Journal of Inclusive Methodology and Technology in Learning and Teaching
ISSN 2785-5104
Anno 6 n. 3 (2026)

EDIZIONI UNIVERSITARIE ROMANE
editoria scientifica dal 1952

Self-regulated engagement in human–AI interaction: an eye-tracking and interview study of the rAIse framework

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Abstract: Generative AI offers new opportunities for learning while raising questions about learners' capacity to maintain active, critical, and self-regulated engagement during interaction. This exploratory mixed-methods study investigates how upper-secondary students exercise metacognitive self-regulation and learner agency while interacting with ChatGPT with the support of the rAIse framework, a pedagogical scaffold for reflective and critical AI use. Eight students completed an individual task combining wearable eye-tracking, conversational logs, and post-task semi-structured interviews. Eye-tracking observations identified three patterns of scaffold use: continuous consultation, intermittent consultation, and visual neglect. Integration with conversational and interview data showed that limited or absent visual consultation of the scaffold did not necessarily correspond to limited self-regulation: students who rarely or never consulted the card could nevertheless display critical evaluation, error correction, source-related strategies, and active regulation of the interaction. These findings highlight the value of integrating visual-attention data with conversational and self-reported evidence when examining self-regulated engagement with generative AI, and suggest that the role of an external scaffold may vary across learners and interaction patterns. Given the small, single-class sample, the findings should be considered preliminary.

Keywords: metacognition; self-regulated learning; learner agency; generative AI; eye-tracking

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1. Introduction

Artificial intelligence has long been discussed in relation to its role in education (Holmes et al., 2019). More recently, generative conversational systems such as ChatGPT have introduced new forms of interaction in which learners request explanations, feedback, and support through natural-language dialogue (Kasneci et al., 2023). Unlike conventional information-retrieval tools, conversational AI allows learners to formulate requests, receive immediate responses, and progressively refine the exchange through further prompts (Dwivedi et al., 2023). This conversational structure creates opportunities for active engagement, but it also raises the question of how learners retain control over the interaction and engage critically with the information the system generates.

Engagement with learning is a multidimensional construct encompassing behavioural, emotional, and cognitive dimensions, with learner agency identified as a

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further component of students' engagement in learning activities (Fredricks et al., 2004; Reeve & Tseng, 2011). In interaction with generative AI this distinction is particularly relevant: the immediacy and fluency of conversational systems can support learning, but they may also encourage exchanges in which generated responses are accepted with limited elaboration. Productive engagement therefore depends not only on access to AI or on the ability to formulate prompts, but on learners' capacity to regulate the interaction, monitor the information received, and retain an active role in directing the exchange.

From this perspective, interaction with generative AI can be examined through the complementary notions of metacognitive self-regulation and learner agency. Metacognition involves planning, monitoring, and evaluating one's own cognitive activity (Flavell, 1979), while models of self-regulated learning describe regulation as a cyclical process of forethought, performance, and self-reflection (Panadero, 2017; Zimmerman, 2002). Applied to conversational AI, these processes concern how learners clarify goals, formulate and revise requests, evaluate generated responses, verify information, and reflect on their own strategies. Learner agency adds the emphasis on the extent to which students actively shape the interaction rather than simply follow the conversational flow.

The rAIse framework provides a procedural structure for supporting these processes (Sansone, 2026). In its evolved form it comprises five phases, namely Reflect, Ask, Interpret, Source, and Evolve, which address goal clarification and prior knowledge, prompt formulation, critical interpretation of AI-generated responses, source verification, and retrospective reflection. These phases map onto the regulatory processes described in self-regulated learning: Reflect and Ask concern planning and forethought; Interpret concerns monitoring during performance; Source and Evolve concern evaluation, verification, and reflection. In this study rAIse serves both as a scaffold available to students and as an interpretive lens for the regulatory behaviours that emerge during interaction with ChatGPT.

The use of an external support during a cognitively demanding task can be understood through the concept of scaffolding: temporary assistance that enables learners to perform activities they cannot yet manage independently, progressively withdrawn as competence develops (Wood et al., 1976; van de Pol et al., 2010). Seen in this way, a decreasing reliance on the scaffold does not necessarily indicate disengagement; it may equally reflect growing independence in the very strategies the scaffold was designed to support. This distinction is central to interpreting cases in which students make little or no use of the scaffold.

A further challenge concerns how such processes can be examined as they unfold. Metacognitive and self-regulatory processes are often investigated through self-report, which captures learners' retrospective accounts but not what occurs during the interaction itself. Eye-tracking offers a complementary observational perspective by recording the allocation and temporal organisation of visual attention (Holmqvist et al., 2011; Rayner, 1998), and is well established in educational research (Lai et al., 2013; Ke et al., 2024). In this study, however, visual attention is not treated as a direct measure of metacognition or agency: gaze behaviour is used as an observational trace to be interpreted alongside conversational logs and post-task interviews, so that what students attend to, what they do, and how they later describe their strategies can be compared.

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The present exploratory study investigates how upper-secondary students exercise metacognitive self-regulation and learner agency while interacting with ChatGPT, supported by a reduced rAIse card that acted as a scaffold throughout the task. By integrating behavioural, conversational, and self-reported evidence at the individual-participant level, it examines both convergences and discrepancies between explicit scaffold use and self-regulated engagement with generative AI.

2. Materials and Methods

2.1 Objectives and research questions

Building on the framework outlined above, the study focuses on how students distribute their visual attention between the conversational interface and the rAIse scaffold, whether distinct patterns of scaffold consultation can be identified, and how these patterns relate to the strategies enacted during the interaction. Accordingly, it addresses three research questions:

(1) What patterns of visual attention emerge across the rAIse scaffold and the conversational interface over the course of the interaction, and what can they reveal about attentional self-regulation? (2) Can distinct profiles of scaffold consultation be identified, and how do they relate to students' interaction strategies? (3) To what extent are metacognitive and agentive behaviours consistent with the rAIse framework, and particularly critical evaluation and source verification, associated with explicit consultation of the scaffold, and to what extent are they observed in its absence?

Given its exploratory nature, the study aims to identify and describe patterns of attention, scaffold use, and self-regulated interaction rather than to test causal relationships.

2.2 Research design and participants

The study adopted an exploratory mixed-methods design integrating eye-tracking data, conversational logs, and semi-structured interviews, each offering a complementary perspective: the allocation of visual attention, the strategies enacted during interaction, and participants' retrospective accounts. The three sources were integrated at the individual-participant level through a joint-display matrix. Given the small sample and the intensive participant-level analysis, the findings are interpreted as preliminary and are not intended to support generalisation.

Participants were students from a single upper-secondary class taking part in the rAIse training project. A preliminary questionnaire was completed by 39 students (27 females, 11 males, and one who preferred not to disclose their gender; mean age 15 years), collecting previous experience with generative AI, frequency and patterns of use, and self-reported critical awareness (Table 1).

Table 1. Class baseline: self-reported critical-awareness items (N = 39; five-point Likert scale).

Critical-awareness item (rAIse phase)	M	SD
D1 – Plan before prompting (Reflect)	3.85	1.04
D2 – Critical reading of responses (Interpret)	3.87	0.80
D3 – Verify with other sources (Source)	3.67	1.01
D4 – Awareness of AI fallibility	4.21	0.92

Critical-awareness item (rAIse phase)	M	SD
D5 – Reflect after use (Evolve)	3.69	1.10
D6 – Ethical considerations	2.90	1.23

A three-cluster K-means solution was specified to distinguish three broad profiles of self-reported critical awareness, which were subsequently used to support purposive sampling. Ten students were then selected for the eye-tracking phase through purposive sampling (Teddlie & Yu, 2007), with the classroom teacher identifying suitable students across the profiles so as to cover variation in familiarity and critical engagement. Two of the ten sessions were later excluded (one for insufficient signal quality, one for a recording failure), yielding a final sample of eight students (three males, five females). Before data collection, school authorisation and the written consent documentation required for the participation of minors were obtained through the school. A pseudonymous alphanumeric code linked data across phases. Data collection took place at Unitelma Sapienza University of Rome, in two quiet rooms: one for the eye-tracking task, with an internet-connected computer and the recording equipment, and a separate one for the interview.

2.3 Instruments and materials

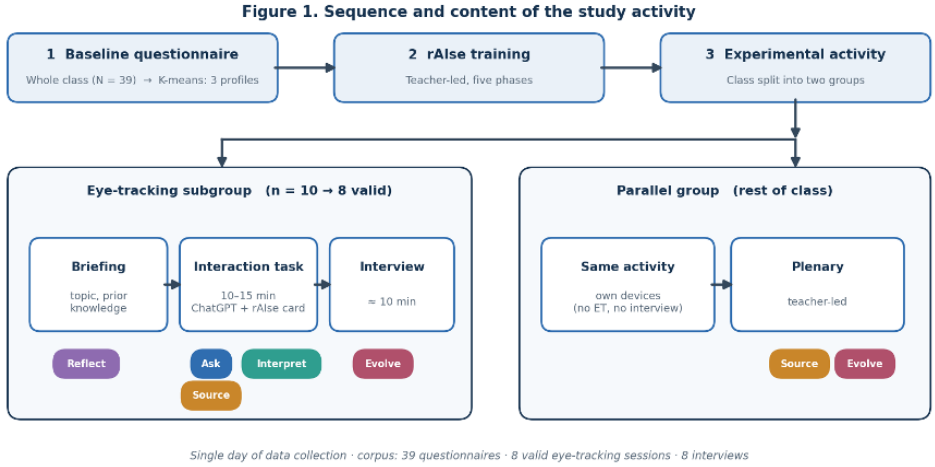
Three sources of data were used. The preliminary questionnaire, administered before the training, collected demographic information, previous experience with generative AI, frequency and modes of use, and six self-reported dimensions of critical awareness (planning before prompting, critical reading of responses, source verification, awareness of possible inaccurate or fabricated information, reflection after use, and ethical considerations); the same six items supported the K-means profiling. Visual attention during the task was recorded with Pupil Invisible wearable eye-tracking glasses (Pupil Labs). Participants used the free version of ChatGPT in a split-screen configuration, with the conversational interface on the left and a static reduced rAIse card on the right. The reduced card included the three phases directly relevant to the live interaction, namely Ask (prompt formulation), Interpret (iterative, critical engagement with responses), and Source (verification beyond the system). Exports included gaze, fixation, and saccade data with synchronised scene video; pupil diameter was not available and was not used. Because automated area-of-interest mapping and heat-map generation proved unreliable under the recording conditions (scene markers were only partially detected), card consultation was assessed through manual observation of the synchronised recordings, focusing on frequency, timing, and context. The semi-structured interview, conducted immediately after the task and audio-recorded, was organised in three parts: overall experience and pre-task reflection; a chronological reconstruction of the interaction (first prompt, evaluation of the response, reformulation, use of the card); and source verification, retrospective evaluation of prompting, and what students had learned about their own way of interacting with AI.

2.4 Procedure and analysis

Data collection began with the questionnaire, completed by the whole class and used to describe prior experience and support participant selection. The class then attended a training session on the evolved rAIse framework, in which the five

phases were introduced together with their associated strategies. Selected students received a short briefing that activated Reflect (why they had chosen the topic, what they already knew, and what they wanted to understand), and then interacted freely with ChatGPT (occupying about 60–65% of the screen) while the reduced card (Ask, Interpret, Source) remained visible on the remaining 35–40%; Evolve was addressed afterwards. Each interaction lasted 10 to 15 minutes, extended beyond ten only to accommodate differences in system response times and in reading and typing pace, with the researcher in a peripheral position. Participants then moved to the separate room for the interview. While selected students completed the sessions, the rest of the class carried out a parallel activity, without eye-tracking or interviews, that was not included in the analytical corpus (Figure 1).

Figure 1. Data collection took place over a single day; the final corpus comprises 39 initial questionnaires, 8 valid eye-tracking sessions, and 8 interviews.



Analysis proceeded through separate but coordinated strands, followed by participant-level integration. Eye-tracking analysis focused on visual behaviour during the interaction and on card consultation; because automated area-of-interest mapping was unreliable, synchronised gaze videos were manually reviewed to identify the frequency, timing, and context of consultation, on the basis of which participants were grouped into three descriptive patterns (continuous consultation, intermittent consultation, visual neglect). Fixation-duration distributions were examined descriptively. Conversational logs were reviewed qualitatively for planning, prompt reformulation, monitoring, critical evaluation, source verification, self-assessment, and regulation of the interaction, with particular attention to sequences in which prompts were modified in response to the output. Interview material was coded on two levels, namely the rAIse phases and the broader metacognitive categories of planning, monitoring, and evaluation, independently by two researchers, who compared classifications and resolved discrepancies through discussion, using spreadsheet-based matrices. Finally, the three sources were integrated in a participant-level joint-display matrix, identifying both convergent cases, in which the sources supported a similar interpretation, and discrepant cases,

in which limited or absent consultation co-occurred with metacognitive or agentive behaviours evident elsewhere.

3. Results

3.1 Visual attention and patterns of scaffold consultation

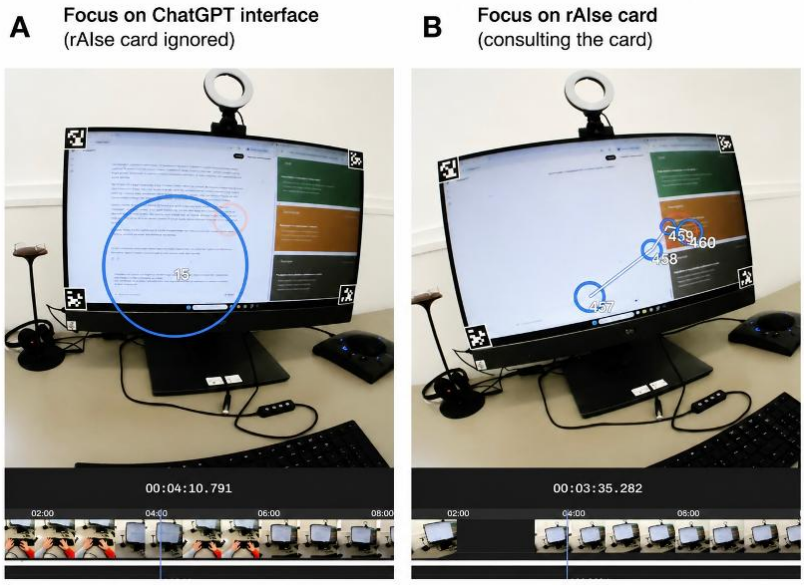
Eye-tracking recordings showed substantial inter-individual variability in the allocation of visual attention between the ChatGPT interface and the rAIse scaffold. Across the eight participants, four consulted the card during the task and four showed no observable consultation (Table 2).

Table 2. Observational coding of rAIse card consultation from synchronised eye-tracking recordings.

Student	No. of card consultations	Consultation phase	Predominant visual focus	Consultation profile
S01	2	Initial stage, with one brief return	Mainly ChatGPT	Intermittent
S02	8	Before starting and throughout the task	Alternates ChatGPT and card	Continuous
S03	5	Initial prompt-planning, with subsequent returns	Mainly ChatGPT, repeated returns to the card	Intermittent
S04	0	No consultation observed	ChatGPT	Visual neglect
S05	0	No consultation observed	ChatGPT	Visual neglect
S06	7	Throughout the interaction	Alternates ChatGPT and card	Continuous
S07	0	No consultation observed	ChatGPT (prompt construction)	Visual neglect
S08	0	No consultation observed	ChatGPT (prompt construction)	Visual neglect

Representative frames are shown in Figure 2.

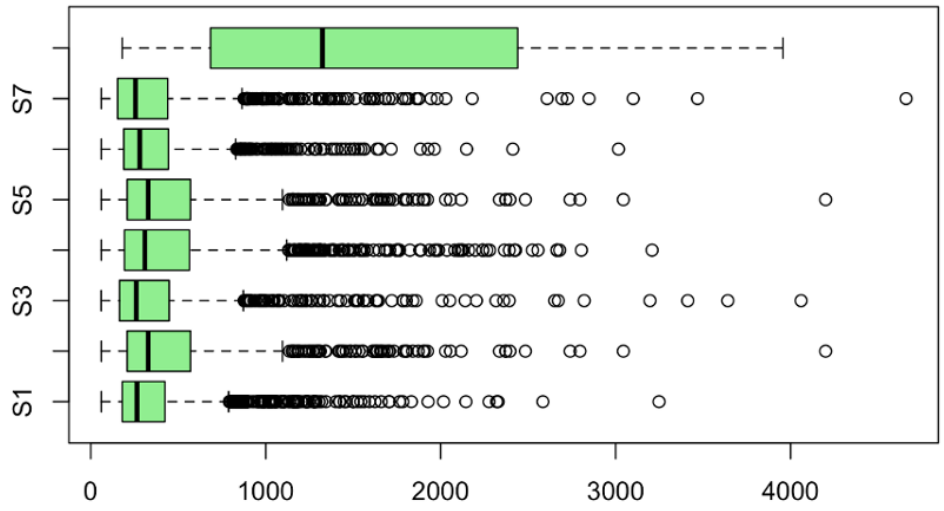
Figure 2. Representative frames from the synchronised eye-tracking recordings. (A) Student S04 (visual neglect): attention on the ChatGPT interface, with the rAIse card not consulted. (B) Student S02 (continuous consultation): attention directed towards the rAIse card during the interaction.



Manual observation identified three patterns. Two participants (S02 and S06) showed continuous consultation, repeatedly returning their gaze to the card throughout the interaction; two (S01 and S03) showed intermittent consultation, using it mainly during the initial stages or returning to it occasionally; and the remaining four (S04, S05, S07, and S08) showed visual neglect, with no consultation observed. Among those who consulted it, use was most evident during prompt planning and at specific points of the subsequent interaction.

Once the conversational exchange was under way, visual attention was directed predominantly to the ChatGPT interface, particularly while participants read responses and prepared subsequent prompts. Fixation-duration distributions showed marked intra- and inter-individual variability (Figure 3): for most participants fixations were concentrated in the lower range, with low median values and positively skewed distributions, alongside occasional isolated fixations beyond 2,000–4,000 ms indicating episodes of sustained attention; one participant (S08) displayed a markedly higher median and wider spread, suggesting a more sustained and heterogeneous allocation. Given the limitations of automated area-of-interest mapping, fixation duration was interpreted descriptively and together with the manual observation of the recordings, rather than as a direct indicator of specific cognitive processes.

Figure 3. Distribution of fixation durations across participants (S01–S08). Boxes represent the interquartile range, central lines the median, whiskers the non-outlier range, and circles observations beyond the whiskers.



3.2 Metacognitive and agentive strategies during interaction

Conversational logs and interviews showed that students adopted different strategies for planning, monitoring, and regulating the interaction. During planning, several participants reported pausing before formulating their first request, and the logs showed several instances of structured prompts that included context, goals, and constraints on the expected response. Monitoring was evident in the ways some students evaluated and modified the exchange: they requested clarifications, reformulated prompts, added constraints, corrected information, or divided requests into successive steps. S05, for example, identified an error in an AI-generated explanation of Greek grammar and issued a corrective prompt, while S01 used ChatGPT as a self-assessment tool by asking it to test his knowledge of Dante Alighieri. Source-related behaviours also emerged, though unevenly: S06 compared the ChatGPT response with Gemini's output, and others reported that they would verify information through textbooks, teachers, or additional sources. Evaluation and source verification were enacted less consistently during the live task than planning and monitoring; some students recognised the importance of verification but described it mainly as something to be done afterwards. The conversational and interview data thus showed heterogeneous forms of self-regulated and agentive engagement, including structured prompting, iterative refinement, error detection, self-assessment, and source comparison.

3.3 Relationship between scaffold consultation and self-regulated behaviour

Integration of eye-tracking observations, conversational logs, and interviews showed that the degree of visual reliance on the scaffold did not map uniformly onto the metacognitive and agentive behaviours displayed. For some students the sources converged: S02 repeatedly consulted the card, reformulated prompts when responses were insufficient, and reported using the framework to guide the interaction; S06 frequently consulted the scaffold and compared ChatGPT with Gemini, consistently with the Source phase; S01 used the card intermittently and

described using ChatGPT to assess his own preparation, a strategy also visible in the log. Other cases showed a different relationship. S04 did not visually consult the card but questioned the reliability of the information and explicitly requested justification and sources, reporting reliance on prior knowledge rather than on the scaffold; S05 likewise showed no consultation but detected and corrected an AI-generated error and described checking the accuracy of the information. S07 and S08 did not consult the card and concentrated on prompt formulation, relying on personal strategies for refining requests and evaluating responses. The participant-level integration thus shows that explicit consultation and self-regulated behaviour were related in some cases but not equivalent: behaviours consistent with the rAIse framework, that is monitoring, critical evaluation, and source-related strategies, were observed both among students who consulted the card and among those who did not (Table 3).

Table 3. Joint display of eye-tracking evidence, conversational behaviour, interview accounts, and the integrated interpretation for each participant.

Student	Eye-tracking evidence	Conversational log evidence	Interview evidence	Integrated interpretation
S01	Occasional consultation; attention mainly on ChatGPT	Asked ChatGPT to act as examiner on Dante Alighieri	Reported using AI to assess his preparation	AI used as a self-assessment tool; metacognitive monitoring and self-evaluation
S02	Frequent regressions to the card throughout the task	Reformulated prompts when explanations were superficial	Reported using the framework to guide interaction	Strong use of rAIse as an external scaffold supporting monitoring and regulation
S03	Periodic consultation during the interaction	Structured prompting and iterative interaction	Reported returning to the framework when uncertain	Moderate integration of rAIse for task regulation and prompt refinement
S04	No fixations on the card	Questioned the reliability and truthfulness of AI output	Reported relying on prior knowledge rather than the card	Critical evaluation without visual reliance on the framework
S05	No consultation observed	Detected and corrected an AI-generated error	Described checking the correctness of the information	Active monitoring and critical evaluation despite absence of consultation
S06	Frequent consultation during the task	Compared ChatGPT outputs with Gemini	Reported intentionally verifying across platforms	Cross-checking across AI systems, consistent with Source verification
S07	No consultation; attention on prompt construction	Invested effort in formulating and refining prompts	Reported focusing on precise outputs through prompt quality	Autonomous regulation centred on prompt refinement rather than the scaffold
S08	No consultation; attention on prompt writing	Interaction focused on prompt formulation and response evaluation	Reported relying on personal strategies	Independent interaction style with limited use of external scaffolds

4. Discussion

The study examined how upper-secondary students regulated their interaction with ChatGPT when the rAIse framework was available as a visual scaffold. Students used the scaffold in markedly different ways (some consulting it repeatedly, others only intermittently, and half not at all), and these patterns did not correspond straightforwardly to the metacognitive and agentive behaviours identified in the logs and interviews. The findings are consistent with a view of interaction with generative AI as a self-regulated activity: students did not simply submit prompts and receive information but, in several cases, modified their requests, questioned responses, corrected inaccuracies, or used the system to assess their own knowledge, behaviours that are consistent with metacognitive monitoring and regulation (Flavell, 1979; Panadero, 2017; Zimmerman, 2002) and with learner agency, insofar as students actively shaped the direction of the exchange. Read through the lens of engagement, these patterns suggest that what distinguishes learners is less the intensity of their activity than its agentive quality: whether attention and effort are directed by the learner or absorbed by the flow of the interface.

The variability in consultation is particularly relevant when interpreted through scaffolding theory. External scaffolds are intended to support performance while learners develop control over the underlying procedures, so their use may change as competence develops (van de Pol et al., 2010; Wood et al., 1976). Limited visual reliance on the card cannot therefore be read in a single way. S04 provides the clearest illustration: the participant did not consult the card but questioned the reliability of the information and requested justification and sources, reporting reliance on prior knowledge. The data, however, do not establish that these strategies were produced by previous exposure to rAIse, nor do they demonstrate internalisation; the finding is more cautiously interpreted as evidence that critical and self-regulatory behaviour can occur in the absence of explicit visual consultation. A similar caution applies to the other neglect cases: S05 identified and corrected an error without consulting the card, while S07 and S08 relied on prompt formulation and personal strategies. Visual neglect is thus not in itself a sufficient indicator of either disengagement or successful internalisation; its meaning depends on the behaviours evident in the interaction and on the learner's own account, which supports the use of multiple data sources when interpreting gaze behaviour.

The findings also indicate a difference between regulatory phases. Planning and monitoring were more evident during the live interaction, whereas source verification and retrospective evaluation were less consistently enacted and more often described as subsequent actions. This should not be read solely as a learner deficit: the reduced card included Ask, Interpret, and Source, while Reflect was activated before the task and Evolve addressed afterwards, so the temporal organisation of the activity itself shaped when some processes could become visible. The participant-level triangulation also proved useful for interpreting these patterns. Eye-tracking alone could show whether and when students consulted the scaffold but not what regulatory process was taking place; the logs documented what students did, and the interviews how they interpreted their own strategies. The cases in which critical behaviour occurred without consultation would have been difficult to interpret from gaze data alone. The results therefore point to rAIse as a scaffold whose role may differ across learners, and to the importance of considering how

external support interacts with learners' existing strategies and prior knowledge, rather than assuming that effective use requires continuous consultation.

5. Conclusions

This exploratory mixed-methods study examined how upper-secondary students regulate their interaction with ChatGPT when the rAIse framework is available as a visual scaffold. Integrating eye-tracking, conversational logs, and post-task interviews revealed substantial variation in scaffold use, ranging from continuous consultation to intermittent use and complete visual neglect, alongside several forms of metacognitive and agentive engagement, including structured prompting, monitoring and correction of responses, self-assessment, and source-related strategies. What emerges most clearly is that visual reliance on the scaffold and self-regulated behaviour did not coincide uniformly: some students consulted the card while regulating the interaction, whereas others displayed behaviours consistent with the framework despite limited or absent consultation. The meaning of both scaffold use and non-use becomes clearer when visual behaviour is read together with conversational evidence and students' own accounts, which supports combining behavioural and self-reported data when investigating self-regulation and learner agency in human–AI interaction. These conclusions remain preliminary: the sample comprised eight students from a single class, data were collected over a single day, topics were self-selected, consultation was assessed through manual observation because automated area-of-interest mapping was unreliable, pupillometric measures were unavailable, and interviews remain subject to the limits of retrospective self-report. Future research should examine these patterns with larger and more diverse samples, more robust quantitative eye-tracking measures, and designs that follow the relationship between scaffold use, prior strategies, and the development of self-regulated interaction over time.

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