Computers & Education 256 (2027) 105749

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Do strategies make a difference? Evaluating the impact on video-based learning and student engagement in K-12 education

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ARTICLE INFO

Keywords:
Self-regulated learning
Learning analytics
Explanatory videos
Log data
Flipped classroom

ABSTRACT

Explanatory videos are central to digital and blended learning environments, especially in student-centered formats such as flipped classroom. Their instructional value depends not only on video design, but also on learners' ability to regulate their engagement with video-based content. Although research on flipped classroom, video analytics, and self-regulated learning has expanded considerably, less is known about how learning strategies designed for explanatory video use shape students' self-reported strategy use, log data-based video interaction, and learning gains in authentic K-12 classroom settings. The present study examined strategy-based support for explanatory video use in a quasi-experimental design with $N = 410$ secondary school students. Students in the strategy group received explicit guidance on video-specific learning strategies (e.g., note-taking, rewinding), whereas the non-strategy group completed the same learning activities without such guidance. Learning outcomes, self-reported strategy use, and log data comprising approximately 24,000 recorded video interactions were analyzed using hierarchical linear modeling. In addition, a newly developed Video Engagement Score (VES) captured overall behavioral engagement beyond isolated log variables. Students in the strategy group reported higher strategy use and showed more intensive video interaction, including more frequent pausing, rewinding, and longer viewing times. However, these changes did not translate into significantly higher learning gains. Across groups, only video viewing compliance predicted learning gains. The findings suggest that learning strategies can shape students' engagement with explanatory videos, but that accessing the assigned videos, rather than assignment to the strategy group, was more closely associated with learning gains.

1. Introduction

The growing use of explanatory videos in educational settings is widely acknowledged for its potential to support multimodal knowledge transfer, enhance learner motivation, and allow for repeated engagement with instructional content (Fiorella & Mayer, 2018; Kulgemeyer & Wittwer, 2021). However, their instructional value depends not only on video availability or design quality, but also on how learners engage with them. Without appropriate support, explanatory videos may encourage passive consumption, emphasize procedural over conceptual knowledge, and fail to cognitively activate learners (Kulgemeyer & Wittwer, 2021; Kuzu &

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https://doi.org/10.1016/j.compedu.2026.105749

Received 18 February 2026; Received in revised form 31 August 2026; Accepted 4 September 2026

Available online 10 September 2026

Open access funding enabled and organized by Projekt DEAL.

Ratzke, 2024). This concern is particularly relevant in flipped classroom settings, where videos often provide the foundation for subsequent in-class learning activities and therefore require students to regulate their own learning during the pre-class phase (Butzler, 2016; Cheng et al., 2019). Effective video-based learning therefore requires students to process verbal and visual information in a coordinated way (Mayer & Moreno, 1998), manage the cognitive demands of learning from dynamic multimedia materials (Sweller, 2011), and engage with video content in ways that go beyond passive viewing (Chi & Wylie, 2014).

The present study examines learning strategies designed to structure students' interaction with explanatory videos (e.g., pausing, note-taking) in an authentic K-12 flipped classroom setting. It addresses a specific gap concerning whether and how such strategy support is reflected across students' self-reported strategy use, log data-based indicators of video interaction, and learning gains. Together, these measures allow us to distinguish between strategy adoption, observable engagement behavior, and learning outcomes.

2. Theoretical background

2.1. Explanatory videos in flipped classroom settings

Explanatory videos are a form of multimedia presentation that combine graphics, narration, and text to clarify complex topics (Mayer, 2014). They enable the dynamic demonstration of step-by-step solutions, including the rationale behind specific problem-solving approaches, which is particularly valuable in cognitively demanding domains (Wirth & Greefrath, 2024). Meta-analyses indicate that explanatory videos can support learning and motivation, although much of the evidence stems from post-secondary settings and findings for K-12 contexts remain less extensive (Akçayır & Akçayır, 2018; Kay, 2012). Beyond informal use, explanatory videos are increasingly integrated into formal instruction through approaches such as flipped classroom (Li et al., 2024; Lin, 2019). In this model, instructional content is shifted to a pre-class phase, typically through video-based homework (van Alten et al., 2019), allowing classroom time to be devoted to applying knowledge, practicing skills, and engaging more deeply with the subject matter (Bergmann & Sams, 2012; Wagner & Urhahne, 2021).

Regardless of whether explanatory videos are voluntarily accessed by students after school or viewed in the context of formal schooling, it is essential to consider how learners process and regulate video-based information. Much research has focused on how instructional videos should be designed to support learning (Cevikbas, 2024; Kulgemeyer, 2020; Wirth & Greefrath, 2024), but effective use also depends on how students regulate their engagement with explanatory videos in authentic K-12 flipped classroom settings. Cognitive Load Theory provides a theoretical foundation for understanding the cognitive demands associated with using instructional videos and the role of strategies in managing these demands (e.g., Minkley et al., 2018; Sweller, 1988). According to Sweller (2011), cognitive load comprises intrinsic, extraneous, and germane components. Intrinsic load reflects content complexity, extraneous load arises from suboptimal presentation, and germane load represents effort invested in meaningful processing, which is essential for learning. Complementing this perspective, the Cognitive Theory of Multimedia Learning (Mayer & Moreno, 1998) highlights that well-designed instructional materials can enhance learning by aligning with human cognitive architecture. Together, these perspectives suggest that explanatory videos can support learning when their design reduces unnecessary processing and when learners regulate how they engage with dynamic multimedia information. This is particularly relevant in flipped classroom settings, where students often encounter new content before class without immediate teacher guidance.

2.2. Self-regulated learning support and strategy use in video-based learning

Given the cognitive demands associated with video-based learning, as described by Cognitive Load Theory and the Cognitive Theory of Multimedia Learning, self-regulated learning (SRL) becomes central to understanding how students plan, monitor, and regulate their engagement with explanatory videos (e.g., J. Lee & Choi, 2019; van Alten et al., 2020a). SRL refers to learners' ability to actively manage and direct their own learning processes and comprises cognitive, metacognitive, and motivational components that enable goal setting, strategy selection, and progress monitoring (e.g., Molenaar et al., 2023; Zimmerman, 2002). Within this framework, learning strategies are defined as specific methods and techniques used to process and retain information more effectively (Schraw et al., 2006). Prior research consistently links SRL and strategy use to academic achievement, motivation, and deeper learning (Dent & Koenka, 2016; Donker et al., 2014; Ng et al., 2024). In video-based learning, such strategies must be enacted while learners control the pace, sequence, and intensity of their engagement with the material. Explanatory videos therefore require students to manage information flow and regulate when to pause, rewatch, or continue viewing (Cheng et al., 2019; Wagner & Urhahne, 2021). Consequently, explicit and context-sensitive support becomes important, because students cannot be assumed to spontaneously apply suitable strategies during video-based learning (Fiorella & Mayer, 2018; van Alten et al., 2020b).

Existing interventions, such as structured prompts and training programs, have been shown to enhance learning performance and increase SRL strategy use (Berthold et al., 2011; Dignath et al., 2008; Moos & Bonde, 2016; Wigfield et al., 2011). Their effectiveness strongly depends on instructional design and contextual factors, underscoring the need for targeted and context-sensitive approaches (Dignath et al., 2008). However, not all interventions are equally successful. Closely related flipped learning studies illustrate this point. Van Alten et al. (2020a) found that video-embedded SRL prompts alone did not significantly improve students' SRL or learning outcomes, whereas van Alten et al. (2020b) reported positive learning effects when prompts were combined with explicit instruction about how and why SRL strategies should be used. Wiesner et al. (2026) similarly emphasize the relevance of additional support for students' self-regulated use of instructional videos in K-12 flipped learning. Together, these findings suggest that SRL support may be beneficial, but that its effects depend on how clearly it is explained, practiced, embedded, and taken up by students.

A central challenge is determining whether such strategies lead to measurable changes in learners' behavior. One established approach is the analysis of log data capturing learners' interactions with video players (He & Cui, 2025; Yoon et al., 2021). Although log data provide manifest behavioral traces of video-watching behavior, the underlying cognitive and self-regulatory processes remain latent. Interpreting these traces as indicators of SRL or strategy use therefore remains theoretically challenging and requires triangulation with complementary evidence, such as self-reports and learning outcomes (Baker et al., 2020; He & Cui, 2025).

The present study addresses this gap by examining strategy-based support for explanatory video use in an authentic K-12 flipped classroom setting. It builds on the principle that SRL support should be explicit and context-sensitive, while extending prior work on digitally embedded prompts by using an offline scaffold to guide students' video use. Because this format makes students' actual engagement with the support less directly observable, the study combines self-reported strategy use, log data-based indicators of video interaction, and learning gains to examine strategy adoption, observable video interaction, and learning progress.

2.3. *Adapting strategy principles from reading to explanatory videos*

Pintrich (1990) categorizes cognitive learning strategies into surface-level and deep-level approaches. Surface-level strategies typically involve rote memorization and repetition, which may support recall but rarely promote deeper understanding or transfer. In contrast, deep-level strategies, such as elaboration and organization, support comprehension and long-term retention by linking new information to prior knowledge and structuring content. Metacognitive strategies, support learners in monitoring and regulating their own learning. Because the depth of processing depends on implementation, these categories are best understood as a continuum rather than as fixed labels for individual strategies. Note-taking, for example, may be relatively reproductive when students mainly copy information, but more generative when they paraphrase, organize, or connect ideas.

Strategy support for explanatory videos can draw on established reading strategies that have been extensively researched and validated (Janzen & Stoller, 1998). However, prior research cautions against directly transferring text-based strategies to multimedia contexts. Strategies such as underlining key passages are often not applicable to explanatory videos, as their multisensory and temporally dynamic nature imposes additional cognitive demands on learners (Schmidt-Borcherding, 2020). For this adaptation, three complementary perspectives are relevant. Pintrich's processing-level distinction informs the intended depth of processing (1990). Zimmerman's SRL model further structures regulation as a cyclical process of forethought, performance, and self-reflection, helping to locate strategy use before, during, and after viewing (Zimmerman, 2002). Finally, the Interactive, Constructive, Active, Passive framework (ICAP; Chi & Wylie, 2014) provides a theoretically grounded and empirically supported model for differentiating levels of cognitive engagement and specifies the intended quality of engagement. ICAP is therefore used as a complementary lens on engagement quality, not as a direct operationalization of SRL.

These considerations underscore the need to selectively adapt learning strategies to the specific affordances of explanatory videos rather than adopting them unchanged. Table 1 therefore presents a theoretically grounded selection of strategy principles that can be adapted to video-based learning and that are supported by empirical evidence. The selected strategies differ in their primary function and intended depth of processing.

3. Aims and research questions

The primary aim of this study was to investigate learning strategies that were specifically developed to support students' learning from explanatory videos. The first two research questions (RQs) examine how these strategies influence students' video engagement through log data and self-reported strategy use. The latter two RQs focus on students' learning gains, investigating both the effect of strategy support and the predictive value of video interaction behaviors.

The research aimed to answer the following research questions.

Table 1
Adaptable reading strategy principles for explanatory videos and their empirical relevance.

Strategy Principle	Core Characteristics	Empirical Evidence
Repetition	Reprocessing content through repeated exposure supports consolidation and distributes cognitive processing over time	Meta-analyses report moderate effects (Cohen, 1988) on learning outcomes (d = 0.50), indicating robust benefits across domains (Hattie, 2023)
Note-taking	Generative processing through selecting, paraphrasing, and structuring information supports comprehension and retention	Small to moderate effects on learning (d = 0.33; Hattie, 2023); consistent benefits for recall and deeper processing (Hadwin & Winne, 2001; Peverly et al., 2003; Winters et al., 2008); supports semantic processing, fosters SRL, and has been widely integrated into video-based instruction, particularly in flipped classrooms (Grypp & Luebeck, 2015; Khurana & Frishman, 2022; Kirvan et al., 2015)
Organization	Structuring information and forming relations between ideas supports elaboration and coherent mental model construction	Associated with higher levels of self-regulation (Pintrich, 2000); facilitates elaboration and deeper cognitive processing by supporting the construction of a coherent mental model through connections between content elements (Kauffman, 2004)
Preparation and reflection	Activating prior knowledge before learning and consolidating information afterward supports integration and long-term retention	Enhanced learning (Hattan et al., 2024; McCarthy & McNamara, 2021), elaboration (van Blankenstein et al., 2013), and retention (Hamilton, 2004) through content preview and prior knowledge activation before exposure, as well as post-learning reflection and consolidation

RQ1 How do learning strategies designed to support the effective use of explanatory videos influence students' self-reported use of strategies during video-based learning?
RQ2 How do learning strategies designed to support the effective use of explanatory videos influence students' interaction with explanatory videos?
RQ3 To what extent do learning strategies designed to support the effective use of explanatory videos contribute to students' learning gains compared to learning without such strategies?
RQ4 To what extent do students' interaction behaviors with explanatory videos predict their learning gains?

4. Methods

4.1. Strategies for enhanced learning with explanatory videos

The goal of this study was to design cognitive learning strategies that would support students in engaging more effectively with explanatory videos. The development process was guided by the three theoretical dimensions introduced in Section 2.3, namely SRL phases (Zimmerman, 2002), processing-level distinctions (Pintrich, 1990), and ICAP levels (Chi & Wylie, 2014). These dimensions were used to align each strategy with a phase of video-based learning, a processing level, and an intended level of engagement. Based on these theoretical considerations, four learning strategies were systematically developed to guide students' interaction with explanatory videos (Table 2).

In line with this, we developed a concise instructional guide to support students as they engage with explanatory videos (Fig. S1–S3). The guide summarizes all strategies in a compact and accessible format and was designed to be placed next to the screen during video viewing. Students fold the guide into a three-sided prism, with each side corresponding to one of the three temporal phases of video engagement: before (pre), during, and after (post) viewing. This physical format ensures that learners have the appropriate strategies for each phase directly in view. Unlike a single embedded prompt, the offline prism remains available throughout the entire video-viewing process and can be consulted flexibly. In addition, the guide includes short instructions to help students understand how to implement each strategy. The strategy prism functioned as a form of offline metacognitive scaffolding. To validly assess the effectiveness of the developed learning strategies, it was essential to provide students with clear guidance and structured opportunities for strategy use. However, despite these efforts, we cannot assume with certainty that all students consistently applied the strategies as intended (see Section 7, Limitations).

4.2. Development of the strategy training

The strategy training was divided into three phases designed to move students from awareness to application, in line with principles of strategy instruction and SRL. Table 3 summarizes the content, objectives, and instructional rationale of each phase.

This structured approach helped students not only understand the strategies and their relevance, but also try them out in a low-pressure setting before using them on their own (Schraw et al., 2006). Embedding guided practice and teacher modeling were especially important to scaffold effective self-regulated learning behavior, which would otherwise be difficult to ensure in real-life

Table 2
Overview of developed learning strategies for video-based learning.

Strategy Name	Processing Level	SRL Phase	ICAP Level	Implementation Instructions
Repetition	Primarily surface-level	Performance	Active	Students first watch the entire video without pausing, rewinding, or taking notes, in order to build a global understanding of its structure and main ideas. After this uninterrupted first pass, they are instructed to rewatch the video, either in full or in selected segments, making active use of video controls (pause, rewind) to focus on key content and improve retention.
Note-Taking	Intermediate/generative, implementation-dependent	Performance	Constructive	While watching the video, students pause regularly to write short bullet-point notes. They are explicitly encouraged to use their own words rather than copying from the video verbatim. Notes should focus on key ideas, examples, and any points of confusion. Students are also instructed to write down questions for follow-up discussion.
Organizing	Deep-level	Self-reflection	Constructive	After watching the video, students review and restructure their notes. This involves grouping related ideas, identifying underlying categories, and, if possible, creating a simple mind map or visual representation. The goal is to promote connections between concepts and deeper understanding of the content's internal structure.
Before-and-After	Deep-level	Forethought & Self-reflection	Constructive	Before watching, students are prompted to read the video title and briefly activate relevant prior knowledge (e.g., by recalling prior lessons). They predict possible topics or questions that may be addressed. After watching, students revisit their notes and summarize what they have learned, explicitly linking it to their prior knowledge and identifying any remaining gaps or new questions.

video learning scenarios. All students in the strategy group completed this training prior to engaging in the experimental learning tasks. This ensured a shared baseline of strategy knowledge and practical experience before the main intervention phase.

4.3. Study design and data collection

To evaluate the effectiveness of the developed learning strategies, a quasi-experimental comparative study was conducted in secondary chemistry education. In this design (Fig. 1), an experimental group (hereafter referred to as the *strategy group*) received strategy training, while a control group (*non-strategy group*) received the same chemistry instruction and access to the same explanatory videos. Both groups participated in four flipped-classroom sessions on redox reactions, with explanatory videos as a central component. Before the intervention, teachers familiarized both groups with the flipped classroom model. Identical instructional materials and media were used across both groups to ensure consistent time on task and to minimize potential confounding variables. The in-class sessions were student-centered and promoted collaborative learning. During the at-home preparation phase, all students watched an explanatory video and completed a cognitively activating task to apply and consolidate the new knowledge.

The only difference between the two groups was that students in the strategy group received explicit strategy training and used the strategy prism as a scaffold to apply the learned strategies while engaging with the explanatory videos. To address RQ1, a questionnaire was administered before and after the intervention. Students rated how frequently they used specific learning strategies while watching explanatory videos, such as taking notes. RQ2 was examined by analyzing how the strategy support influenced students' actual video interaction behavior. This was assessed using objective log data. To investigate RQ3, students' content knowledge gains were measured using a digital knowledge test conducted at three time points: pretest, posttest, and a follow-up eight weeks later. All tests were completed in supervised classroom settings to ensure that no external resources were used. RQ4 was addressed using the same log data to examine the extent to which students' interaction behaviors with the explanatory videos predicted their learning gains.

4.4. Materials and participants

All instructional materials used in this study, including explanatory videos, worksheets, PowerPoint presentations, and an online platform based on Moodle for completing preparatory homework, were developed by the authors. In line with recommendations from Fiorella and Mayer (2018), the production of explanatory videos adhered to the principles of the Cognitive Theory of Multimedia Learning. This included the deliberate exclusion of distracting or redundant elements. Information was presented in a clear and logically structured format to support efficient processing and long-term retention. The design of the Moodle-based learning platform was also guided by didactic and cognitive-psychological considerations. Overall, the design of all materials aimed to reduce extraneous cognitive load and conserve students' cognitive resources.

All materials underwent a review and revision process by an expert panel consisting of an experienced teacher, a teacher trainer, a subject department head, and a professor of chemistry education. In addition, the instructional sessions were piloted in a school setting with a class of 25 students and subsequently revised based on feedback from the classroom teacher.

The study was conducted in regular Grade 10 chemistry classes at academic-track secondary schools in Bavaria, Germany. Initially, 422 students were eligible to participate. During the intervention period, consent was withdrawn for 12 students, and the corresponding pseudonymized records were removed before analysis. The final sample consisted of $N = 410$ students from six different schools. Of these, $n = 248$ belonged to classes in the strategy group and $n = 162$ to classes in the non-strategy group. This imbalance resulted from the class-based assignment of entire school classes, with 11 classes in the strategy group and seven classes in the non-strategy group. Average class size was comparable across groups, with $M = 22.5$ in the strategy group and $M = 23.1$ in the non-strategy group. Students' age was not collected individually because participation was restricted to regular Grade 10 chemistry classes, which typically include students aged 15 to 16 years in the respective school system. Gender information was available for $n = 375$ students.

Table 3
Structure and content of the strategy training.

Phase	Time	Objective	Activities & Materials
1 *Raising Awareness*	5 min	Sensitize students to the importance of using strategies during video learning	- View the video "Monkeying around with the gorillas in our midst" (Simons, 2010) - Instruction: Count passes by players in white shirts - Group discussion on overlooked content - Elicit student-generated strategies
2 *Strategy Introduction*	10 min	Explain the four strategies, their benefits, and correct usage	- PowerPoint presentation - Teacher explanation and modeling of each strategy (Bandura & Richard, 1963) - Explicit demonstration of strategy prism
3 *Guided Practice*	30 min	Enable students to apply strategies independently and under supervision	- Individual practice with a short (1–2 min) non-academic video, as recommended by Kirvan et al. (2015) - Use of digital devices and headphones - Teacher support and feedback - Group reflection and discussion of one student's notes - Second practice video

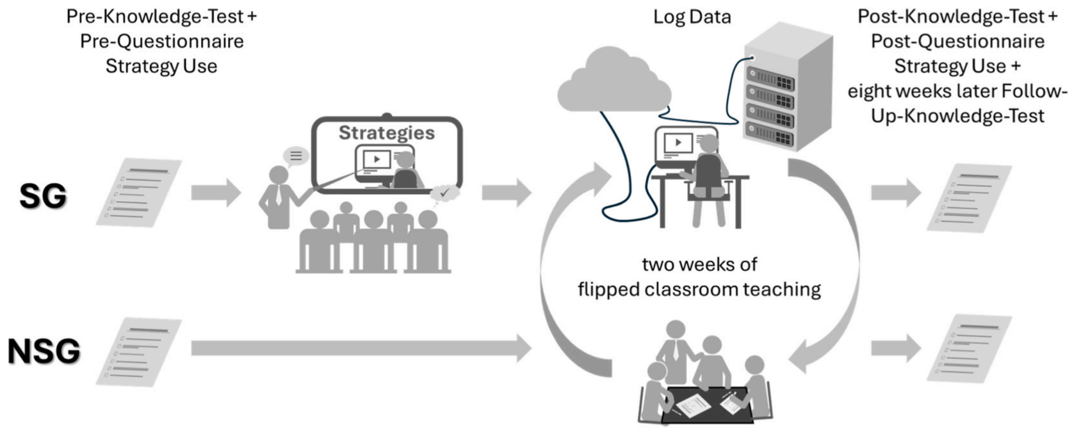


Fig. 1. Study design (SG: strategy group; NSG: non-strategy group).

In the strategy group, 67 students identified as male (30.0%), 150 as female (67.3%), and 6 as diverse (2.7%). In the non-strategy group, 96 students identified as male (63.2%), 47 as female (30.9%), and 9 as diverse (5.9%). Because of this asymmetric distribution, a chi-square test was conducted for male and female students and confirmed that gender distribution differed significantly between groups, $\chi^2(1) = 44.28$, $p < .001$. Because including gender as an additional covariate would have reduced the analytic sample, gender was not included in the reported main model. Instead, we conducted a complete-case sensitivity analysis including gender to examine whether the inclusion of gender changed the substantive interpretation of the *Time* × *Group* effects.

To ensure consistent implementation, all 16 teachers involved in the participating classes received training before the study. Teachers registered voluntarily for one-day professional development workshops, which determined the condition to which their entire classes were assigned. Because assignment occurred at the class level and was linked to this registration, systematic selection effects cannot be fully ruled out. By participating, the teachers also agreed to take part in the accompanying research. The goal of the training was to ensure that teachers were well prepared to implement the developed instructional materials using the flipped classroom approach. Teachers in the strategy group received additional training on the cognitive learning strategies developed for explanatory videos, as well as on how to deliver the strategy training session before the first lesson. To ensure that the duration of professional development was consistent, teachers in the non-strategy group received training on how to create explanatory videos. Since the teachers were not required to produce any videos themselves during the study, and all video content was created by the first author, the influence of this control group's training content on study outcomes is considered highly unlikely.

4.5. *Measuring instruments*

The knowledge test on redox reactions was developed for this study to assess the content covered in the four explanatory videos and classroom activities. Each of the 18 items contributed a maximum of one point. For constructed-response and equation-completion items, partial credit in 0.5-point increments was awarded where applicable. Item scores were summed to a total score ranging from 0 to 18 points, with higher scores indicating greater content knowledge. Example items illustrating the main item formats are provided in Table S1. The test content was reviewed by the expert panel described above to ensure alignment with the curricular content, instructional materials, and intended learning objectives. The same test version was administered at pretest, posttest, and follow-up. Internal consistency varied across measurement occasions, with $\omega_{McDonald} = 0.64$ at pretest, $\omega_{McDonald} = 0.87$ at posttest, and $\omega_{McDonald} = 0.90$ at follow-up. Students had 20 min to complete the test, which was administered online using LimeSurvey.

Self-reported video-related strategy use was assessed with a nine-item questionnaire developed for this study. The instrument was intended to capture the specific strategies targeted by the intervention, not SRL as a broad dispositional construct or distinct SRL subscales. Therefore, existing general SRL questionnaires were not adopted directly. Instead, the items were aligned with the strategy framework described in Section 4.1 and reviewed by the multidisciplinary project team. This provided initial content-based validity evidence for the intervention-specific score but did not establish construct validity for a broader SRL measure. Because the items covered different facets and phases, their mean was used as an overall indicator of self-reported video-related strategy use. Responses were given on a six-point scale from 1 = strongly disagree to 6 = strongly agree, with values above 3.5 indicating increasing agreement with using the targeted strategies and values below 3.5 indicating increasing disagreement. The full item set, including the related strategy and response scale, is provided in Table S2. Item-level descriptive statistics are reported in Table S3. Internal consistency was acceptable to good, with $\omega_{McDonald} = 0.79$ at pretest and $\omega_{McDonald} = 0.85$ at posttest (Hayes & Coutts, 2020).

4.6. *Log data and preprocessing*

Behavioral log data were collected to assess students' engagement with the instructional videos. Six log data-based interaction parameters capturing video access and engagement were derived (Table 4). The raw log data (39,982 recorded video interaction events) were preprocessed individually for each student to remove technical artifacts while preserving personal interaction patterns.

Technical artifacts included implausible event patterns, such as pauses immediately before video completion or resumptions after a student had exited the video page, which may result from connectivity losses or automated system responses. Short event sequences, including starts, loadings, and seeking actions with viewing durations of 4 s or less, were excluded because they likely reflected automatic platform activity rather than intentional behavior. Events with a viewing duration of 1 s or less (paused, resumed), paused events at position 0, and events with positions exceeding the recorded video length were also excluded. Because extremely long pauses are difficult to interpret and can distort skewed distributions, the upper 5% of pause durations were winsorized. Pause values above the 95th percentile (>115 s) were capped at this threshold, allowing more robust estimation without excluding data points (Tukey, 1962; Wilcox, 2017). After preprocessing, 23,894 interactions remained.

To derive an exploratory composite indicator of behavioral video engagement, four of the six log data-based interaction parameters were combined into a *video engagement score* (VES). This approach aligns with learning analytics research emphasizing that behavioral engagement is multidimensional and should be operationalized through a theory-anchored combination of relevant log data-based indicators (Papageorgiou et al., 2025; Vytasek et al., 2020). The VES summarized manifest video interaction patterns rather than a validated latent engagement construct. It combined video viewing time, pause count, forwarding, and rewinding, which represent exposure to content, interruption of playback, and navigation within the video. Because forwarding is theoretically ambiguous and video viewing time partly overlaps with rewinding, the VES summarized overall video interaction intensity rather than independent behavioral components. *Forwarding* was included as an indicator of learner-controlled navigation, but its interpretation is ambiguous because it may reflect targeted search behavior as well as skipping of content. Likewise, *video viewing time* and *rewinding* are not fully independent, because repeated viewing can contribute to both measures. The VES was calculated in two steps. First, for each video, *video viewing time*, *pause count*, *forwarding*, and *rewinding* were *z*-standardized across all valid observations from both groups and averaged with equal weight. Non-accessed videos were treated as missing, whereas zero values for pausing, forwarding, or rewinding were retained for accessed videos. Second, each student's overall VES was calculated as the mean of the available video-specific VES values across watched videos. Higher values indicate more intensive behavioral video engagement, but not necessarily deeper cognitive or self-regulatory engagement. *Video viewing compliance* and *pause time* were excluded from the composite score and analyzed separately. Compliance reflects access rather than interactive engagement. *Pause time* was excluded because it showed no meaningful association with the other indicators and is theoretically ambiguous. Although pausing itself was part of the strategy instruction and is reflected more directly in *pause count*, pause length may indicate note-taking or reflection, but also distraction, interruptions, or multitasking.

4.7. Statistical background

To account for the nested structure of the data, several hierarchical linear models (HLMs) were estimated. Students were nested within classes, which in turn were nested within schools, reflecting a typical hierarchical structure in educational research (Hox et al., 2018). Ignoring this dependency would violate the assumption of independent observations and could lead to biased parameter estimates (Raudenbush & Bryk, 2010). HLM enables the simultaneous modeling of variance at the student, class, and school levels and requires fewer assumptions regarding homoscedasticity and variance homogeneity (Hilbert et al., 2019; Y. Lee et al., 2020). Missing outcome data were not imputed. The HLMs were estimated using all available outcome observations, allowing students with incomplete data at individual measurement occasions to contribute information from their available observations (Hilbert et al., 2019).

To examine within-class and within-school dependencies, an unconditional random-intercept model was estimated first. The intraclass correlation coefficients were 0.199 at the class level and 0.193 at the school level, indicating the necessity of including both levels in the analyses. Accordingly, students (Level 1) were modeled as nested within classes (Level 2) and schools (Level 3; Table 5).

Table 4
Overview of log data variables: operationalization and theoretical rationale.

Variable	Operationalization and Calculation	Theoretical Rationale
Video Viewing Compliance	Binary indicator of whether each assigned video was accessed. Analyzed at the video level in logistic regressions and aggregated across four videos as percentage of accessed videos for descriptive summaries and HLMs (0%, 25%, 50%, 75%, or 100%).	Serves as an indicator of students' willingness to engage with the preparatory phase of instruction within a flipped classroom model.
Video Viewing Time	Percentage of the total video duration that was viewed. Values exceeding 100% indicate that certain segments were watched multiple times.	Reflects the extent of students' exposure to the instructional content.
Pause Count	Number of average pauses students made per video.	Reflects learners' active regulation of the learning process, including possible note-taking.
Pause Time	Average duration of a pause per video (in seconds), based on the pauses made by each student.	Indicates the extent of interruption during video engagement and provides a measure of the temporal scope of self-regulated breaks.
Forwarding	Number of forwarding/rewinding jumps per video, based on user navigation via the video player's progress bar.	May indicate selective navigation, skipping of already understood content, or search behavior in combination with rewinding.
Rewinding		May indicate review, clarification, or repeated processing of previously presented content.

Multiple-testing correction was applied separately for the two main sets of analyses. For RQ2, the fixed-effect tests reported for the log data-based models specified in Table 5 were treated as one set of behavioral process analyses, excluding intercepts. Because these models captured several related but distinct dependent variables of video use, the corresponding p values were adjusted using the Benjamini-Hochberg false discovery rate procedure (Benjamini & Hochberg, 1995; Williams et al., 1999). Adjusted p values are reported as p_{BH} and were used for statistical decisions. For the learning-gain analyses, all eight models predicted the same dependent variable and were therefore treated as a separate outcome set. The significance threshold for these models was adjusted to $p = .006$ using the Bonferroni correction (Bruce et al., 2020). For each model, marginal and conditional R^2 values were reported to quantify variance explained by fixed effects alone and by the full model including random effects (R^2_{marginal} and $R^2_{\text{conditional}}$; Hilbert et al., 2019).

Unstandardized coefficients (b) were reported to preserve the original metric of the predictors and facilitate substantive interpretation. For models predicting learning gains, standardized coefficients (β) were additionally reported to enable comparison of effect sizes across predictors measured on different scales. Reporting both coefficient types is recommended when models include conceptually heterogeneous predictors or when interpretation targets both practical relevance and relative contribution (Gelman & Hill, 2006; Schielzeth, 2010).

5. Results

5.1. Self-reported use of strategies

To examine whether students applied the strategies while watching the videos (RQ1), pre- and post-intervention measures were analyzed using HLM (Fig. 2). In the strategy group, self-reported strategy use increased significantly ($b = 0.23$, $p = .002$). In contrast, the non-strategy group showed a significant decrease ($b = -0.24$, $p = .006$), resulting in a significant between-group difference ($b = -0.47$, $p < .001$). The groups already differed significantly at pre-test ($b = -0.31$, $p = .002$). Despite the statistically significant effects, the observed changes should be interpreted as moderate shifts around the scale midpoint rather than strong endorsement or rejection of the strategies. Although the interaction explained only a small proportion of variance ($R^2_{\text{marginal}} = 0.08$), random effects across hierarchical levels accounted for a substantial share ($R^2_{\text{conditional}} = 0.51$). Descriptive statistics are reported in Table S4.

5.2. Extent of video engagement by students

To assess students' engagement with the explanatory videos, six behavioral parameters were analyzed and summarized in Fig. 3. *Video viewing compliance* was examined using logistic regression (Fig. 3, top left). Compliance decreased significantly over time in the strategy group ($p_{BH} < 0.002$), and no significant group interactions were observed (all $p_{BH} > 0.050$), indicating a similar decline in the non-strategy group. Thus, video access declined over time in both groups. Full statistical results are reported in Table S5. At the class level, *video viewing compliance* varied between 25.0% and 75.0% in the strategy group and between 29.4% and 85.7% in the non-strategy group. Mean class-level compliance was comparable across groups ($M_{SG} = 58.9\%$, $M_{NSG} = 62.9\%$).

Average *video viewing time* (Fig. 3, top right) differed markedly between groups at the beginning of the intervention but converged over time. The video-specific model showed that viewing time in the strategy group declined significantly for later videos ($p_{BH} \leq 0.002$), whereas viewing time in the non-strategy group fluctuated irregularly but remained comparatively stable. The initial group difference was significant ($b = -50.66$, $p_{BH} < 0.001$), and significant *Time* × *Group* interactions indicated that this difference decreased over the course of the intervention (Table S6).

Regarding the number of pauses (Fig. 3, middle left), no clear temporal trends were observed in either group. Across all four videos, strategy-group students made about five more pauses per video ($b = -5.09$, $p_{BH} = 0.008$). In contrast, pause duration showed no significant group difference ($p_{BH} > 0.050$, Fig. 3, middle right).

Navigation behavior showed no consistent temporal trends for either *forwarding* or *rewinding* (Fig. 3, bottom left and right). Across videos, strategy-group students performed slightly more *forwarding* actions per video than non-strategy-group students ($b = -0.77$, $p_{BH} = 0.044$). More pronounced differences were observed for *rewinding*, with students in the strategy group performing on average about three more *rewinding* actions per video ($b = -3.16$, $p_{BH} = 0.025$).

Table 5
Overview of hierarchical linear models (HLMs) computed for RQ1–RQ4. RQ = research question, DV = dependent variable, VES = video engagement score, p_{BH} = Benjamini-Hochberg-adjusted p value.

Model No.	RQ	Model Description	DV(s)	Predictors	Significance Criterion
1	RQ1	Group comparison of self-reported strategy use across time	Self-reported strategy use	Time x Group	$p < .050$
2-8	RQ2	Seven separate models with different video engagement measures as DVs	Log data parameters and VES	Video x Group	$p_{BH} < 0.050$
9	RQ3	Learning gains predicted by group over time	Learning gains	Time x Group	$p < .006$
10-16	RQ4	Seven separate models predicting learning gains using individual behavioral predictors; estimated separately due to multicollinearity	Learning gains	Time x Group x six log data parameters + VES	$p < .006$

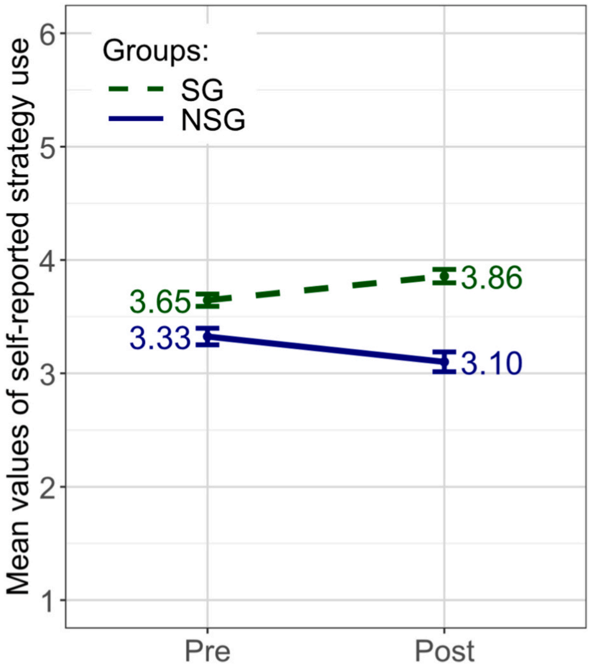


Fig. 2. Mean values and standard errors of self-reported strategy use pre and post. Valid questionnaire scores were available for $n_{pre} = 370$ and $n_{post} = 292$ (SG = strategy group; NSG = non-strategy group).

Similarly, the exploratory VES displayed no systematic trends across the four videos (Fig. 4). Although the trends for the strategy and non-strategy groups moved in opposite directions, the strategy group consistently exhibited higher VES values ($b = -0.50$, $p_{BH} = 0.010$), indicating more intense video engagement.

Visual inspection of the strategy group's trajectories in Fig. 3 suggested similar temporal patterns for *pause count*, *forwarding*, and *rewinding*, indicating potential co-occurrence among recorded interaction behaviors. To examine this more systematically, a correlation heatmap of the five video usage metrics was computed for the strategy group (Fig. 5). *Pause count*, *forwarding*, and *rewinding* showed strong positive intercorrelations. *Video viewing time* was also strongly correlated with *pause count* and *rewinding*, whereas its association with *forwarding* was weak. *Pause duration* showed no meaningful correlations with any other metrics.

5.3. Learning gains and log data-based predictors

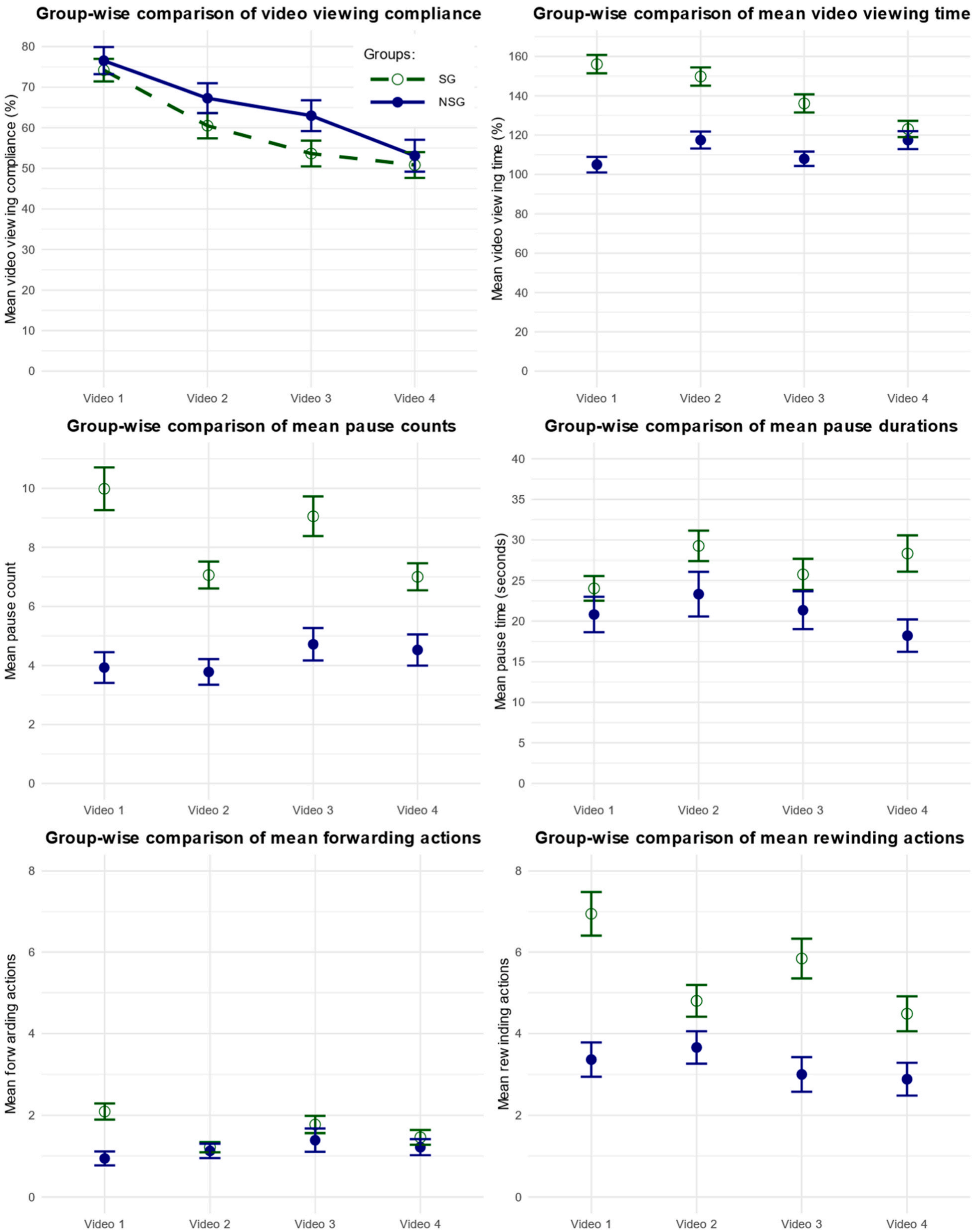
Fig. 6 illustrates learning gains in the strategy and non-strategy groups. Inferential analyses (Table 6) showed that the strategy group achieved significant learning gains both pre-post ($b = 5.11$, $p < .001$) and pre-follow-up ($b = 4.80$, $p < .001$). However, differences in learning gains between groups were not significant (pre-post: $b = 0.80$, $p = .050$; pre-follow-up: $b = 0.19$, $p = .661$). No significant differences were found between post-test and follow-up scores ($p > .006$). Given the coding of the model, the significant time effects represent learning gains within the strategy group, whereas the non-significant interaction terms indicate that these learning gains did not differ significantly in the non-strategy group. At pre-test, the non-strategy group did not differ reliably from the strategy group ($b = 1.19$, $p = .368$). The complete-case sensitivity analysis including gender (Table S7) yielded the same substantive interpretation as the main learning gain model. Accordingly, Table 6 reports the full-sample model without gender.

Additional models examined whether students' video interaction during the preparatory phase predicted learning gains (RQ4). *Video viewing compliance* was significantly associated with learning gains within the strategy group ($b = 0.03$, $p < .001$), and this association did not differ significantly between groups ($b = 0.01$, $p = .370$). In contrast, none of the individual log data-based interaction parameters, including *pause count/time*, *forwarding*, and *rewinding*, were significantly associated with learning gains ($p > .006$). The exploratory VES also showed a positive but non-significant association with learning gains within the strategy group ($b = 0.53$, $p = .130$). This association did not differ significantly between the strategy and non-strategy groups ($b = 0.34$, $p = .636$).

6. Discussion

6.1. From training to application: analyzing behavioral changes in strategy use

The post-intervention self-reports, which referred to the intervention period, indicated more frequent use of the promoted learning strategies in the strategy group than in the non-strategy group and a significant increase over time (see RQ1). Because the groups already differed in self-reported strategy use at pre-test, this increase is best understood as an intervention-period change and does not



(caption on next page)

Fig. 3. Summary of six video usage metrics across videos, including viewing, pausing, and navigation. Group means ± standard errors are shown for SG (strategy group, green) and NSG (non-strategy group, blue). Video viewing compliance was based on the full analytic sample for each video, N = 410. For all other indicators, n refers to students who watched the respective video, with viewed-video sample sizes of n = 308, 259, 235, and 212 for Videos 1 to 4, respectively. Non-viewed videos were treated as not applicable. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

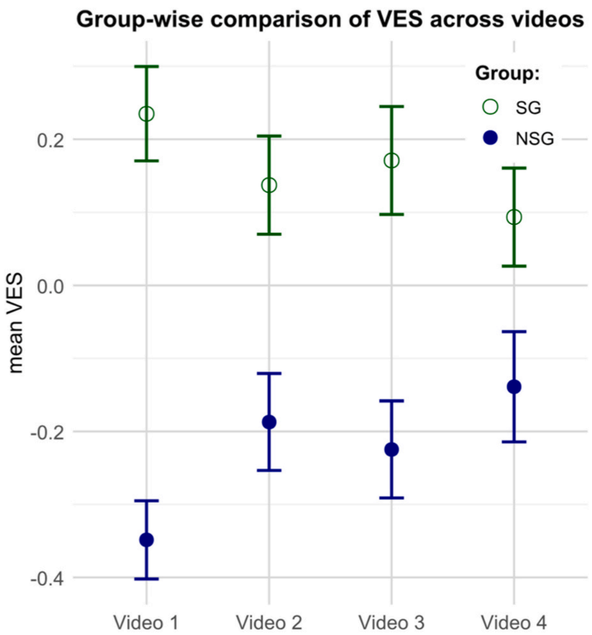


Fig. 4. Mean values and standard errors of video engagement scores (VES) across all four videos (SG: strategy group; NSG: non-strategy group). The VES was calculated for students who watched at least one video, n = 332.

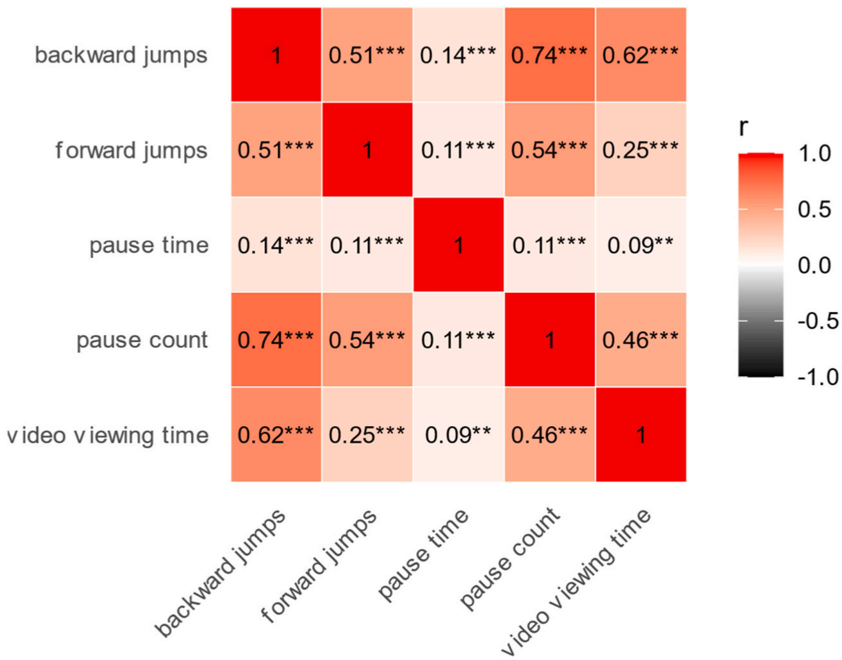


Fig. 5. Pearson correlation matrix of five aggregated video usage metrics across all four explanatory videos: video viewing time, pause count, pause time, forwarding and rewinding. Values represent correlation coefficients (r). Asterisks indicate significance levels: p < .05 (*), < 0.01 (**), < 0.001 (***).

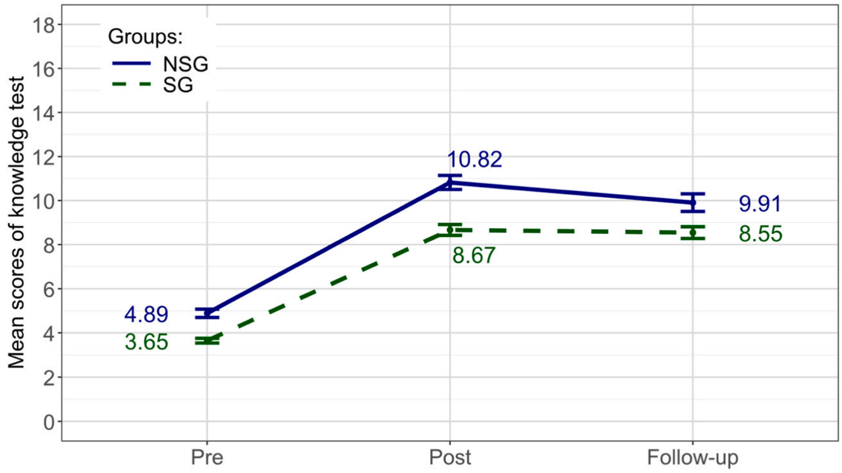


Fig. 6. Average results and standard errors of knowledge test at three time points (SG: strategy group; NSG: non-strategy group).

Table 6
Results of the HLMs with strategy group and pre-test set as reference.

		b	β	SE_b	*t*	*p*
Learning Gains	Intercept	3.51	−0.87	0.563	6.236	0.043
	PT	5.11	1.15	0.258	19.815	<0.001
	Follow-Up-Test	4.80	1.08	0.271	17.720	<0.001
	NSG	1.19	0.27	0.902	1.319	0.368
	PT: NSG	0.80	0.18	0.408	1.967	0.050
	Follow-Up-Test: NSG	0.19	0.04	0.424	0.439	0.661
Log Data Variables as Predictors of Learning Gains	Intercept	3.30	−0.85	0.342	9.669	<0.001
	Video Viewing Compliance: PT	0.03	0.25	0.006	4.645	<0.001
	Video Viewing Compliance: PT: NSG	0.01	0.08	0.010	0.897	0.370
	Intercept	3.12	−0.86	0.474	6.565	<0.001
	Average Video Viewing Time: PT	0.74	0.10	0.436	1.687	0.093
	Average Video Viewing Time: PT: NSG	0.30	0.04	0.793	0.375	0.708
	Intercept	3.62	−0.85	0.300	12.051	<0.001
	Average Pause Count: PT	0.06	0.11	0.026	2.118	0.035
	Average Pause Count: PT: NSG	0.09	0.18	0.066	1.400	0.163
	Intercept	4.01	−0.84	0.417	9.619	<0.001
	Average Pause Time: PT	−0.01	−0.06	0.014	−0.908	0.365
	Average Pause Time: PT: NSG	0.00	−0.02	0.020	−0.232	0.817
	Intercept	3.80	−0.84	0.304	12.476	<0.001
	Average Forwarding: PT	−0.03	−0.01	0.140	−0.230	0.819
	Average Forwarding: PT: NSG	0.03	0.01	0.244	0.125	0.900
	Intercept	3.75	−0.84	0.321	11.678	<0.001
	Average Rewinding: PT	0.08	0.09	0.047	1.736	0.084
	Average Rewinding: PT: NSG	0.02	0.02	0.109	0.166	0.868
	Intercept	3.65	−0.78	0.230	15.902	<0.001
	Video Engagement Score: PT	0.53	0.12	0.352	1.518	0.130
	Video Engagement Score: PT: NSG	0.34	0.08	0.711	0.474	0.636

Baseline Model: $N = 410$, $n_{\text{pre}} = 389$, $n_{\text{post}} = 345$, $n_{\text{follow-up}} = 310$, $R^2_{\text{marginal}} = 0.34$, $R^2_{\text{conditional}} = 0.65$; PT: post-test; NSG: non-strategy group.

show that the post-test difference was caused solely by the strategy support. The observed mean scores were close to the scale midpoint, indicating moderate self-reported strategy use rather than strong endorsement of the strategies. Item-level descriptives (Table S3) further suggest that this change was not uniform, but appeared most pronounced for note-taking, organizing content, and watching the video at least twice in the strategy group. These self-reports also require caution, because increased strategy use does not necessarily imply that students perceived the strategies as helpful or desirable. Van Alten et al. (2020a) highlight this ambiguity, showing that students exposed to SRL prompts often perceived them as distracting and questioned their value because they were unaccustomed to reflecting on their own learning processes. Similarly, Caspi et al. (2005) found that core features of video learning (such as pausing or skipping) were sometimes viewed negatively because they may disrupt the flow of information and increase cognitive load. Thus, perceived behavioral change does not necessarily coincide with a positive learning experience.

Further analysis of the log data (see RQ2) showed no significant group difference in *video viewing compliance*, meaning whether students accessed the assigned videos. Thus, strategy support did not translate into higher rates of video access. *Video viewing compliance* declined significantly over time in both groups. This decline may reflect a fading novelty effect in repeated flipped-classroom homework (Sanchez et al., 2020), consistent with research showing that initial motivation in such interventions can diminish over time (Chen et al., 2014; Clark, 2015). Other explanations, including differences in video content, difficulty, duration, teacher implementation, or general homework fatigue, cannot be ruled out.

A more nuanced picture emerged for *video viewing time*, with significantly longer viewing times in the strategy group than in the non-strategy group. A similar pattern was observed by van Alten et al. (2020a), who found that students receiving SRL prompts exhibited higher video completion rates than those in the control group. This suggests increased engagement with the instructional videos as a result of particular learning support. The strong correlation between *video viewing time* and *rewinding* actions is consistent with the possibility that specific video segments were revisited, suggesting repetition-related behavior. Across the four measurement points, the strategy group showed a significant decline in *video viewing time*. This may indicate that the initially higher level of video exposure was not maintained and could reflect a reversion to more familiar, less strategy-driven usage patterns (Hattie et al., 1996). Because students' use of the offline strategy prism and the quality of strategy implementation were not directly observed, this interpretation remains tentative.

Strategy-group students also paused the video significantly more often, which may indirectly indicate use of the pause function for active processing, including taking and structuring notes. Studies by Schwan and Riempp (2004) and Kalyuga (2009) support this interpretation, showing that deliberate pausing is important for effective video-based learning. Moreover, strong to very strong correlations between *pausing*, *forwarding*, and *rewinding* actions suggest coordinated learner-controlled navigation. Such behavior may be compatible with constructive engagement in the sense of the ICAP model (Chi & Wylie, 2014), but it cannot be treated as direct evidence of learners' cognitive processing.

In contrast, there was no significant group difference in average pause duration. Together with its weak correlations with other interaction parameters, this suggests that pause duration is a relatively unspecific indicator of learning-related cognitive processing. Longer pauses may reflect cognitive processing or reflection, but they may equally indicate distraction, external interruptions, or disengagement.

Additionally, navigation behavior provides insights into learners' video control, although its cognitive meaning remains ambiguous. While group differences in *forwarding* behavior were minimal, more pronounced distinctions were observed in *rewinding* behavior. Students in the strategy group rewound the video significantly more often than students in the non-strategy group. This may indicate a more frequent use of repetition-related behavior, which is considered a central component of SRL (Costley et al., 2021).

A consolidated view is offered by the exploratory VES. Students in the strategy group consistently achieved higher engagement scores than those in the non-strategy group, indicating more intensive recorded interaction with the videos. As a compact composite, the VES summarized broader behavioral patterns across viewing time, pausing, and navigation, but it should be interpreted as a descriptive indicator of observable video behavior rather than as a validated measure of cognitive engagement or strategy quality.

The log-data findings broadly align with the self-reports, but this parallel pattern should be interpreted cautiously because self-reports capture retrospective perceptions, whereas log data capture observable interaction traces. Together, they provide complementary descriptive evidence of intervention-period group differences, but not construct-validation evidence for the VES or direct evidence of the quality of strategy implementation. Following recent work on log-based process data, stronger claims about construct validation would require further examination of the VES across tasks, samples, and measurement models (He & Cui, 2025). The present pattern contrasts with van Alten et al. (2020b), who found positive learning effects of video-embedded SRL prompts and explicit instruction, but no corresponding differences in SRL self-reports or online SRL activity. This may indicate that different forms of SRL support affect different aspects of learning and behavior.

6.2. Design and effectiveness of the implemented learning strategies for video-based instruction

The analysis of learning gains (see RQ3) showed that no significant differences emerged between the strategy group and the non-strategy group. This finding contributes to a mixed pattern of evidence regarding SRL support in flipped learning contexts. Positive effects on performance outcomes have been reported for self-regulated learning prompts (Lai & Hwang, 2016; Moos & Bonde, 2016) and for embedded SRL prompts combined with explicit instruction (van Alten et al., 2020b), and for additional SRL support in K-12 flipped learning (Wiesner et al., 2026). In contrast, Butzler (2016) found no significant performance differences after a multi-week note-taking intervention, despite positive student feedback. Similarly, large-scale studies by Wagner and Urhahne (2021) and van Alten et al. (2020a) found no measurable effects of SRL skills on learning outcomes, even though such skills are theoretically considered important (Blau & Shamir-Inbal, 2017; Lai & Hwang, 2016).

One possible explanation for the lack of impact is that the training, which consisted of a single lesson, was insufficient to induce a robust and sustainable behavioral change when interacting with explanatory videos. As shown in Section 6.1, the strategy group did exhibit distinct engagement patterns, indicating at least a temporary adoption of the promoted strategies. Nevertheless, these behavioral changes did not translate into significantly greater learning gains. This may indicate that the observed engagement was either too limited in intensity or duration to unfold its full learning potential, or that the strategies were not applied with sufficient quality or consistency (see Limitations, section 7). Alternatively, the strategies themselves may not have produced a measurable positive effect on learning outcomes (see RQ4). Among the log data-based indicators, only *video viewing compliance* was significantly associated with learning gains, indicating that whether students accessed the assigned videos was the most robust behavioral predictor. This finding is particularly relevant because accessing preparatory video materials is a basic prerequisite for benefiting from flipped classroom arrangements (Awidi & Paynter, 2019; Bouwmeester et al., 2019). It is also consistent with evidence that pre-class video watching is associated with achievement and knowledge retention even when motivation and prior achievement are controlled (Förster et al., 2022). The remaining individual interaction indicators showed no significant associations with learning gains. The exploratory VES showed a positive but non-significant association with learning gains, and this association did not differ significantly between the strategy and non-strategy groups. Thus, the present analyses suggest that learning gains were more closely related to whether students accessed the preparatory videos at all than to the broader interaction patterns captured by the VES.

Together, these findings raise the question of why the theoretically grounded strategy support was associated with observable behavioral differences, but not with higher learning gains. One plausible, but untested, explanation is provided by cognitive load theory. Learning strategies may support cognitive processing but also impose additional demands when they are not yet automated (Sweller, 2011). The strategies in this study were based on established SRL concepts and the ICAP framework, but they were likely novel for many students in video-based learning. As a result, cognitive resources may have been required not only for processing the video content but also for deliberately applying the strategies. This dual demand may have increased extraneous cognitive load and interfered with effective learning. Kester et al. (2005) showed that simultaneously engaging with learning tasks and process support materials can lead to cognitive overload, particularly when element interactivity is high. In these situations, learners must process multiple sources of information or concurrent tasks, which can hinder the effective use of individual strategies. Similar trade-offs have been described by Berthold et al. (2011), who showed that instructional supports can facilitate learning while simultaneously interfering with other cognitive processes when they increase extraneous load. This phenomenon has also been referred to as a "double-edged sword" (Kirschner et al., 2011, p. 103). Comparable warnings are also reported by Schmidt-Borcherding (2020) and in K-12 flipped learning research by van Alten et al. (2020a), where students described feeling overwhelmed by the simultaneous demands of content processing and strategy application. Indeed, studies on reading strategy instruction have shown no or negligible effects on learning outcomes when strategies are insufficiently practiced or have not become automated (e.g., Cooper et al., 2024; Lenhard et al., 2013). The present findings are compatible with this possibility, but do not provide direct evidence for it. The final model showed that the non-strategy group had a descriptively larger pre-post learning gain than the strategy group, but this difference did not meet the corrected significance threshold ($b = 0.80$, $p = .050$, $\beta = 0.18$). Thus, no reliable difference in learning outcomes can be concluded. The non-significant direction of this effect is compatible with the possibility that the strategy instruction introduced additional cognitive demands, but this interpretation remains tentative because cognitive load and mental effort were not measured. Rather than demonstrating the inefficiency of the strategies, these findings may suggest that their implementation under demanding conditions requires further investigation. Importantly, cognitive load may not manifest in performance alone, and mental-effort measures can provide additional insight (Paas & van Merriënboer, 2020). Similarly, van Merriënboer and Sweller (2005) emphasize that equivalent learning outcomes can be achieved with substantially different levels of cognitive effort. Thus, relevant cognitive processes may remain undetected when no additional measures are considered.

Overall, the results suggest that the effectiveness of new learning strategies depends on providing sufficient time for practice. Learners require opportunities to familiarize themselves with new approaches. Only under such conditions can germane load be supported, extraneous load reduced, and strategic self-regulation in dealing with complex learning materials be sustainably strengthened (Farrell, 2001; Janzen & Stoller, 1998).

7. Limitations

Several limitations must be considered when interpreting the results. Because the identical knowledge test was administered at pretest, posttest, and follow-up, retest effects cannot be fully ruled out, although the same test version was used in both groups and was therefore unlikely to systematically favor one condition. Although we collected log data on students' click behavior, the underlying activity remains unclear. We cannot determine whether the recorded interactions genuinely reflect the use of intended learning strategies or whether the learner was merely letting the video play in the background while multitasking. A key limitation of click-based data is precisely this inability to distinguish between focused engagement and passive or distracted behavior (Guo et al., 2014). Although a thorough preprocessing procedure was applied to remove technical artifacts and implausible event patterns, the interpretation of log data remains limited to observable surface behavior and does not capture cognitive engagement. Furthermore, even assuming that students applied the intended strategies at the relevant moments, no conclusions can be drawn about the quality of their implementation. This limitation is particularly relevant because the strategy prism was implemented as an offline scaffold, meaning that students' actual engagement with this support could not be tracked directly. Qualitative data, such as notes, learning products, or observations, were not collected. These could have clarified how well and consistently the strategies were executed (Pekrun, 2020; Schmidt-McCormack et al., 2017). Relatedly, the questionnaire classifications reflected the intervention-specific framework used in the training and should not be read as unambiguous SRL categories. For example, looking up unfamiliar words and asking others for help may also reflect clarification or help-seeking processes (Karabenick & Dembo, 2011). In addition, because the intervention was implemented in entire classes, classroom-level factors such as teachers' emphasis on homework completion, classroom norms, or teacher-student relationships may have influenced students' video viewing behavior. Although the analyses accounted for the nested structure of students within classes, these relational and classroom-level factors, as well as variation in implementation fidelity, were not directly measured.

8. Conclusion and implications

This study investigated how the use of targeted learning strategies relates to students' engagement with explanatory videos in a flipped classroom context. Although no significant differences in learning gains were found between the groups, the behavioral log data and students' self-reports indicated intervention-period differences in students' video-related behavior, such as more intensive video use and higher self-reported use of cognitive strategies in the strategy group. At the same time, *video viewing compliance* was the only log data-based indicator that was significantly associated with learning gains. Given the nonrandom allocation of intact classes, these findings should be interpreted as evidence of group differences during the intervention rather than as definitive causal evidence of intervention effects. The Video Engagement Score (VES) provided an exploratory summary of learner-controlled interaction with the video material by integrating viewing time, pausing, and navigation into a single behavioral index. In the present study, the VES captured more intensive recorded video interaction in the strategy group, but it was not significantly associated with learning gains. Its measurement properties and predictive value should therefore be examined further across different samples, tasks, and video-based learning contexts.

The findings highlight that the effectiveness of learning strategies may depend on how well they are practiced, understood, and transferred into real learning situations. A tension emerges between supportive instructional structure and cognitive overload, a potential side effect of instructional interventions (Kirschner et al., 2011). A deliberate regulation of germane load alongside the reduction of extraneous load thus appears essential to support sustainable learning processes.

Future research should focus more on the quality of strategy implementation, compare different modes and intensities of SRL support, and include performance data alongside qualitative learning products, subjective measures of effort, indicators of cognitive load, and student-level prerequisites for accessing preparatory video materials. Only by combining different types of data can we more accurately assess whether strategies are implemented with sufficient quality to promote learning or whether they do not translate into measurable learning benefits.

CRediT authorship contribution statement

Sebastian Rohr: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mario Frei:** Writing – review & editing, Visualization, Software, Project administration, Data curation, Conceptualization. **Sven Hilbert:** Writing – review & editing, Visualization, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Oliver Tepner:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Ethics approval and consent

The school-based data collection was formally reviewed and approved by the Bavarian State Ministry of Education and Cultural Affairs (Bayerisches Staatsministerium für Unterricht und Kultus) as part of the official approval procedure for conducting research in schools (approval no. IV.7-BO4106.2021/64/24; approval date May 3, 2022). The approval was granted on the basis of the submitted study documents and included both content-related and data-protection review. At the school level, implementation required approval by the school principal in consultation with the relevant school body.

Before data collection, school principals, teachers, parents or legal guardians, and students received written information about the study. The information described the aims of the study, the voluntary nature of participation, the types of data collected, including questionnaire data, knowledge-test data, and digital log data from the learning platform, and the intended scientific use of the data. Written consent was obtained from parents or legal guardians, and students additionally provided written assent. Participating teachers also provided written consent. Participation was voluntary, nonparticipation had no disadvantages, and consent could be withdrawn at any time.

Data were processed in pseudonymized form using study-specific alphanumeric codes. Tracking data, questionnaire data, and knowledge-test data were linked through these codes and transmitted to the research team without student names. The learning platform and survey software were hosted on secure internal servers of the University of Regensburg. Access to personal data and the pseudonymization list was restricted to designated project staff. Data were stored securely, used only for research, teacher education, and scientific dissemination in anonymized form, and handled in accordance with the approved data-protection procedures.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the revision of this work, the authors used ChatGPT to support linguistic refinement, readability, and the exploration of alternative formulations. The tool was not used for data collection, data processing, data analysis, coding, interpretation of results, or theory development. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Funding

This study was conducted within the project FALKE-d, which is part of L-DUR. The project is part of the “Qualitätsoffensive Lehrerbildung”, a joint initiative of the Federal Government and the *Länder*, which aims to improve the quality of teacher training. The programme is funded by the Federal Ministry of Education and Research under funding code 01JA2010. The authors are responsible for the content of this publication. The funder had no role in the study design, data collection, analysis, interpretation of data, writing of the report, or decision to submit the article for publication.

Acknowledgements

The authors thank all participating teachers and students for their support of the study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2026.105749.

Data availability

Data will be made available on request.

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