



Mind wandering in Video-Based learning: Self-Regulated learning and student responses in a naturalistic setting

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Received: 27 April 2025 / Accepted: 6 February 2026
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Abstract

Video-based learning is a prevalent instructional method in higher education. Although video offers increased flexibility for learning, students face inherent challenges in maintaining attention and engagement. Mind wandering is a common challenge that can negatively impact learning outcomes. While prior research has examined the impact of mind wandering, less is known about how students respond when they become aware of mind wandering. This naturalistic case study explored how self-regulated learning relates to students' awareness of mind wandering. It also examined the temporal focus of these thoughts and whether students choose to rewind videos after noticing they were mind wandering. A total of 53 university students from eight courses participated, reporting instances of mind wandering while watching short (<30 min) instructional videos and completing the self-regulation for learning online (SRL-O) questionnaire. Students with stronger effort regulation and planning and time management skills, reported less mind wandering. Analysis of video navigation revealed only 15 instances where students rewound the video after reporting mind wandering, representing less than 5% of the 317 total thought reports and involving only 10 of 53 participants. These findings raise questions about whether learners need explicit instruction on how to respond when they catch themselves mind wandering, or whether such reactive behaviours develop naturally as part of self-regulated learning skills.

Keywords Self-regulated learning · Mind wandering · Task-related interference · Video-based learning · Adaptation

Introduction

Instructional videos have become a foundational learning resource in higher education (Colasante, 2022; Rodríguez & Pulido-Montes, 2022). These videos range from lecture recordings to purpose-made content covering course concepts or demonstrations of required skills. The videos are commonly accessible online, providing flexibility for when and where

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students engage in their learning. However, this increased flexibility also brings additional learning challenges. Most notably, the ability for students to sustain attention and autonomy (Brady et al., 2021). A challenge in video-based learning is mind wandering, broadly defined as thoughts unrelated to the current task. Mind wandering is a frequent cognitive phenomenon, with a recent meta-analysis showing that students engage in mind wandering approximately 30% of the time during learning activities (Wong et al., 2022). These frequent episodes of mind wandering have been shown to negatively impact on learning outcomes (Wong et al., 2022).

The relationship between mind wandering and learning outcomes may be more nuanced than it initially appears. Perceiving mind wandering only as a deficit overlooks the role of the learner's metacognitive control and agency in mitigating these effects. Learner agency in educational contexts is often conceptualised through the lens of self-regulated learning. This framework refers to the processes by which learners set goals, monitor their progress, and adapt their strategies to achieve learning objectives (Panadero, 2017). Self-regulated learning theory posits that effective learners actively monitor and control their cognitive processes. Within this framework, metacognitive monitoring (the ability to assess one's own cognitive state) serves as a core component of self-regulated learning (Winne & Azevedo, 2022). Meta-awareness, or the explicit recognition that one's mind has wandered, represents a form of this monitoring. In short, learners become aware of their attentional state (Schooler et al., 2011; Zedelius et al., 2015). Self-regulated learning can be conceptualised in two ways: as an aptitude or as a series of events (Winne & Perry, 2000). In the present study, we incorporate both views to examine how self-regulated learning aptitude relates to behavioural responses during video-based learning.

When learners become meta-aware of mind wandering, they may intentionally adjust their learning behaviour in response (Ebbert et al., 2026; Varao-Sousa et al., 2017). For example, a student may reread a text or rewind a video (Seo et al., 2021). Such behavioural adjustments represent observable traces of self-regulation in action. However, prior studies on mind wandering have tended to constrain learner agency by limiting their ability to stop, rewind, or pause videos (e.g. Kane et al., 2017; Welhaf et al., 2022). This methodological limitation has precluded examination of the role of learner agency in responding to mind wandering during video-based learning. Consequently, there is a lack of empirical evidence on whether, and how, learners with different levels of self-regulated learning aptitude demonstrate meta-awareness of mind wandering and enact behavioural responses in naturalistic learning contexts.

This naturalistic case study investigates how students' self-regulated learning aptitude relates to their awareness of mind wandering and their behavioural responses. In addition, we observe whether students choose to rewind videos after recognising an attentional lapse, a behavioural trace that would indicate active self-regulation. The study extends prior research on self-regulated learning and meta-awareness by linking mind wandering to behavioural responses in a real-world learning context. The study offers new insights into the role of learner agency during video-based learning.

Literature review

Off-task thoughts

Students often experience thoughts that are not entirely focused on their learning task. For example, they could be thinking about what to eat for dinner or how they had previously learned something related. To study these types of cognitive activity, a conceptualisation of the multiple types of thoughts is needed. In this study, the term off-task thoughts refers to any thoughts that are not entirely focused on the learning task.

The typology proposed by both Stawarczyk et al. (2011) and Smallwood and Schooler (2015) distinguishes between three types of off-task thoughts – task-unrelated thoughts (TUTs), task-related interference (TRI), and external distractions. TUTs refer to thoughts that bear no relationship to the task and are not triggered by something in the learner's environment. For example, thinking about clothes shopping during an in-class lecture. In contrast, TRI is characterised as having some relationship to the learning task. For example, a student may start thinking how the lecture content relates to a future assignment. As such, TRI is a hybrid concept between TUTs and having complete focus on the specific task (Welhaf et al., 2020). These thoughts can be metacognitive in nature but are not intentionally initiated by the learner (Jordano, 2018). External distractions are thoughts unrelated to a learning task and triggered by an environmental stimulus. For example, hearing music played by a student walking by might cause another student to lose focus.

Off-task thoughts can be further classified by their temporal orientations. That is, whether the off-task thought is concerned with the past, present, or future, or lacks a precise temporal orientation (Stawarczyk et al., 2013). For example, past thoughts may involve a learner recalling a related lecture or concept. Present-oriented thoughts are often triggered by something in the learners' immediate environment (e.g., a phone ringing, leading to the thought, "Who just called me?"). However, future-oriented thoughts often take the form of autobiographical planning (Baird et al., 2011; Kvavilashvili & Rummel, 2020), such as thinking about the next meal or thinking about how the content they are currently learning relates to a future assessment. Atemporal thoughts involve more imaginative scenarios, such as a learner thinking, "I imagine myself sitting on top of a mountain" (Jackson et al., 2013). All external distractions have a temporal orientation that is anchored in the present. By studying thought type in parallel with temporal orientation, a more nuanced understanding of student's cognitive engagement in video-based learning can be established.

How often off-task thoughts occur during learning and how they impact learning outcomes varies by thought type. Wong et al. (2022) reported that TUTs occur about 30% of the time while learning. The authors also identified that TUTs have a negative impact on learning outcomes (Wong et al., 2022). TRIs are estimated to occur 20%–25% of the time and are hypothesised to have no impact on learning outcomes (Welhaf et al., 2020). How often external distractions occur and how they affect learning outcomes is dependent on the study environment. Regardless of the frequency and type of thought, learners can become aware of their off-task thoughts. This awareness of one's thoughts is referred to as meta-awareness (Schooler et al., 2011).

Meta-awareness and self-regulated learning

Meta-awareness is defined as someone becoming aware of their mental state, including their current thoughts (Schooler et al., 2011). This form of metacognitive monitoring (Schooler & Smallwood, 2009) enables learners to recognise that they are experiencing off-task thoughts. When this occurs, meta-aware learners can choose to either refocus on the task, stop learning, or continue with their off-task thoughts. If they choose to refocus on the task, they need to make a further decision as to whether to continue learning using the same study strategy or adjust their learning strategy in reaction to their off-task thoughts. For example, when reading, learners may choose to revisit and reread a few sentences, or when learning from a video, they may choose to rewind the video. These study adjustments are representative of a learner's ability to both monitor and control their learning behaviour, core dimensions of self-regulated learning (Van Alten et al., 2020).

Self-regulated learning describes how learners monitor, evaluate and control their learning process. Within the COPEs model (Winne, 1997; Winne & Hadwin, 1998), these processes are understood as interacting components: Conditions, Operations, Products, Evaluations and Standards. Meta-awareness functions as a form of monitoring to detect when an off-task thought becomes a Product, which is then Evaluated against a perceived Standard. In short, if a learner determines that an off-task thought was detrimental to their learning progress, they may enact a reaction tactic (e.g., reread a text or rewind a video). Self-regulated learning provides a structured account of how meta-awareness can initiate reaction tactics as part of the learning process.

Each component in the COPEs model supports this process. Initially, Conditions refer to the internal and external factors influencing learning, such as prior knowledge, motivation, or the task design. Then, Operations involve the cognitive processes learners employ to complete a task (e.g. practising quiz questions to study for a future exam). The Operations yield Products, such as quiz scores or draft essays. Finally, the Products are Evaluated against a perceived Standard, such as a learning goal or grade. The COPEs model involves four recursive phases of self-regulated learning (Winne & Hadwin, 1998): (1) task definition, (2) goal setting and planning, (3) enacting study tactics and strategies, and (4) meta-cognitively adaptive studying. Collectively, the model describes how learners manage and adjust their learning behaviour in response to both cognitive and contextual factors.

In the context of video-based learning, a student would typically operate in the third phase of the COPEs model - "enacting study tactics and strategies". The Operations facet for this phase consists of the SMART operations (searching, monitoring, assembling, rehearsing, and translating; Winne & Hadwin, 1998). As a result of the monitoring operation, a learner would become meta-aware. Within the COPEs model, information about the content of their thoughts resulting from the monitoring operation becomes the Product. A learner would next evaluate (Evaluations) the contents of their thoughts (Product) against prior established standards (Standards). In other words, if learners become aware that they are experiencing off-task thoughts, they will judge these thoughts, including whether they should or should not react. This judgement is influenced by the content of the thought and the learners' perception of its impact on their learning progress.

Whether learners make these critical judgements and are aware of how off-task thoughts affect their learning has been previously studied. For example, Was et al. (2019) combined thought probes with judgments of learning and found that although self-regulated learners

are aware of the detrimental impact of TUTs on their learning outcomes, they did not consider TRI to be harmful to their learning progress. This finding suggests that learners aware of TUTs are more likely to modify or adapt their learning behaviour than when experiencing TRI.

A common factor among many studies aiming to reduce off-task thoughts during video-based learning is prohibiting participants from interacting with the video player, limiting their ability to pause or seek (rewind or skip ahead) (e.g. Kane et al., 2017; Welhaf et al., 2022). This restriction ensures consistency in time on task across participants, viewing time, and exposure to specific video content to prevent confounding the study results. However, it also restricts participants from having the option to react to their off-task thoughts. The present study addresses this gap by examining learner behaviour in a naturalistic setting, where students can interact with the video player in response to off-task thoughts.

Rewinding

Video analytics research has established that students engage in self-regulated learning by pausing, rewinding, or revisiting content to enhance comprehension (Mirriahi et al., 2016; Poquet et al., 2018). Rewinding, in particular, is enacted with specific intent: learners use this feature to repeat difficult sections and to ensure they have not missed content after experiencing off-task thoughts (Seo et al., 2021). However, despite this prior work, there has been limited exploration of how learners engage with videos when they become aware of their off-task thoughts such as rewinding to the location in the video where they think their off-task thoughts began.

Our work is grounded in metacognition (Flavell, 1979), specifically the cycle of metacognitive monitoring and control (Nelson, 1996; Nelson & Narens, 1990, 1994) that underpins the research we are drawing from, namely, self-regulated learning (Winne, 1997; Winne & Hadwin, 1998) and is related to the concept of meta-awareness (Schooler et al., 2011). While metacognitive monitoring is a core component of self-regulated learning theory, individual differences in self-regulated learning aptitude may influence how frequently learners engage in such monitoring during naturalistic learning activities. We posit that self-regulated learners who intermittently engage in metacognitive monitoring will occasionally realise that they are engaged in off-task thoughts, as evidenced by self-caught thought reports. Following such instances, students may engage in metacognitive control. This act of metacognitive control in reaction to off-task thoughts could take the form of the learner choosing to rewind the video. We thus aim to determine, in a naturalistic setting, the association between thought types and temporal orientation, whether self-regulated learning aptitude is predictive of off-task thoughts by thought type and temporal orientation, and whether learners rewind videos following off-task thoughts.

Research questions

The first research question is based on the observation that the temporal orientation of off-task thoughts has not been previously studied in a naturalistic educational setting.

RQ1 Is there an association between thought type and temporal orientation?

The second to fourth research questions examine whether individual differences in self-regulated learning aptitude relate to students' awareness and reporting of off-task thoughts during video-based learning. While self-regulated learning theory suggests that learners with higher self-regulated learning aptitude should be better at monitoring their cognitive states, it remains an empirical question whether this aptitude translates into greater meta-awareness of mind wandering as measured by self-caught thought reports in naturalistic settings where learners have full control over the learning environment.

RQ2 Is there a relationship between self-regulated learning aptitude and the rate of self-caught thought reports during video watching?

RQ3 Is there a relationship between self-regulated learning aptitude and the rate of self-caught thought reports by thought type during video watching?

RQ4 Is there a relationship between self-regulated learning aptitude and the rate of self-caught thought reports by temporal orientation during video watching?

RQ2 examines the overall relationship between self-regulated learning aptitude and awareness of off-task thoughts, while RQ3 and RQ4 explore whether this relationship varies depending on the specific characteristics of those thoughts (type and temporal orientation). The fifth research question examines whether meta-awareness of off-task thoughts leads to a specific self-regulated learning behaviour: rewinding the video. This question addresses whether students actively respond to off-task thoughts by re-engaging with content they may have missed.

RQ5 To what extent do participants rewind educational videos following self-reported off-task thoughts?

Methods

Procedure

A naturalistic approach was used to explore the research questions, allowing participants to engage with the learning materials in their typical study environment. The study was undertaken at an Australian university. After receiving institutional ethics approval, we used a purposive selection of courses to conduct the study. The courses selected all required the use of videos as part of their learning design, and all videos were required to be shorter than 30 min. We invited students enrolled across eight courses from various disciplines (see Table 1) including enabling education pathway and undergraduate courses. Across the eight courses, 26 different videos were used: 18 contained audio over slides, and eight used a picture-in-picture format with the instructor visible in a corner along with audio over slides. Video durations ranged from 4 to 27 min. Students were recruited across two semesters (July–December 2023 and February–July 2024). For each course, one content topic was chosen in collaboration with the instructors, based on the availability of videos for the topic and in consideration of the course workload and assessments. In each case, the students

Table 1 Number of participants, number of videos watched, how often the students in a course watched these videos, and thought reports written by course and semester

Semester	Course	<i>n</i> Participants	<i>n</i> Videos	Recorded video-watching sessions	Thought Reports
1	English	9	3	16	37
1	Physiology	12	5	27	74
1	Quantitative Methods for Business	1	1	1	1
2	Learning Theories	18	2	31	136
2	Mathematics	8	2	11	38
2	Biochemistry	3	8	12	22
2	Quantitative Methods for Business	1	3	3	6
2	Statistical Methods	1	2	2	3
	Total	53	26	103	317

were supposed to watch the videos before coming to class to be prepared for in-class activities. However, all data collection occurred over a two-week period during the second or third quarter of the semester. The participants could participate during the week the required videos were scheduled or the week prior. Participation started with completing a survey that included demographic questions, followed by subscales of the self-regulation for learning online (SRL-O) questionnaire (Broadbent et al., 2022), as outlined in the following section. After completing the survey, the participants watched the required videos for the particular weekly topic and asked to report their off-task thoughts. Table 1 shows the number of participants in each course, the number of videos involved in the study for the particular course, how many times participants watched a video, and the number of thought reports reported. There was no compensation for participation.

Measures

Self-regulated learning

Self-regulated learning can be viewed as either a series of events or an aptitude. In this work, we incorporate both views of self-regulated learning (Winne & Perry, 2000). In this study, we measured self-regulated learning aptitude using a seven-point Likert-scale questionnaire comprising five subscales of the self-regulation for learning online (SRL-O) questionnaire (Metacognition, Online Task Strategies, Online Effort Regulation, Study

Environment, and Planning and Time Management; Broadbent et al., 2022). The SRL-O was specifically designed to measure self-regulated learning aptitude in online or blended learning contexts. It has been developed and validated by Broadbent et al. (2022) using confirmatory factor analysis. The Metacognition subscale was selected as metacognition forms the foundation of meta-awareness (Schooler & Smallwood, 2009). The subscales for Online Task Strategies and Online Effort Regulation were included as they relate to learners' ability to sustain engagement during learning, such as responding to off-task thoughts by rewinding a video. Finally, the Study Environment, Planning, and Time Management subscales were chosen because learners conducted the study in their chosen environment and at their preferred time. Depending on these factors, participants may have experienced more external distractions, such as family members in the same room, while learning. Therefore, the choice of study environment and when to study could influence how attentive a learner was, and the context of their external distractions could influence the participants' off-task thoughts (Faber & D'Mello, 2018). A list of the subscales used, along with example items, is included in Table 2.

In our work, self-regulated learning as a series of events is measured using thought reports and rewinding logs. When self-regulated learning is measured as a series of events, the trace data generated by learners is analysed, and traces indicative of self-regulated learning are identified. Such traces can be classified using three levels of complexity: occurrence, contingency, and patterned contingency. An occurrence is a transition from one state to another, such as engaging in a task and then making a judgment of learning. A contingency is an occurrence followed by an action that can be described as an IF-THEN combination. For example, if the learner realises the task is difficult, they break it down into smaller sections that are easier to learn. Lastly, a patterned contingency is a sequence of contingencies (Winne & Perry, 2000). In this work, we consider a thought report as an occurrence, since it signals a transition from engaging in off-task thoughts to becoming aware of them. To count the thought report as self-regulated learning requires the inference that (a) the learner was monitoring their thoughts, (b) these thoughts crossed a threshold where the learner no longer considered them to be on-task and thus classified them as off-task, and (c) the learner reported this as a consequence of these cognitions. If learners then rewind the video following off-task thoughts, this constitutes a contingency, as rewinding a video is an act of metacognitive control, usually performed to increase comprehension or to ensure no parts of the video are missed (Seo et al., 2021). The combination of these two measures of self-regulated learning, aptitude measured using the SRL-O and events (contingency of IF off-task thoughts THEN rewind) allows us to answer RQs 2–4.

Table 2 Subscales used in this study and example items from Broadbent et al. (2022, pp. 157–159)

Subscale	Example Item
Metacognition	I spend time trying to interpret the task to ensure I understand accurately what I need to do.
Online Task Strategies	When studying online, I try and relate the content to what I already know.
Online Effort Regulation	When my mind begins to wander during a learning session for this online course, I make a special effort to keep concentrating.
Study Environment	I have access to a quiet and distraction-free place to study.
Planning and Time Management	I break larger goals into smaller actionable goals.

Thought reports

A core component of our theoretical framework was to test whether self-regulated learners are increasingly meta-aware. Based on this interpretation, we chose to measure off-task thoughts using self-caught thought reports instead of probe-caught thought reports (Weinstein, 2018). For this purpose, the course videos were uploaded to an in-house video player, Online Video Annotation for Learning (OVAL) (Mirriahi et al., 2021). The OVAL video player was adjusted to enable the creation of free-text thought reports. Participants would click a button in the bottom-right corner of the video player to open a text box for reporting their off-task thoughts, as shown in Fig. 1. When the participants clicked the button to report an off-task thought, the video also paused. Before the participants accessed the videos, they were instructed to be aware of their thoughts and to report their off-task thoughts once they realised they had occurred. Off-task thoughts were described as thoughts unrelated to the video's content when participants became aware they had become distracted.

Video player tracking data

The OVAL video player recorded all video interactions and navigation. No instruction was given regarding their interaction with the video player. Therefore, any video rewinding is not an artefact of the task instructions.

Coding

In this work, we draw upon the phenomenologies of Stawarczyk et al. (2011) and Smallwood and Schooler (2015). We distinguish between TUTs, TRI, and external distractions. Additionally, given that we are studying learners' thoughts in a naturalistic setting and aim to understand how their thoughts become part of their learning process, we also classify the learners' thoughts according to their temporal orientation, for which we are drawing on Stawarczyk et al. (2013) and divide these thoughts to be either oriented towards the past, present, future, have no precise temporal orientation, or be atemporal. All thought reports were coded following the conceptual divisions in Table 3. The thought reports were coded independently by the first author and the lecturers in whose courses the data was collected. When discrepancies arose between a lecturer's coding and the first author's assessment, these instances were resolved through discussion. No inter-rater agreement was determined

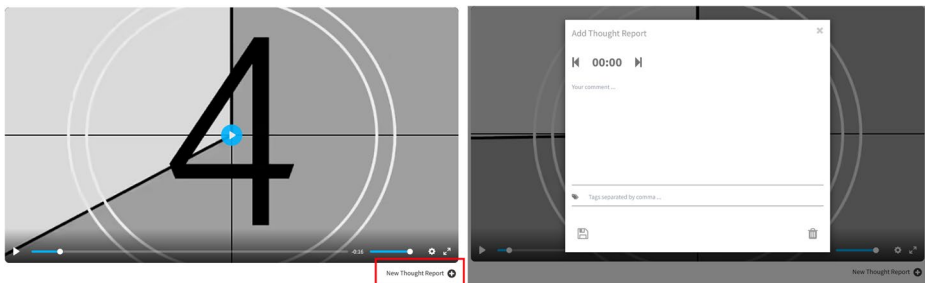


Fig. 1 Thought Report Interface. Left is the video player interface showing the button to initiate a thought report highlighted in red. Right is the reporting interface in which the participants entered their thought reports

Table 3 Conceptual divisions of Off-Task thoughts used throughout this work

Thought Type ^a		Temporal Orientation ^b	
Type	Description	Orientation	Description
Task-unrelated Thoughts (TUTs)	Thoughts that are entirely unrelated to the task but not triggered by something in the learners' environment. For example, thinking about the next meal.	Past	These thoughts are in reference to the past, e.g., previous events, experiences, or memories.
	Thoughts that are not on the task at the point in time they occur but still show some relationship to the task. For example, relating the lesson content to previously learned information or thinking about how it relates to an upcoming assignment.	Present	These thoughts are about the present moment.
Task-related Interference (TRI)	Thoughts that are triggered by distractions in the learners' environment. For example, a pet walking into the room.	Future	These thoughts are about the future, such as planning.
		No precise temporal orientation	The temporal orientation of these thoughts is ambiguous. For example, one might think about a workout, but it is not clear whether the workout has already happened or is planned for the future.
		Atemporal	These thoughts have no temporal orientation, e.g., imagining oneself in a fantasy setting.
External Distractions ^c			

^a Based on Stawarczyk et al. (2011) and Smallwood and Schooler (2015) ^b Based on Stawarczyk et al. (2013) with the addition of atemporal thoughts (Jackson et al., 2013) ^c Given that external distractions are always triggered by something in the learners' environment, these thoughts will always have a temporal orientation in the present. However, not all thoughts with a temporal orientation in the present will be external distractions

as the coders were purposefully selected for their different understanding of the data (Elliott, 2018), the first author to ensure consistent application of the coding framework and the lecturers to ensure differentiation between TUT and TRI depending on the video content at the time these off-task thoughts were reported.

Analysis

RQ1 was addressed by fitting a mixed logistic regression model to examine the association between thought types and temporal orientation, with a random effect for participants. Results are reported as odds ratios with 95% confidence intervals. Pairwise comparisons between temporal orientation categories were conducted using estimated marginal means with Tukey adjustment for multiple comparisons. External distractions were excluded as these are always present-oriented.

To answer RQ2, a zero-intercept generalised linear model (GLM) with a negative binomial distribution was fit to predict thought counts. The zero-intercept approach, combined with the offset term, allowed for modelling rates rather than raw counts. The model included five fixed effects corresponding to participants' mean scores on the five SRL-O subscales (Metacognition, Effort Regulation, Task Strategies, Planning and Time Management, and Study Environment). Video duration was included as an offset to account for time-dependent variations in thought frequency.

RQs 3 and 4 were answered using the same modelling approach as RQ2, fitting one model per thought type (RQ3) and per temporal orientation (RQ4). Significance levels were adjusted using the Bonferroni correction ($\alpha=0.0167$ for thought types; $\alpha=0.01$ for temporal orientations).

RQ5 examined patterns of video rewinding after off-task thoughts. A windowing approach analysed three events (play, pause, or rewind) following each thought report. Rewinds were considered relevant if they occurred within this window, moved the video to a point before the thought report, and happened within two minutes. Thought reports were also screened for rewind intentions using relevant keywords (rewatch, rewind, and back) and manual review.

Results

Descriptive statistics

Demographics

The participants were, on average, 21.2 years old ($SD=5.6$). 31 of the participants were female, 6 male, and 3 identified as non-binary. 13 participants did not report their gender.

Number of thought reports

The participants wrote a total of 317 thought reports with three thought reports on average per participant ($SD=3$) during each video-watching session with a range from 1 to 18. A histogram showing the distribution of thought report counts is included in Fig. 2.

Distributions of thought types

Table 4 includes the distribution of thought reports by the coded categories of thought type and temporal orientation. The most common thought type was TRI, and the most com-

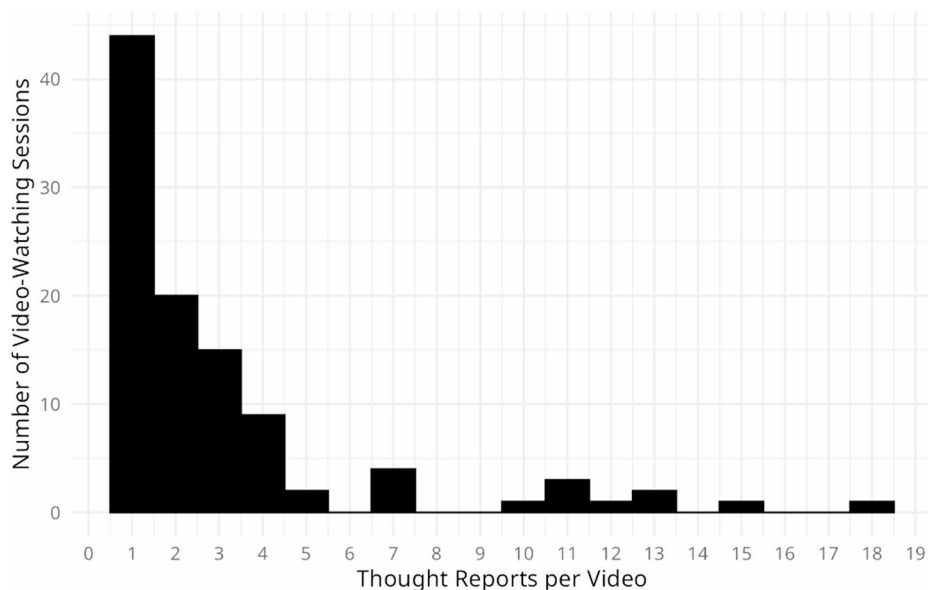


Fig. 2 Distribution of thought reports across video-watching sessions. Each bar represents the number of sessions (participant-video combinations) in which a given number of thought reports were submitted

Table 4 Contingency table of thought type and Temporal orientation

Temporal Orientation/Thought Type	External Distractions	TRI	TUT	Row Total
Past	0	31	8	39
Present	84	53	7	144
Future	0	30	38	68
No precise temporal orientation	0	14	21	35
Atemporal	0	18	13	31
Column Total	84	146	87	317

mon temporal orientation was the present. Note that external distractions are always in the present.

Self-regulated learning scores

An overview of participants' scores on the SRL-O subscales is presented in Table 5. Scores ranged from $M=4.31$ to $M=5.08$ across the five subscales. Planning and Time Management received the highest mean score ($M=5.08$, $SD=1.12$), indicating that participants generally reported being able to set goals and allocate study time effectively in the online learning environment. Metacognition ($M=4.95$, $SD=1.12$), which reflects awareness and monitoring of one's own learning processes, and Effort Regulation ($M=4.79$, $SD=1.15$), which captures persistence despite distractions or difficulties, showed similar patterns. Study Environment ($M=4.61$, $SD=1.23$) and Task Strategies ($M=4.31$, $SD=1.19$), which measure the ability to create conducive learning conditions and employ specific learning techniques,

Table 5 SRL-O subscale scores measured on a 7-point likert scale (1 = not at all true of me, 7 = very true of me), where higher scores indicate stronger self-regulated learning aptitude in online or blended learning contexts

Subscale	<i>n</i>	Mean (SD)
Metacognition	53	4.95 (1.12)
Effort Regulation	53	4.79 (1.15)
Task Strategies	53	4.31 (1.19)
Planning and Time Management	47	5.08 (1.12)
Study Environment	47	4.61 (1.23)

Table 6 Pairwise comparisons for association between TUT (vs. TRI) and Temporal orientation

Contrast	OR [95% CI]	<i>p</i>
Past/Present	2.41 [0.38, 15.20]	0.691
Future/Present	11.74 [2.39, 57.63]	<0.001
Future/Past	4.88 [1.07, 22.22]	0.035
No precise temporal orientation/ Present	15.91 [2.5, 101.34]	<0.001
No precise temporal orientation/Past	6.61 [1.14, 38.46]	0.028
No precise temporal orientation/ Future	1.36 [0.33, 5.62]	0.978
Atemporal/Present	9.04 [1.36, 60.10]	0.013
Atemporal/Past	3.75 [0.58, 24.42]	0.303
Atemporal/Future	0.77 [0.16, 3.78]	0.992
Atemporal/No precise temporal orientation	0.57 [0.09, 3.41]	0.911

Odds Ratios > 1 indicate higher odds of TUT vs. TRI

respectively, showed the lowest scores. The relatively consistent scores across subscales indicate that participants possessed a reasonably balanced self-regulated learning profile.

Association between thought types and temporal orientation (RQ1)

The first research question was addressed using a mixed logistic regression model to examine the association between thought type (TUT vs. TRI) and temporal orientation. The model included 233 observations and had an AIC of 260. Compared to present-oriented thoughts, future-oriented thoughts had significantly higher odds of being TUT (OR = 11.74, 95% CI [2.39, 57.63], $p < .001$), as did thoughts with no precise temporal orientation (OR = 15.91, 95% CI [2.5, 101.34], $p < .001$) and atemporal thoughts (OR = 9.04, 95% CI [1.36, 60.1], $p = .013$). Past-oriented thoughts were not significantly different from present-oriented thoughts (OR = 2.41, 95% CI [0.38, 15.2]). These results indicate that thoughts temporally disconnected from the present moment were more strongly associated with TUT, whereas present-focused thoughts were more characteristic of TRI. The pairwise odds ratios and *p*-values for associations are shown in Table 6. A contingency table of thought type and temporal orientation is included in Table 4.

Relationship between self-regulated learning and number of thought reports (RQ2)

A fixed-effects zero-intercept generalised linear model using a negative binomial distribution with an offset for task duration was fit to examine the relationship between the SRL-O subscales and the number of thought reports. The model's Akaike Information Criterion (AIC) was 303.28, with a log-likelihood of -145.64. The dispersion parameter (theta) was

estimated at 0.893 ($SE=0.181$), indicating some overdispersion in the data. The subscales Metacognition, Online Task Strategies, and Study Environment were not statistically significant as predictors of the number of thought reports. In contrast, the subscales of Online Effort Regulation and Planning and Time Management were significant predictors. Online Effort Regulation showed a significant negative association with the number of thought reports ($b = -0.433$, $p = .016$). The corresponding Incidence Rate Ratio (IRR) of 0.65 indicates that for each increase of Online Effort Regulation by 1, the expected number of thought reports decreased by 35%. Similarly, Planning and Time Management showed a significant negative association with the number of thought reports ($b = -0.387$, $p = .013$). The corresponding IRR of 0.68 indicates that for each Planning and Time Management increase, the expected number of thought reports decreased by 32%. The estimates, IRRs, and p-values are shown in Table 7, and a forest plot of the IRRs is provided in Fig. 3.

Relationship between self-regulated learning and number of thought reports by thought type (RQ3)

Fixed-effects zero-intercept generalised linear models with a negative binomial distribution and an offset for task duration were fit to examine relationships between the SRL-O subscales and the number of thought reports by thought type. The model fit statistics for each model are shown in Table 8.

For the thought type of TUTs, the subscales of Metacognition, Online Effort Regulation, Online Task Strategies, and Study Environment were not statistically significant as predictors of the number of TUT thought reports. The Planning and Time Management subscale was a significant predictor ($b = -0.813$, $p < .001$), with an IRR of 0.44. This IRR indicates that for each increase in Planning and Time Management, the number of TUT thought reports decreased by 66%. For the thought type of TRI, none of the SRL-O subscales were significant predictors, whereas for external distractions, the Online Effort Regulation subscale was a significant predictor ($b = -0.615$, $p = .006$). The corresponding IRR of 0.54 indicates that for each step increase in Online Effort Regulation, the number of external distractions thought reports decreased by 46%. The subscales of Metacognition, Online Task Strategies, Planning and Time Management, and Study Environment were not significant predictors for external distraction thought reports. The estimates, IRRs, and p-values are shown in Table 9, and a forest plot of the IRRs is provided in Fig. 4.

Table 7 Results of a Zero-Intercept generalised linear model predicting total thought reports from SRL-O subscales

SRL-O Subscale	Estimate ^a (SE)	z	p	IRR ^b [95% CI]
Metacognition	-0.105 (0.182)	-0.576	0.565	0.90 [0.63, 1.29]
Online Effort Regulation	-0.433 (0.180)	-2.400	0.016*	0.65 [0.46, 0.92]
Online Task Strategies	0.097 (0.169)	0.572	0.567	1.10 [0.79, 1.54]
Planning and Time Management	-0.387 (0.155)	-2.495	0.013*	0.68 [0.50, 0.92]
Study Environment	-0.194 (0.161)	-1.205	0.228	0.82 [0.60, 1.13]

^a Unstandardised estimate from a negative binomial model (log-duration offset). ^b Incidence Rate Ratio shows the relative change in outcome rate per unit increase in a predictor variable.

* Significant at $p < .05$

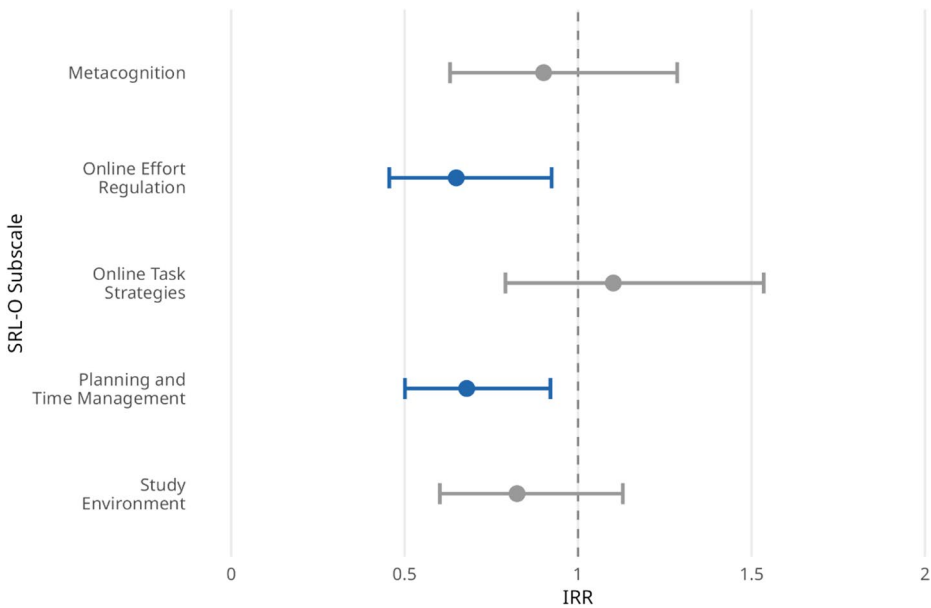


Fig. 3 Incidence Rate Ratios (IRR) for the association between SRL-O subscales and rate of off-task thoughts. Error bars represent 95% confidence intervals. Significant relationships are shown in blue

Table 8 Model fit statistics for Zero-Intercept generalised linear models predicting counts of thought types from SRL-O subscales

Model	AIC	log-likelihood	theta (SE)
TUT	197.500	-92.750	0.525 (0.145)
TRI	230.870	-109.430	0.374 (0.087)
External Distractions	178.620	-83.310	0.732 (0.211)

Relationship between self-regulated learning and number of thought reports by temporal orientation (RQ4)

Fixed-effects zero-intercept generalised linear models with a negative binomial distribution and an offset for task duration were fit to examine the relationships between the SRL-O subscales and the number of thought reports across temporal orientations. The model fit statistics for each model are shown in Table 10.

For the temporal orientation of thoughts about the present, the subscale of Online Effort Regulation was predictive ($b = -0.709, p = .001$). The corresponding IRR of 0.49 indicates that an increase in Online Effort Regulation is associated with a 51% decrease in thought reports about the present. The subscales of Metacognition, Online Task Strategies, Planning and Time Management, and Study Environment were not predictive of the number of present-oriented thought reports. For the number of thought reports with a temporal orientation in the past, none of the SRL-O subscales was predictive, while for thought reports with a temporal orientation in the future, the SRL-O subscale of Planning and Time Management was predictive ($b = -0.972, p < .001$). The IRR of 0.38 indicates that an increase of 1 in Planning and Time Management is associated with a 62% decrease in future-oriented thought reports. For thought reports with no precise temporal orientation, none of the SRL-O sub-

Table 9 Results of Zero-Intercept generalised linear models predicting counts of thought types from SRL-O subscales

SRL-O Subscale	Estimate ^a (SE)	<i>z</i>	<i>p</i>	IRR ^b [95% CI]
TUTs				
Metacognition	-0.330 (0.251)	-1.318	0.187	0.72 [0.44, 1.17]
Online Effort Regulation	-0.136 (0.251)	-0.541	0.588	0.87 [0.53, 1.43]
Online Task Strategies	0.108 (0.235)	0.457	0.647	1.11 [0.70, 1.77]
Planning and Time Management	-0.813 (0.220)	-3.693	<0.001*	0.44 [0.29, 0.68]
Study Environment	-0.083 (0.226)	-0.367	0.713	0.92 [0.59, 1.43]
TRI				
Metacognition	-0.087 (0.278)	-0.311	0.756	0.92 [0.53, 1.58]
Online Effort Regulation	-0.520 (0.276)	-1.886	0.059	0.59 [0.35, 1.02]
Online Task Strategies	0.151 (0.259)	0.581	0.561	1.16 [0.70, 1.93]
Planning and Time Management	-0.408 (0.237)	-1.717	0.086	0.67 [0.42, 1.06]
Study Environment	-0.281 (0.246)	-1.142	0.253	0.76 [0.47, 1.22]
External Distractions				
Metacognition	-0.049 (0.222)	-0.219	0.826	0.95 [0.62, 1.47]
Online Effort Regulation	-0.615 (0.225)	-2.729	0.006*	0.54 [0.35, 0.84]
Online Task Strategies	-0.107 (0.218)	-0.491	0.623	0.90 [0.59, 1.38]
Planning and Time Management	-0.298 (0.196)	-1.521	0.128	0.74 [0.51, 1.09]
Study Environment	-0.329 (0.212)	-1.553	0.120	0.72 [0.47, 1.09]

^a Unstandardised estimate from a negative binomial model (log-duration offset). ^b Incidence Rate Ratio shows the relative change in outcome rate per unit increase in a predictor variable. * Significant at adjusted $p < .0167$

scales were predictive, while for atemporal thought reports, the Study Environment subscale was predictive ($b = -2.595$, $p = .009$). The subscales of Metacognition, Online Effort Regulation, Online Task Strategies, and Planning and Time Management were not predictive of the count of atemporal thought reports. The estimates, IRRs, and p -values are shown in Table 11, and a forest plot of the IRRs is provided in Fig. 5.

Rewinding after off-task thoughts (RQ5)

To answer RQ5, we identified instances of rewinding following a thought report. We identified 15 cases (6 TUTs, 5 TRI, and 4 external distractions) in which 10 participants rewound the video after writing a thought report. The rewind duration was, on average, 87 s ($SD = 172$) and ranged from 2 s to 654 s. Findings also revealed two cases from two participants who stated in their thought reports that they would react by rewinding the video. These two participants did not rewind a video in reaction to any reported off-task thoughts.

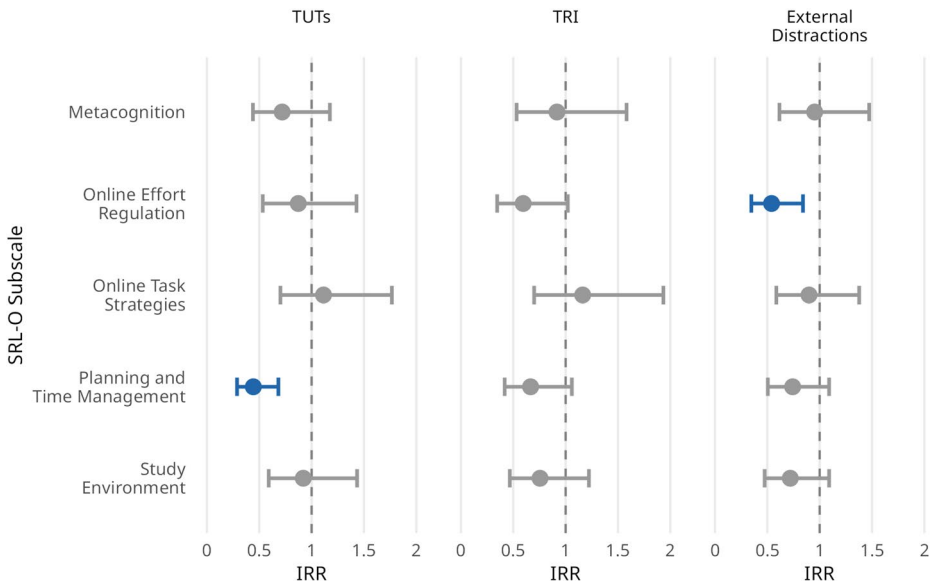


Fig. 4 Incidence Rate Ratios (IRR) for the association between SRL-O subscales and rate of off-task thoughts by thought type. Error bars represent 95% confidence intervals. Significant relationships are shown in blue

Table 10 Model fit statistics for Zero-Intercept generalised linear models predicting counts of Temporal orientations from SRL-O subscales

Model	AIC	log-likelihood	theta (SE)
Present	221.540	-104.770	0.771 (0.196)
Past	145.420	-66.710	0.207 (0.063)
Future	174.660	-81.330	0.354 (0.098)
No precise temporal orientation	115.400	-51.700	0.179 (0.067)
Atemporal	116.590	-52.290	0.271 (0.108)

Summary of key findings

In answer to RQ1, we found that thought reports related to TRIs are more likely to be focussed on the present, while those reporting TUT are more likely to be either about the future, to lack precise temporal orientation, or to be atemporal. RQs 2, 3, and 4 were answered using zero-intercept generalised linear models based on a negative binomial distribution with an offset for task duration. These models showed that the score on the SRL-O scales of Online Effort Regulation ($b = -0.433$, $p = .016$) and Planning and Time Management ($b = -0.387$, $p = .013$) were negatively predictive of the number of thought reports submitted. When these thought reports were broken down into thought types and temporal orientation, we could observe that Planning and Time Management were negatively predictive of TUTs ($b = -0.813$, $p < .001$), while Online Effort Regulation was negatively predictive of the number of external distractions ($b = -0.615$, $p = .006$). As for temporal orientation, Online Effort Regulation was negatively predictive of thoughts with a temporal orientation in the present ($b = -0.709$, $p = .001$), while Planning and Time Management was

Table 11 Results of Zero-Intercept generalised linear models predicting counts of Temporal orientations from SRL-O subscales

SRL-O Subscale	Estimate ^a (SE)	z	p	IRR ^b [95% CI]
Present				
Metacognition	0.007 (0.207)	0.032	0.974	1.01 [0.67, 1.51]
Online Effort Regulation	-0.709 (0.209)	-3.396	0.001*	0.49 [0.33, 0.74]
Online Task Strategies	-0.024 (0.199)	-0.121	0.903	0.98 [0.66, 1.44]
Planning and Time Management	-0.282 (0.179)	-1.575	0.115	0.75 [0.53, 1.07]
Study Environment	-0.254 (0.192)	-1.323	0.186	0.78 [0.53, 1.13]
Past				
Metacognition	0.000 (0.383)	0.000	1	1.00 [0.47, 2.12]
Online Effort Regulation	-0.458 (0.382)	-1.200	0.230	0.63 [0.30, 1.34]
Online Task Strategies	0.135 (0.360)	0.375	0.708	1.14 [0.57, 2.32]
Planning and Time Management	-0.833 (0.331)	-2.515	0.012	0.43 [0.23, 0.83]
Study Environment	-0.168 (0.343)	-0.490	0.624	0.85 [0.43, 1.66]
Future				
Metacognition	0.179 (0.302)	0.595	0.552	1.20 [0.66, 2.16]
Online Effort Regulation	-0.413 (0.301)	-1.371	0.170	0.66 [0.37, 1.19]
Online Task Strategies	0.092 (0.285)	0.324	0.746	1.10 [0.63, 1.92]
Planning and Time Management	-0.972 (0.264)	-3.680	<0.001*	0.38 [0.23, 0.63]
Study Environment	-0.181 (0.273)	-0.664	0.506	0.83 [0.49, 1.42]
No precise temporal orientation				
Metacognition	-1.057 (0.438)	-2.412	0.016	0.35 [0.15, 0.82]
Online Effort Regulation	-0.172 (0.425)	-0.404	0.686	0.84 [0.37, 1.94]
Online Task Strategies	0.341 (0.400)	0.852	0.394	1.41 [0.64, 3.08]
Planning and Time Management	-0.467 (0.375)	-1.247	0.212	0.63 [0.30, 1.31]
Study Environment	-0.082 (0.388)	-0.212	0.832	0.92 [0.43, 1.97]
Atemporal				
Metacognition	-0.232 (0.358)	-0.649	0.516	0.79 [0.39, 1.60]
Online Effort Regulation	0.360 (0.393)	0.916	0.360	1.43 [0.66, 3.09]
Online Task Strategies	-0.442 (0.361)	-1.225	0.221	0.64 [0.32, 1.30]
Planning and Time Management	-0.450 (0.329)	-1.368	0.171	0.64 [0.33, 1.21]
Study Environment	-0.866 (0.334)	-2.595	0.009*	0.42 [0.22, 0.81]

^a Unstandardised estimate from a negative binomial model (log-duration offset). ^b Incidence Rate Ratio shows the relative change in outcome rate per unit increase in a predictor variable. * Significant at adjusted $p < .01$

negatively predictive of thoughts with a temporal in the future ($b = -0.972$, $p < .001$), and study environment for atemporal thoughts ($b = -2.595$, $p = .009$). Lastly, in relation to RQ5, 15 instances of rewinding by 10 participants were identified, indicating that rewinding following off-task thoughts rarely occurred.

Discussion

This study aimed to investigate how individual differences in self-regulated learning aptitude relate to learners' awareness of off-task thoughts and their behavioural responses during video-based learning in a naturalistic setting. Overall, students who scored higher on Planning and Time Management and Effort Regulation reported fewer off-task thoughts.

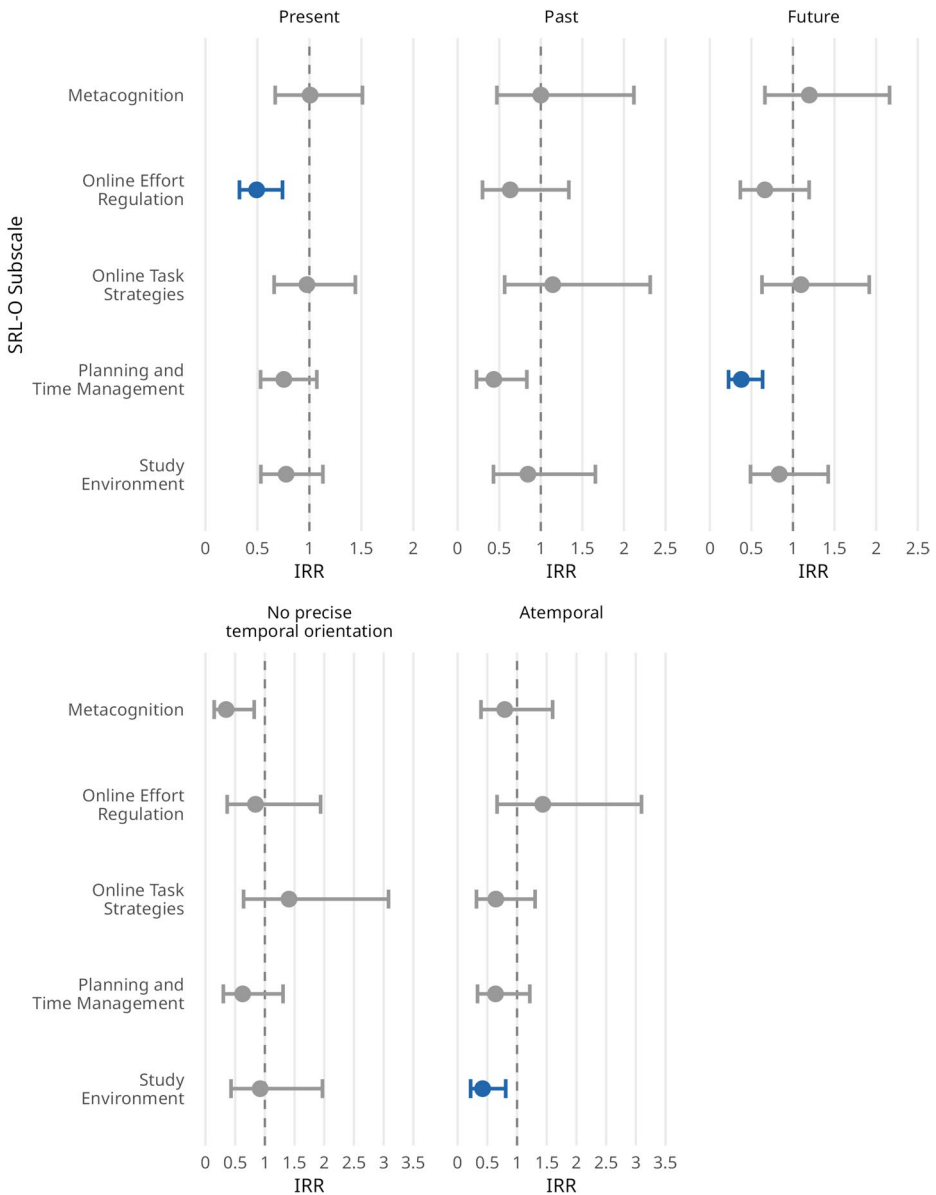


Fig. 5 Incidence Rate Ratios (IRR) for the association between SRL-O subscales and rate of off-task thoughts by temporal orientation. Error bars represent 95% confidence intervals. Significant relationships are shown in blue

These results support the role of self-regulated learning proficiency in managing off-task thoughts in unstructured and independent learning contexts.

Temporal orientation of off-task thoughts

The observed association between thought types and their temporal orientation suggests that the nature of learners' off-task thoughts is closely aligned with their underlying cognitive goals. Task-related interferences, which were more frequently phrased as being present-oriented, appear to reflect learners' ongoing efforts to monitor and regulate comprehension in (close to) real time. This is consistent with their immediate objective of understanding the content. Our results, thus, support prior findings that current goals often drive spontaneous thoughts (Klinger et al., 2017). In contrast, task-unrelated thoughts showed a stronger orientation toward the future. This may indicate moments when learners' attention shifted toward planning or anticipating future activities, an interpretation supported by research linking mind-wandering to prospective thinking (Baird et al., 2011; Kvavilashvili & Rumel, 2020). As such, our findings highlight the nuanced ways in which the content and timing of off-task thoughts reflect learners' shifting cognitive priorities during learning tasks.

Self-regulated learning aptitude and off-task thoughts

In response to the second research question, the SRL-O subscales of Planning and Time Management and Online Effort Regulation predicted the rate of self-caught thought reports significantly. Specifically, students with stronger planning and time management skills reported fewer task-unrelated thoughts and fewer future-oriented thoughts. Students with higher effort regulation reported fewer external distractions and fewer present-oriented thoughts. This suggests that learners who plan their study sessions and regulate their effort experience fewer off-task thoughts. These difficulties could include finding the task uninteresting, prioritising other activities, or experiencing distractions while learning. One of these distractions could be task-unrelated thoughts, which can be seen as a cognitive distraction (Brady et al., 2021). Learners who scored highly on Online Effort Regulation appear to be able to maintain focus when faced with external distractions, such as phone notifications. Prior work indicates that task-unrelated thoughts increase over time (Krimsky et al., 2017; Risko et al., 2012) and that learners who are skilled at planning, time management, and effort regulation tend to have more and longer learning sessions (De Barba et al., 2020). Hence, the findings in our study could be attributed to learners planning how to approach a video-watching task and determining how much effort to exert, thereby delaying the onset of frequent task-unrelated thoughts and enabling longer video-watching sessions.

Unexpectedly, an increase in the SRL-O subscale of metacognition did not correspond with an increase in the number of thought reports written overall or by thought type, even though metacognition is a core component of the COPES model of self-regulated learning (Winne & Hadwin, 1998) and the basis for meta-awareness (Schooler & Smallwood, 2009). A possible explanation for this lies in the measurement of meta-awareness. We used the number of thought reports written as an approximation for meta-awareness. However, this only indicates how often a student was aware of their off-task thoughts, not how often someone was engaged in off-task thoughts without realising it. It could be that a learner's score on the metacognition subscale would only be predictive of the proportion of off-task

thoughts they were aware of, rather than the total number of thought reports they wrote. Furthermore, metacognitive processes can occur without conscious awareness (Reder & Schunn, 1996), indicating that learners might return to a task following off-task thoughts without being aware that they had been engaged in off-task thoughts.

Rewinding in response to off-task thoughts

The fifth research question assumed that self-regulated learners will adjust their learning process after realising they are engaged in off-task thoughts. This learner agency would be enacted through rewinding the video to the point at which the off-task thoughts occurred. Given that learners need to be aware of their off-task thoughts to realise they are experiencing them, they would be engaged in metacognitive monitoring. Our study identified 15 instances, by 10 participants, in which the learners exhibited this expected behaviour. The relatively small number of rewinding instances (15) compared to the total number of written thought reports (317) indicates that the learners in our sample did not commonly respond to their off-task thoughts by rewinding. When learners did rewind following off-task thoughts, this can be interpreted as recognising the detrimental effect of their off-task thoughts, as demonstrated by Was et al. (2019), and as choosing to respond to these thoughts by rewinding the video. A plausible alternative explanation is that learners may rewind videos to review content they initially did not understand.

This finding extends the prior research by Varao-Sousa et al. (2017), who found that learners reread a part of a text about half the time after realising task-unrelated thoughts. However, unlike Varao-Sousa et al.'s (2017) findings, our study revealed that participants generally did not rewind the video after realising they were engaged in off-task thoughts. This can be explained by assuming that the learners did not consciously evaluate their situation and just continued learning as usual, or they evaluated their situation and chose not to react to their off-task thoughts. This interpretation raises the question for future research about which factors influence learners' decision to react to their off-task thoughts. In the study by Varao-Sousa et al. (2017), the influencing factor was whether the learners needed clarification about the part they missed. Additionally, factors such as interest (Greene & Azevedo, 2007; Unsworth & McMillan, 2013) or motivation (Brosowsky et al., 2023; Greene & Azevedo, 2007; Zedelius et al., 2015) may influence both self-regulated learning and off-task thoughts and could, therefore, be potential moderators for whether an evaluation to react occurs, including the resulting action. To identify further factors that influence whether a learner enacts a reaction following off-task thoughts, qualitative studies aimed at identifying the learners' reasons for adjusting or not adjusting their learning process could be conducted. For example, stimulated recall studies in which the learners are interviewed about why they did or did not enact a reaction tactic, such as rewinding or rereading, following their off-task thoughts.

Failed self-regulation

In two cases, a discrepancy emerged between the participants' self-reported intentions and their actual behaviours. Specifically, participants indicated in their thought reports that they intended to rewind the video following off-task thoughts; however, video player tracking data revealed no such action was taken. This divergence can be interpreted in various ways.

One interpretation is that the students reported the intention to rewind because they believed it conformed to researcher expectations, suggesting the influence of social desirability bias. Another interpretation would be that these are instances of failed self-regulation (Cosnefroy et al., 2018), specifically under regulation in which a person fails to act to change their behaviour (Baumeister et al., 1994). From this perspective, the intention to rewind was genuine at the point of writing the thought reports, however the action was not followed through (Cosnefroy et al., 2018). Reasons participants did not follow through on their intent to rewind the video could be explored as part of studies aimed at understanding why learners sometimes enact a reaction tactic and sometimes do not, as outlined above.

Limitations

This study has three main limitations: sample size, the naturalistic setting, and meta-awareness measurement. Despite collecting data from eight courses over two semesters, only a small sample could be recruited, which reduced the power of our analysis. Additionally, since participation was voluntary, those who self-selected may already be more inclined to self-regulate their learning.

While the naturalistic setting of our study was essential for addressing the research questions, it introduced several confounding factors. Participants viewed videos in their own diverse learning environments. These learning environments may have varied in terms of external distractions present. Additionally, participants came from different courses, meaning they engaged with varying content domains. The type of video also varied across courses, potentially affecting engagement, as eight of the videos used in this study included a picture-in-picture view of the instructor, and seeing the instructor might have affected engagement. Lastly, we did not know what the learners perceived the task to be and what their goal for the learning session was. While we presumed participants understood the task as learning video content before class, we lacked explicit confirmation of their individual goals. Task definition and goal setting are the first two phases of the self-regulated learning model underpinning this work (Winne & Hadwin, 1998) and thus influence the third phase, enacting study tactics and strategies, including how often off-task thoughts are reported and whether to rewind the video after such thoughts (Ebbert et al., 2026). These uncontrolled factors could have influenced our measures of off-task thoughts and should be considered when interpreting the results.

Meta-awareness was measured using the number of self-caught thought reports. These reports only capture off-task thoughts that participants were aware of and chose to report. It was an intentional decision to use self-caught thought reports as the focus of this work was on the relationship between self-regulated learning aptitude and awareness of off-task thoughts in a naturalistic setting. However, this approach overlooks instances in which off-task thoughts occurred but were not recognised or reported. It is possible that participants had episodes of off-task thoughts and did not realise they were engaged in such thoughts. Furthermore, participants may have been aware of off-task thoughts but chose not to report them (Chu et al., 2023). This limitation could be overcome by including an objective measure of off-task thoughts that does not rely on the participants' self-reports, such as eye-tracking (Kovar et al., 2023). Such a measure could quantify meta-awareness as the number

of off-task thoughts the learner was aware of. This could have downstream effects on the association between self-regulated learning subscales and meta-awareness.

Conclusion

This study offered insights into the association between self-regulated learning and self-caught off-task thoughts and whether learners react to realising their off-task thoughts in a naturalistic setting. While the Planning and Time Management and Effort Regulation subscales predicted self-caught off-task thoughts, the metacognition subscale was not a significant predictor, contrary to our expectations. Furthermore, only 10 out of 53 participants reacted to their self-caught off-task thoughts in 15 cases. While our sample size does not allow for broad generalisation, our findings raise interesting questions about self-caught off-task thoughts in a naturalistic learning environment. Future research could explore whether learners need to be taught how to respond when they realise they are having off-task thoughts, or whether such reactive behaviour naturally develops as part of a learner's self-regulated learning skills. Furthermore, we observed that about 26% of self-caught thought reports concerned external distractions. Consequently, learners could also be guided to choose a study environment conducive to learning to minimise distractions.

Acknowledgements Daniel Ebbert is supported by an Australian Government Research Training Program international (RTPi) Scholarship.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

Data Availability Data and analysis code are available at: <https://doi.org/10.25909/30578243>.

Declarations

Disclosures The authors have no relevant financial or non-financial interests to disclose.

Conflict of interest The authors declare that they have no conflict of interest.

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