-tool evaluation	93	-.085	[-.284, .121]	.671

The clearest positive association was observed for one privacy-related indicator. General perceptions of personal-data and privacy competence were positively associated with understanding personal-data risks in AI systems (ρ = .284, 95% CI [.070, .481], adjusted p = .043). This was the only association that remained statistically significant after Benjamini–Hochberg correction. However, the same general privacy indicator showed little association with knowledge of data-protection regulation (ρ = .045, 95% CI [−.164, .252], adjusted p = .841). Thus, the two GenAI-specific privacy indicators showed different patterns of association with the same general privacy measure.

These uncertain associations and variation within competence areas provided the focus for qualitative exploration.

4.3 Qualitative Insights into the Quantitative Patterns

The interview accounts provided further insight into how students approached the GenAI-related issues represented in the quantitative analysis. Three themes were identified: selective activation of verification, differences in the regulation of human–AI interaction, and uneven alignment between awareness, understanding and action.

4.3.1 Verification was selectively activated

Participants' accounts suggested that verification depended partly on their existing knowledge and whether they recognised a reason to question AI-generated information. Participant H described using prior knowledge as an initial basis for judgement, followed by further checking when uncertain:

> *"I first judge based on my existing knowledge. If there is something I am unsure about, I will search it myself. Sometimes I also use different models to cross-check the answers."*

Participant M similarly described switching systems when an answer conflicted with her understanding:

> *"If I feel the answer is very different from what I know and seems unreliable, I will switch to another AI and compare the responses."*

However, she qualified this strategy by explaining that it worked only when the topic remained within her knowledge domain. Outside familiar areas, she reported greater reliance on AI because she lacked a basis for judging its responses. Participant L also described comparing responses from different AI systems without being able to determine which answer was correct.

These accounts illustrate how prior knowledge could support both the recognition of uncertainty and subsequent verification. Comparing outputs provided an additional source of information, but did not necessarily resolve uncertainty when participants lacked the knowledge needed to judge between competing answers.

4.3.2 Regulating the human–AI interaction

Participants described different ways of directing and revising their interactions with GenAI. Participant H described a process in which she supplied initial ideas, used AI to organise them, and evaluated the resulting structure against task requirements:

> *"I tell it my thoughts and let it generate a framework. Then I revise the framework against the assignment requirements and improve each part step by step."*

Her account positioned AI-generated content as material to be reviewed and developed. She also described revising her prompts to bring the output closer to her intentions.

Participant M acknowledged that wording could affect output quality, but described herself as "very rigid… I just ask AI for answers." Participant L described repeating questions or switching models when dissatisfied with an output. These accounts indicated that responding to an unsatisfactory answer could involve different approaches, from revising instructions to seeking an alternative response.

These accounts illustrate different ways of managing instructions and reviewing outputs, although the effectiveness of the reported strategies was not independently assessed.

4.3.3 Awareness, understanding and protective action were unevenly aligned

Participants' privacy accounts involved different judgements about how AI systems handled their inputs and what information required protection. Participant H expressed concern about data retention, stating that "everything I say will be recorded and used to improve the model." This statement reflected her understanding of the system rather than verified information about a particular tool's data practices. She described avoiding the disclosure of sensitive personal details.

Participant M recognised potential privacy risks, but her caution varied across contexts. She described sharing personal information for everyday queries without consistently treating that information as sensitive. Participant L explained her limited concern by referring to the perceived value of her academic work:

> *"I currently don't worry about this, because my essays are not anything valuable."*

Privacy decisions involved risk awareness and judgements about input sensitivity or value. Awareness did not necessarily imply understanding data processing or consistent protective action. Evidence about regulatory knowledge remained limited.

4.4 Mixed-methods Integration

Table 2 integrates the matched correlations and interview accounts across the four competences. Interviews illustrated how prior knowledge supported verification, how students directed content generation, and how perceived data sensitivity informed privacy decisions.

Accounts distinguished privacy awareness, understanding and action, but provided limited evidence about regulation, authorship, or tool accessibility and fairness.

These accounts contextualised reported practices without establishing why correlations were weak. Differences in item content, specificity and response format remain alternative explanations.

Table 2: Joint Display of Quantitative Findings and Qualitative Interview Accounts

DigComp competence	Quantitative findings	Relevant interview evidence	Integrated interpretation
1.2 Information evaluation	Both correlations were small; confidence intervals included zero.	Prior knowledge informed plausibility judgements; source or model comparisons could leave uncertainty unresolved.	Accounts illustrate verification conditions, without explaining the weak matched associations.

DigComp competence	Quantitative findings	Relevant interview evidence	Integrated interpretation
3.2 Content integration	Both correlations were small; confidence intervals included zero.	Students reviewed frameworks against task requirements, revised prompts, repeated questions or switched systems.	Accounts elaborate content generation and revision; authorship and originality received less direct attention.
4.2 Personal data and privacy	Risk awareness: ρ = .284, adjusted p = .043. Regulatory knowledge: small, uncertain association.	Students differed in data-retention concerns, perceived input sensitivity and reported protection.	Awareness, understanding and action were distinguishable. Limited evidence about regulation left the contrasting correlations unexplained.
5.3 Creative technology use	Both correlations were small; confidence intervals included zero.	Students described different ways of developing ideas and directing AI outputs.	Accounts illustrate reported creative use; tool accessibility and fairness were insufficiently explored.

5. Discussion

This study compared students' general digital competence self-perceptions with theoretically matched GenAI-contextualised self-report indicators. Most estimated associations were small and uncertain. Interviews added accounts of how students verified information, directed AI interactions and judged privacy risks. Together, the findings highlight the importance of specifying what students are being asked to assess when investigating digital competence in GenAI contexts.

The limited associations suggest that general and GenAI-contextualised self-reports should be interpreted separately. Beckman et al. (2025) similarly identified differing combinations of self-reported digital and AI literacy among university students. The present study extends this discussion through comparisons within four DigComp competences. However, the questionnaire components differed in content, specificity and response format: general proficiency descriptions were compared with agreement statements about particular knowledge, awareness and practices. These differences offer plausible explanations for the observed associations alongside technological context. Jin et al.'s (2025) distinction between GenAI knowledge-test scores and perceived proficiency further underlines the need to distinguish what different instruments measure. Here, both components assessed self-perceptions, so the findings concern relationships between reported judgements rather than discrepancies between perceived and demonstrated ability.

The interviews illustrated some decisions underlying students' reported GenAI use. Existing knowledge helped participants identify reasons to question outputs, while comparing models could leave uncertainty unresolved. Accounts of revising frameworks and prompts also showed how students directed content generation and reviewed its results. These practices relate to the emphasis on output assessment and prompting in Annapureddy, Fornaroli and Gatica-Perez's (2025) framework, and on prompt skills and autonomous learning in Gümüş and Kara's (2025) scale. The interviews provide examples of these practices, although their effectiveness was not independently assessed. They also offered less direct insight into authorship judgements and evaluations of tool accessibility and fairness.

Privacy findings further illustrate the value of distinguishing related indicators. General privacy self-perception was positively associated with personal-data risk awareness after adjustment, while its association with reported regulatory knowledge was small and uncertain. This pattern does not establish that the two correlations differed statistically. Interview accounts nevertheless showed different judgements about data retention, input sensitivity and protective action. Yan et al. (2026) also distinguish literacy dimensions and examine their associations with self-reported privacy protection and information verification. The present findings support examining these aspects separately, while the limited interview evidence about regulation leaves that indicator insufficiently explained.

The second-level digital divide provides a perspective for considering differences beyond access to technology (van Deursen and van Dijk, 2011). Participants described different evaluative and interactional approaches despite sharing an educational setting. These accounts draw attention to the knowledge and strategies students bring to GenAI use. Establishing whether such differences produce unequal learning benefits, or whether GenAI widens existing inequalities, would require evidence about learning outcomes and change over time.

For assessment, the findings suggest value in combining clearly specified self-report indicators with tasks that elicit students' judgements and explanations. Future studies could compare general self-perceptions, GenAI-contextualised self-reports and task performance using more closely matched content and response demands. This would help distinguish contextual differences from those introduced by measurement design.

Several limitations constrain interpretation. The 95 questionnaire respondents came from two classes within one programme and cohort, limiting generalisability. The sample also provided limited precision for estimating small associations. Interview recruitment included one willing and accessible participant from each score group, leaving substantial within-group variation unexplored. The aggregate score served as a recruitment device rather than a validated classification of competence. Three interviews could contextualise selected experiences but could not establish comprehensive explanations for the correlations. Some interview prompts included explanations that may have influenced responses. Finally, both questionnaire components and the interviews relied on self-report; the study therefore provides no direct assessment of competence or its transfer across contexts.

Ethics Declaration: Ethical approval for this study was obtained through the University of Glasgow's low-risk ethics review process. Participation was voluntary, and informed consent was obtained before the questionnaire and interviews. Interview participants are identified by the labels H, M and L in this paper.

AI Declaration: ChatGPT was used to assist with language editing and the organisation of parts of the manuscript. The author reviewed and revised the resulting text and takes full responsibility for the analysis, interpretations, and final paper.

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