Computers in Human Behavior 118 (2021) 106676

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: http://www.elsevier.com/locate/comphumbeh

Full length article

Secondary students' online self-regulated learning during flipped learning: A latent profile analysis

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ABSTRACT

Flipped learning (FL) makes greater use of students' self-regulated learning (SRL) skills when they regulate their online learning behavior. Previous research has shown the value of SRL support during FL to enhance students' SRL and learning outcomes. However, as previous studies have indicated that SRL behavior varies, should SRL support be tailored to these differences in SRL? We applied latent profile analysis to identify subgroups in 150 eighth-graders during FL. We used practically relevant online behavioral data to represent students' online SRL activities, which we gathered unobtrusively in an ecologically valid secondary educational classroom setting. We found five distinct SRL profiles from low completion and no activity to full completion and very high activity. In addition, students in the profile who showed low SRL activity achieved significantly worse learning outcomes than students in the three profiles with higher SRL activity. Finally, we explored whether SRL activity profile membership can be explained by student characteristics (i.e., self-reported SRL, motivation, and prior knowledge). None of the student-level variables predicted profile membership, but our approach offers leads for future research to further investigate the potential of tailored SRL support.

1. Introduction

The most basic definition of flipped learning (FL) is that it is a teaching method by which students learn instructional material before class (e.g., by watching videos) and apply the content of the instructional material during class (van Alten, Phielix, Janssen, & Kester, 2019). Several meta-analyses have confirmed that FL enhances learning outcomes (e.g., van Alten, Phielix, Janssen, & Kester, 2019; van Alten et al., 2019; Låg & Sæle, 2019). However, the role of students' self-regulated learning (SRL) skills in regulating their learning behavior in FL is less well validated in previous research. Self-regulated learning skills are utilized when students need to regulate where, when, and how they study instructional material outside of the classroom, especially if pre-class learning takes place in an online learning environment (He, Holton, Farkas, & Warschauer, 2016; Kim, Kim, Khera, & Getman, 2014; Lee & Tsai, 2011; Shih & Huang, 2019; Sletten, 2015; Tan, Yue, & Fu, 2017). As the increase in students' autonomy in pre-class online learning puts a higher demand on their SRL skills, this could lead to ineffective study behavior, such as inadequate time management due to the freedom of navigation or sequencing of instruction (Butzler, 2016; H. W.; Lee, Lim, & Grabowski, 2010; Sletten, 2015).

Some researchers have been exploring the question of whether a personalized learning approach, which aims to tailor the pace of learning and the instructional approach to the needs of individual learners (Xie, Chu, Hwang, & Wang, 2019), could offer a solution for the higher demand on SRL skills in online learning. Personalized learning has gained popularity amongst educators and researchers due to the increased possibilities that online education could offer, such as implementing intelligent learning systems and analyzing individual learners' data (Xie et al., 2019). Therefore, educational researchers question if and how online learning environments can be adapted to the individual learner (e.g., Vandewaetere, Desmet, & Clarebout, 2011). This personalization can be achieved in different forms. For example, what kind of feedback about learning behavior should be provided to the learner and the teacher to enhance learning (Ali, Hatala, Gašević, & Jovanović, 2012; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2020)? Personalization of online learning environments also uses different personalization parameters (e.g., difficulty, sequence and pace of the materials, and student variables such as cognitive, SRL, and motivational abilities; Xie et al., 2019).

Previous research has shown the value of SRL support to the whole group of students during online pre-class FL. This *variable-centered approach* demonstrated that SRL support on average enhances students' SRL and learning outcomes (e.g., van Alten et al., 2020; Lai & Hwang, 2016; Moos & Bonde, 2016; Yılmaz, Olpak, & Yılmaz, 2018). However, given the personalized learning perspective, previous research on students' SRL in online learning environments showed that students' SRL skills vary greatly (Barnard-Brak, Lan, & Paton, 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales,

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https://doi.org/10.1016/j.chb.2020.106676
Received 17 July 2020; Received in revised form 3 November 2020; Accepted 24 December 2020
Available online 28 December 2020

& Munoz-Gama, 2018; Ning & Downing, 2015; Vanslambrouck et al., 2019). The question that prompts the current study is whether the differences in students' SRL skills should form the basis for tailoring SRL support in online learning environments (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Lehmann, Hähnlein, & Ifenthaler, 2014; Vanslambrouck et al., 2019). Therefore, we take a *person-centered approach* to narrow this knowledge gap by identifying if subgroups exist amongst secondary education students corresponding to their online SRL behavior in an FL setting. The novelty of our contribution to the scientific debate is twofold. First, we used practically relevant and available online behavioral data that represented students' online SRL activities. Second, we unobtrusively gathered these data in an ecologically valid secondary educational classroom setting. This yields important insights, as no studies have been conducted to date in secondary education taking a *person-centered approach* towards online SRL activities. In addition, previous research suggested that focus on the development of SRL skills is of particular importance for younger students (Dignath & Büttner, 2008, 2018; Muijs & Bokhove, 2020; Ramdass & Zimmerman, 2011; Veenman, Van Hout-Wolters, & Afflerbach, 2006; Wigfield, Klauda, & Cambria, 2011).

1.1. The demand on younger students' self-regulated learning skills in online learning environments

Self-regulated learning has been conceptualized in different ways (Panadero, 2017). Most researchers agree that self-regulated learners regulate and monitor their own learning by making use of cognitive and metacognitive strategies and simultaneously regulate their motivation to perform these strategies. A common definition of SRL is that it is a cyclical process during which students sequentially move from the forethought phase via the performance phase to the self-reflection phase (Zimmerman, 2000; Zimmerman & Moylan, 2009). In the *forethought* phase, students analyze the task (e.g., goal setting and planning). Motivational beliefs, such as self-efficacy, task value, and goal orientation, affect students' task analysis and the activation of learning strategies (Panadero, 2017). In the *performance* phase, students work on the learning tasks, while actively metacognitively monitoring their progress. They perform self-control strategies such as time management and help seeking. Metacognition, which can be defined as knowledge, awareness, and regulation of one's learning, is one of the important skills for students to guide them through the SRL phases. In the *self-reflection* phase, students evaluate their performance and could adapt their approach to future learning.

Previous research has shown that students' SRL skills predict their learning outcomes during online FL pre-classroom preparations (Jovanović, Mirriahi, Gašević, Dawson, & Pardo, 2019; Sun, Xie, & Anderman, 2018; Yilmaz & Baydas, 2017). For example, students with better SRL skills achieve improved learning outcomes during FL compared with those with poorer skills (J. Lee & Choi, 2019; Shibukawa & Taguchi, 2019). However, acquiring and performing SRL is difficult, and in particular for younger students age plays an important role in developing SRL skills. First, although SRL skills begin to develop during pre-school and early-school years, they tend to strengthen and continuously develop during primary and secondary education (Muijs & Bokhove, 2020; Veenman et al., 2006). In addition, it seems that secondary school students have less confidence in their SRL skills in comparison with primary school pupils (Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006; Wigfield, Klauda, Cambria, & S, 2011). This could mean that students in secondary education, with less confidence in their ability to regulate their learning than primary education pupils, set easier goals which could lead to a negative influence on learning outcomes (Wigfield et al., 2011). Research has shown that SRL instruction can help young students to develop SRL skills faster and in a more structured manner (Dignath & Büttner, 2008, 2018; Muijs & Bokhove, 2020). For example, SRL support has an impact on learning outcomes in secondary education if the SRL support includes elaboration of the application of SRL strategies that students have already acquired (Dent & Koenka, 2016; Dignath & Büttner, 2008).

Second, students' SRL skills also develop through maturation, interaction, and imitation of older peers, regardless of SRL instruction (Muijs & Bokhove, 2020). This implies that children develop SRL skills differently, according to the opportunities they receive at school but also at home, in which social background potentially also plays a role (Muijs & Bokhove, 2020; Veenman et al., 2006). Therefore, we argue that it is important to investigate the differences in SRL behavior in the secondary school context. We already know from previous research that SRL support can enhance students' SRL development and learning outcomes (Dignath & Büttner, 2008, 2018; Muijs & Bokhove, 2020). What we do not know yet is whether there are significant differences amongst secondary education students' online SRL behavior. If this is the case, SRL support in school environments can play an important role in recognizing these differences in SRL development amongst children to further enhance their confidence and skills in performing SRL activities. We argue that this is especially important for students with a social background that offers fewer opportunities to develop SRL at home (Muijs & Bokhove, 2020; Veenman et al., 2006).

1.2. Supporting self-regulated learning during flipped learning

Previous research has found positive effects of SRL support on FL outcomes in primary education (e.g., Lai & Hwang, 2016), secondary education (e.g., van Alten et al., 2020), and higher education (e.g., Moos & Bonde, 2016; Yılmaz et al., 2018). In these studies, students' SRL was supported during learning in (online) pre-class activities, for instance by SRL prompts in the instructional videos, a self-regulated monitoring system to provide students feedback on their SRL activities, or SRL instructions about effective SRL behavior. These studies showed that a one-size-fits-all approach to SRL support enhanced the learning outcomes of students who received the SRL support in contrast to those without SRL support. This type of research can be characterized as a *variable-centered approach*: it describes associations among variables and assumes that the students are homogeneous with respect to how the predictors operate on the outcomes (Laursen & Hoff, 2006). This approach clarifies the relative importance of predictor variables in explaining variance amongst the included students with regards to outcome variables (Laursen & Hoff, 2006) and is helpful in demonstrating the main effects of SRL support on the average SRL behavior and learning outcomes of the student population.

In contrast, however, a *person-centered approach* distinguishes different subgroups amongst this population and assumes that the population is heterogeneous with respect to how the predictors operate on the outcomes (Laursen & Hoff, 2006). This approach describes differences among individuals in how variables are related to each other and identifies groups of individuals who share particular attributes or relationships among attributes (Laursen & Hoff, 2006). In SRL research, such an approach adds valuable insights, as it investigates the possibility that some subgroups benefit more from SRL support than others (Barnard-Brak, Lan, & Paton, 2011; Broadbent & Fuller-Tyszkiewicz, 2018; Kizilcec et al., 2017; Laursen & Hoff, 2006; Ning & Downing, 2015).

Previous research that took a *person-centered approach* towards students' SRL in online learning environments (e.g., blended learning types such as FL or massive open online courses) showed the existence of student subgroups with divergent SRL profiles and learning patterns (Barnard-Brak et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Jovanović et al., 2017; Maldonado-Mahauad et al., 2018; Ning & Downing, 2015; Vanslambrouck et al., 2019). These studies used SRL self-report questionnaires for latent profile analyses (LPA) to identify and analyze the subgroups within the student population. However, previous research suggested the supplementation of self-report data with observational data (Panadero, Klug, & Järvelä, 2016; Rovers, Clarebout, Savelberg, de Bruin, & van Merriënboer, 2019). For example, because students' SRL behavior changes throughout a course, which cannot be captured in a time-fixed questionnaire (Wang, 2019). Self-reports also stimulate students to think about their own learning and therefore possibly also affect their SRL behavior (Greene & Azevedo, 2010). In addition, students can have difficulty in accurately assessing their own SRL activity (e.g., due to overconfidence) or are simply subject to response sets and memory biases (Li, Baker, & Warschauer, 2020; Pekrun, 2020; Wang, 2019). Therefore, our aim in the current study was to complement self-report data by log data that were unobtrusively gathered in online learning environments. Recent studies used online traces of SRL behavior in LPA to identify patterns by which students can be grouped (Jovanović et al., 2017; Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015; Maldonado-Mahauad et al., 2018). In fact, other research has shown that online traces of SRL better predict SRL behavior that enhances learning outcomes compared with self-reports alone (Li et al., 2020; Rovers et al., 2019; Wang, 2019). Several online SRL behavioral patterns have been identified, such as *comprehensive* learners, *targeting* learners, and *sampling* learners in the context of massive open online courses (Maldonado-Mahauad et al., 2018) and *intensive* learners, *strategic* learners, *highly strategic* learners, *selective* learners, and *highly selective* learners in the context of an FL setting (Jovanović et al., 2017). Students who were more active in regulating their learning (e.g., students showed more online SRL activities) also achieved improved learning outcomes compared with less active regulating students (Jovanović et al., 2017).

1.3. Current study

By taking a *person-centered approach* toward online SRL behavior in secondary education, the current study addresses several existing knowledge gaps. First, there is a need to study the relationship between SRL and FL in secondary education, as previous research has shown the importance of supporting students' SRL at younger ages when they acquire and further develop their SRL skills (Dent & Koenka, 2016; Dignath & Büttner, 2008, 2018; Muijs & Bokhove, 2020). Moreover, previous SRL profile research has almost exclusively focused on blended learning contexts in higher education. One exception is the study of Abar and Loken (2010), who included a sample of 11th and 12th graders in high school, but the difference between this research and the current study is twofold. The intervention of Abar and Loken (2010) was mainly classroom based, and an online web-based study tool was presented to students as supplementary material. In our study, we examine eighth-grade secondary school students' SRL in an ecologically valid FL setting, where they watched instructional videos in the online learning environment before every class. Also, Abar and Loken (2010) based the clustering of students on students' self-reported SRL. In our study, we take online SRL activity trace data to cluster students. Accordingly, our first research question is: *Which SRL profiles can be identified for secondary education students during FL according to their online SRL activities?*

Second, empirical research has shown that students with better SRL skills revisit previously studied learning content more often than those with poorer SRL skills (Kizilcec et al., 2017). In addition, You (2016) found that regularity as indicator of SRL behavior (i.e., accessing and watching instructional videos) was the strongest predictor of learning outcomes. Therefore, it can be hypothesized that students with better SRL skills engage in online SRL activities more often than those with poorer SRL skills, which in turn will predict their learning outcomes. However, Vanslambrouck et al. (2019) suggested that a quantitative interpretation of SRL activities (i.e., more is better) could fall short, as students with fewer SRL skills may undertake more but inadequate SRL activities, and students with better SRL skills may undertake fewer but more efficient SRL activities (Wormington, Corpus, & Anderson, 2012). To address this knowledge gap, we relate the latent SRL profiles and their distinct SRL behaviors to their learning outcomes. Therefore, our second research question is: *To what extent do SRL activity profiles of secondary education students in FL differ in learning outcomes?*

Third, previous research has shown that students' self-reported motivation, self-reported SRL skills, and prior knowledge play a critical role in the motives of students to perform SRL activities (Abar & Loken, 2010; Kizilcec et al., 2017; Ning & Downing, 2015; Sun et al., 2018; Vanslambrouck et al., 2019; Yang, Chen, & Chen, 2018). Therefore, the last question we address in the current study is to what extent the SRL activity profiles can be explained by student characteristics. If these variables on the student level predict SRL activity profile membership, this information can be used to guide further research into tailoring SRL support to other SRL-related individual differences (Kizilcec et al., 2017; Vanslambrouck et al., 2019; Wang, 2019). Therefore, our third research question is: *To what extent do self-reported motivation, self-reported SRL, and prior knowledge in secondary education students in FL predict SRL profile membership?*

2. Method

2.1. Participants

The sample of 150 second-year students (grade 8, 13–14 years old) consisted of six pre-existing classes with three teachers (including the first author), who each taught two classes. The Netherlands has a tracked secondary education system (from grade 7 onwards), and the participating students were enrolled in the two highest tracks: senior general ($n = 21$) and pre-university level, consisting of *atheneum* level ($n = 119$) and *gymnasium* ($n = 10$) level (which includes Latin and Greek as compulsory courses). The study took place in the school's regular History curriculum in one secondary school in the Netherlands. This school is a large urban school (2200 students) that is generally representative of the majority of secondary schools in the Netherlands. Ethical approval was obtained from the Faculty Ethics Review Board, and students and parents gave permission for the authors to obtain students' data for study purposes.

2.2. Instruments

2.2.1. Online self-regulated learning activity log data

In online learning environments, trace data that indicates SRL behavior can be gathered automatically and unobtrusively. Previous research has shown the potential of data-mining processes (e.g., sequential pattern mining) to gather these traces of students' SRL from online learning environments (Jovanović et al., 2017; Kovanović et al., 2015; Maldonado-Mahauad et al., 2018). In contrast to these previous studies, which used complicated clustering and pattern-mining techniques to extract SRL activity indications from large amounts of clickstream data, we used SRL activity indications from online learning environments in secondary education. These variables, such as video viewing time or rewind actions, are commonly provided by online learning environments and can be easily interpreted by teachers, which makes them practically relevant. We used Edpuzzle (www.edpuzzle.com) as a freely available online learning environment and collected the following online SRL activity variables: *completion rate*, *watch time*, *on time rate*, *rewind actions,* and *revisit actions*.

We obtained log data for each video that the students watched in the online learning environment over the course of eight weeks (eight videos in total). We aggregated the SRL activity variables from the extracted log data variables in the following way. *Completion rate* indicated to what extent the student watched each individual instructional video (on a scale from 0 to 100%). We calculated the total percentage of all the video completions for each individual student. *Watch time* was the total time a student spent on a particular instructional video. Edpuzzle did not take into account the paused time. This was unfortunate, as deliberate pausing actions could indicate SRL behavior (e.g., monitoring), but also fortunate, because this prevented a long watch time from being measured if students just ran the videos but were not watching them. We added the individual scores of each student to create a total sum of video watch time. *On time rate* indicated if a student completed the instructional video on time (i.e., before the deadline, which was the beginning of class), too late, or never completed the assignment. We coded this variable for each video (i.e., 0 for not complete, 1 for too late, 2 for on time) and created a sum score that indicates a student's overall degree of completing video instructions before the deadline. *Rewind actions* referred to occasions when a student watched a portion of a video more than once. Every video was automatically divided into 10 segments, and log data were available about how often a student watched a particular segment. We created a sum score for all the deliberate rewind actions, which we calculated by taking the total sum of portions viewed and subtracting the number of segments that indicated a first-time viewing action. *Revisit actions* indicated the number of occasions when students watched (a portion of) an instructional video on another part of the day (i.e., spacing principle). Edpuzzle provides trace data of the time when a student completed a video for the first time and the time when a student watched that particular video for the last time. For each video, we calculated if these dates were similar (i.e., no revisit action, 0) or different (i.e., at least one revisit action, 1) and created a sum score for all the videos. In comparing the first-time completed and last-watched dates, we set a minimum interval of 6 h, to ensure that this variable is an indication of a deliberate revisit action after one part of a day (e.g., not a difference of a few minutes due to technical issues).

In Table 1, we indicate how these practically relevant trace-data variables relate to each phase of the SRL model (Zimmerman & Moylan, 2009). Each SRL phase is covered by at least one SRL activity measurement that best assesses that SRL phase. For example, student learning in the forethought phase requires planning and regulation of motivation to complete the video instructions before the deadline. Previous research has shown that late submissions from students in an online learning environment predict learning outcomes (You, 2016). This makes the on time rate a suitable indication of SRL activities related to planning skills in the forethought phase. In the performance phase, students control and regulate their learning behavior to complete learning tasks. Studies have shown that these trace data variables suitably represent SRL behavior; for example, it was found that low-achieving students often fail to successfully complete assignments (Jovanović et al., 2017). This makes watch time and completion rate suitable indications of SRL activities in the performance phase. In the self-reflection phase, students monitor and evaluate their understanding of the video and can decide to watch (a part of) the instructional video again (i.e., rewind and revisit actions). For instance, the variable revisit actions indicated a deliberate SRL action of a student to revisit already-completed videos at least 6 h after completion. Table 2 presents the descriptive statistics for the online SRL activity variables.

2.2.2. Self-regulated learning and motivation questionnaire

To measure how students themselves assessed their SRL skills and motivation before the flipped classroom started, we developed a pre-test with a focus on learning tasks that they had to complete at home (i.e., homework for History). The Likert-scale range for each question was 1 (disagree) to 7 (agree). For each individual scale, we calculated means for the relevant items, and then we calculated two separate mean values for the SRL and motivation scores.

The first part of the questionnaire was largely based on the revised self-regulated online learning questionnaire (SOL-Q-R; Jansen, van Leeuwen, Janssen, & Kester, 2018). We maintained the questionnaire's seven constructs of SRL: *metacognition* (i.e., activities) *before learning* (e.g., "I ask myself questions about what I am to study before I begin"), *during learning* (e.g., "I am aware of what learning strategies I use"), and *after learning* (e.g., "After studying History, I reflect on what I have learned"), *time management* (e.g., "I make good use of my study time for History homework"), *environmental structuring* (e.g., "I find a comfortable place to complete my History homework"), *persistence* (e.g., "When History homework is difficult, I continue to keep working"), and *help seeking* (e.g., "When I have trouble learning, I ask for help"). We did not include environmental structuring, due to the low Cronbach's α (.55). We contextualized the questions to the student's age and environment context (e.g., we changed "I set specific goals before I begin a task in this online course" to "I set specific goals before I begin working on my History homework").

The second part of the questionnaire was largely based on the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991). The four constructs *intrinsic goal orientation*, *extrinsic goal orientation*, *task value,* and *self-efficacy for learning* were used to measure how students valued and perceived these motivational aspects while completing homework for History. Table 3 presents the descriptive statistics of the pre-test self-report questionnaires' scales of SRL and motivation.

2.2.3. Prior knowledge test

We developed a prior knowledge test, which assessed how much students already knew about the content of the FL lessons. The test contained seven multiple-choice questions on the recall level (e.g., "Which concept does not belong to the Industrial Revolution?") and comprehension level (e.g., "Explain if there was a population growth or decline after the new agricultural developments in the 18th century"). Two additional open questions on the transfer level tested their knowledge about the Industrial Revolution by analyzing a historical source (e.g., "Name two differences between Robert Owen and other factory bosses in his day"). One item was deleted due to a negative distinctive value. The first author scored all the tests and created a sum score. As the items together measured an underlying construct that was difficult to measure (e.g., students with less prior knowledge tend to guess more), we accounted for a low reliability (8 items; $\alpha = .44$) in terms of Cronbach's α (Taber, 2018; Taub, Azevedo, Bouchet, & Khosravifar, 2014). Table 4 presents the descriptive statistics of the prior knowledge test.

2.2.4. Learning outcomes test

The learning outcomes test consisted of 24 items (four multiple-choice questions) and was similar to other tests that students were used to completing to assess their learning about different History topics. The test contained recall questions (e.g., "Define urbanization"), comprehension questions (e.g., "Explain if Karl Marx would support the idea of labor unions"), and transfer questions (e.g. "Analyze the following historical source and argue if this is a reliable source for the working conditions in the 19th century"). As each teacher scored their own students, the inter-rater reliability of the open question scores was assessed. The first author independently scored a random sample of five unscored tests from the other classes (20 tests and 400 items in total). These scores were compared with the other teachers' scores. One item was deleted due to a low Cohen's κ ($\kappa = 0.30$, 60% agreement rate). The inter-rater reliability for the remaining items was substantial: an average Cohen's κ of 0.80 ($SD = 0.14$, range $\kappa = 0.53$ to 1, $p < .001$) and an average total agreement of 85%. In general, the learning outcomes test was found to be reliable (23 items; $\alpha = 0.82$). Finally, we created a sum score for the learning outcomes test and used this in further analyses. Table 4 presents the descriptive statistics of the learning outcomes test.

Table 1
Relationship between the online SRL activity measurements and the three-phase model of SRL by Zimmerman and Moylan (2009).

Online SRL activity measurement	Forethought phase	Performance phase	Self-reflection phase
On time rate	X		
Watch time		X	
Completion rate		X	
Rewind actions			X
Revisit actions			X

Table 2
Descriptive statistics for the online SRL activity variables: mean, standard deviation, median, and two-tailed Pearson correlation coefficients (1–5).

Online SRL activity variable	*M*	*SD*	Median	Min. - Max.	2.	3.	4.	5.
1. Completion rate	94.33	16.39	100	0–100	.46*	.88*	.22*	.24*
2. Watch time	78.37	36.83	67	0–209	–	.45*	.96*	.81*
3. On time rate	14.35	3.20	16	0–16		–	.24*	.27*
4. Rewind actions	38.02	45.21	20	0–228			–	.82*
5. Revisit actions	2.57	3.01	1	0–8				–

Note. * = $p < .01$. Interpretational guidance: 1 = mean percentage of watched videos (0–100); 2 = total minutes watching videos (total length without repeating portions was 54 min); 3 = high score (16) means that a student completed every video on time; 4 = all deliberate rewind actions; 5 = high score (8) means that a student revisited already-completed videos after more than 6 h at least once.

Table 3
Descriptive statistics for each questionnaire scale (1–7) of SRL and motivation: mean and standard deviation, Cronbach's α, and Pearson correlation coefficients (1–10).

Scale of the pre-test	Items	*n*	*M (SD)*	*α*	2.	3.	4.	5.	6.	7.	8.	9.	10.
Self-regulated learning													
1. Metacognition before	4	145	3.04 (1.23)	.78	.65**	.69**	.42**	.28**	.52**	.47**	.49**	.41**	.14
2. Metacognition during	6	145	3.95 (0.97)	.66	–	.66**	.52**	.44**	.59**	.47**	.36**	.46**	.25**
3. Metacognition after	4	147	3.02 (1.23)	.84		–	.47**	.32**	.54**	.47**	.41**	.46**	.18*
4. Persistence	5	147	4.44 (1.23)	.84			–	.26**	.60**	.60**	.47**	.60**	.48**
5. Help seeking	4	143	4.63 (1.21)	.77				–	.34**	.12	.28**	.26**	.04
6. Time management	4	146	4.14 (1.27)	.71					–	.57**	.42**	.58**	.31**
Motivation										–			
7. Intrinsic goal orientation	4	146	3.96 (1.15)	.70							.40**	.73**	.48**
8. Extrinsic goal orientation	4	144	4.77 (1.29)	.74							–	.45**	.27**
9. Task value	4	146	4.01 (1.52)	.91								–	.50**
10. Expectancy: self-efficacy	4	146	4.75 (1.13)	.81									–

Note. * = $p < .01$, ** $p < .001$.

Table 4
Descriptive statistics for the prior knowledge and learning outcomes tests.

Cognitive variable	*n*	*M*	*SD*	Median	Min.–Max.	Correlation 1–2
1. Prior knowledge pre-test	141	9.62	1.89	9.50	4–15.50	.30**
2. Learning outcomes post-test	149	18.41	5.73	18.50	3–29.50	–

Note. ** = $p < .001$.

2.3. Procedure, design, and course materials

The students completed the questionnaire and the prior knowledge test during regular class time, before the flipped lesson series started. The final learning outcomes test was given to the students in a regular test week at the end of the school year, one week after the last lesson. Before the lesson series started, students were briefed about the workings of FL and how to access the videos in the online learning environment Edpuzzle.

The design and data of the current study originated from a previously conducted quasi-experiment, in which the researchers asked the *variable-centered* question as to what was the effect of SRL support in FL pre-class videos on students' SRL and learning outcomes (van Alten, Phielix, Janssen, & Kester, 2020). The lesson series was about the Industrial Revolution and consisted of 10 lessons, with eight instructional videos, over the course of eight weeks. The learning materials (both online and offline) were exactly the same for all the students, except for one difference in the online instructional videos. The content of the video was similar, but a total of 75 students received three SRL prompts at the start, middle, and end of the video (e.g., "Did you accomplish the goals you have set at the beginning of this knowledge clip? If not, what can you still do to reach them?"). In addition, they received a short (<60-s) spoken SRL instruction about effective SRL activities (e.g., instruction on why it is effective to think about setting goals before learning) during some of the videos. The other 75 students received no SRL prompts or SRL instruction.

The three participating teachers each taught two classes, in which both types of support occurred once. Teachers were instructed not to change their usual teaching interaction with their students. They received training on how to apply the learning materials for each lesson and were also asked to give feedback on all the learning materials before the intervention started. We provide a detailed analysis of the impact of these two types of support in the Appendix, which shows that it did not significantly affect SRL behavior in the current study.

The workbooks with additional content questions (e.g., "What are the advantages of building steam factories in the city?") and all the face-to-face lessons were the same for all the students. The videos had an average length of 7 min and were developed and recorded by the first author. Fast-forwarding was disabled for students when they watched the video for the first time. Students were rewarded with a little extra credit on their final mark if they completed the video instructions on time.

During the 65-min class time, the teachers started with retrieval practice activities about the content of the videos, and students could ask questions. This was usually followed by a complementary micro lecture (approximately 10 min) to address students' misconceptions that came forward during the retrieval practice activities and to provide more in-depth aspects of the learning content from the video (e.g., appealing examples and primary source material). For the greatest part of class time, students engaged in learning activities that applied the learning materials (e.g., analyzing historical sources or creating advertisement posters about industrial machines).

2.4. Data analysis

To answer the first research question as to which SRL profiles can be identified according to the online SRL activity variables, we performed LPA in Mplus 8.3 (Muthén & Muthén, 2012) with maximum likelihood estimation. As our trace data also provides values for students who did not engage in SRL activities online, we had no missing data to address. Latent profile analysis consists of evaluating a series of iterative LPA models, in which each model adds the possibility of one more profile (Ferguson, Moore, & Hull, 2019). We explored the hypotheses of one to seven different profiles, and the following model fit criteria were used to evaluate the best model fit and interpretability (Ferguson et al., 2019; Vanslambrouck et al., 2019). Model retention in LPA is evaluated by the Bayesian Information Criterion (BIC), Sample-Adjusted BIC (SABIC), and Akaike's Information Criterion (AIC), for which lower values indicate a better fit (Ferguson et al., 2019). Log-likelihood values can be used to determine where the difference between models (i.e., lower indicates better fit) starts to become relatively small (Ferguson et al., 2019; Masyn, 2013). Entropy was used as an indication of classification uncertainty. Higher entropy values indicate a model that better divides the data into profiles, with values of > 0.80 supporting the minimal uncertainty of the profile classification of students (Celeux & Soromenho, 1996; Ferguson et al., 2019; Masyn, 2013). The Lo, Mendell, and Rubin (LMR) test was used to test the likelihood ratio of one model to the model with k - 1 profiles (Y. Lo, Mendell, & Rubin, 2001). The LMR test assesses significance across differences in degrees of freedom, and significance indicates that the model with fewer profiles fits the data significantly worse than the model with more profiles (Ferguson et al., 2019; Y.; Lo et al., 2001). We considered the sample size of the smallest latent profile, as profiles with less than 5% of the total sample should be carefully considered for interpretability (Ferguson et al., 2019; Masyn, 2013). Finally, we further tested with a one-way MANOVA the statistical significance between the latent SRL profiles identified, with SRL profile membership as an independent variable and the online SRL activity variables as dependent variables (e.g., Kovanović et al., 2015; Vanslambrouck et al., 2019). For completeness, we also performed a one-way MANOVA with SRL profile membership as the independent variable and the student level pre-test variables as dependent variables to further ascertain differences between SRL profiles.

To answer the second research question of whether there is a difference in learning outcomes between the latent SRL profiles, we conducted a one-way ANOVA in SPSS with the learning outcomes test as the dependent variable and SRL profile membership as the independent variable. *Post hoc* comparisons between the SRL profiles were used to further explore differences in learning outcomes between SRL profiles.

To answer the third research question of whether certain student-level variables predict SRL profile membership, we conducted a multinomial logistic regression with profile membership as the dependent variable and the individual scales of the self-reported motivation and SRL questionnaire and also the prior knowledge test as predictor variables in one model. We centered the predicting variables around the mean.

3. Results

3.1. Self-regulated learning activity profiles

3.1.1. Selection of the number of clusters

As presented in Table 2, the standard deviations for the online SRL activity variables are rather high (especially for watch time, rewind actions and revisit actions). This confirms our hypothesis that there is large variance in students' SRL behavior.

Table 5 contains seven different model fit statistics that were used to evaluate which LPA model fits the data best. We concluded that model 5 was the best model fit to the data based on the lower log-likelihood, AIC, BIC, and SABIC values, the higher entropy value, and the nonsignificant LMR test. The log-likelihood, AIC, BIC, and SABIC values showed relatively large decreases in the comparison between model 1 and 2, 2 and 3, until the difference between models 5 and 6. Entropy was best (i.e., >0.80) in models 3, 4, and 5. The results of the LMR test indicate that model 5 was a better fit than model 4, and that model 4 was not a better fit than model 3. The smallest profile was <5% in models 3–7, which could indicate a statistically spurious profile. However, closer examination of this profile revealed that this small profile was aligned with theory and previous LPA in education, as this was the small group of students who engaged very little in the online learning activities. As a means of control, we also performed an LPA analysis in which we excluded these non-active students and concluded that the clustering of the other profiles remained stable. Therefore, we argue that it is justifiable to consider models 3–6 including the non-active students' distinguishable cluster. Overall, model 5 indicating five different SRL profiles fits the data best.

3.1.2. Description and analysis of the self-regulated learning profiles

Table 6 contains descriptive statistics of the five SRL profiles we found. We labeled each SRL profile after careful analysis and interpretation of the differences (cf. Ferguson et al., 2019). In these interpretative labels, we contrast the two main differences between profiles: the completion rate of the instructional videos and the indication of the relative intensity of SRL activities that involved watching the videos such as rewinding, revisiting, and completion on time. We regarded 12% completion rate as low, 73% as medium, 99% as high, and 100% as full. We regarded virtually no rewind and revisit actions and a very low on time rate as no SRL activity, in comparison with low SRL activity (50% on time rate, few rewind and revisit actions), medium SRL activity (94% on time, few rewind and revisit actions), high SRL activity (99% on time, more than 4 times more rewind and revisit actions than medium), and very high SRL activity (99% on time, approximately 2 times more rewind and revisit actions than high). Fig. 1 visualizes the differences between the profiles based on standardized z-scores for each SRL activity variable. The zero line represents the mean score for all the students for that particular variable.

We conducted a one-way MANOVA with SRL profile membership as the independent variable and the online SRL activity variables as dependent variables. This was performed to further ascertain statistically significant differences between the five SRL profiles. We followed Kovanović et al. (2015) using the Pillai's trace statistic in combination with the conservative Bonferroni correction for *post hoc* testing, as it is more robust to the assumption of homogeneity of covariances violation (Field, 2018). We found a significant main effect of profile membership on the online SRL activity variables, Pillais' trace = 2.34, F (20, 576) = 40.94, $p < .001$; partial $\eta^2 = 0.59$. Results of the Bonferroni *post hoc* pair-wise tests are provided in Table 5, with subscripts indicating significant differences between profiles.

Table 5
Latent profile analysis model fit summary for different models with a number of clusters of 1–5.

Model	# of free parameters	AIC	BIC	SABIC	Log-likelihood	Entropy	Smallest profile %	LMR p and meaning	
1	10	5887.09	5917.20	5885.55	−2933.55	–	–	–	–
2	16	5465.74	5513.91	5463.27	−2716.87	0.978	27	.010	2 > 1
3	22	5175.46	5241.70	5172.07	−2565.73	0.989	4	.071	3 < 2
4	28	4960.75	5045.05	4956.43	−2452.38	0.988	3	.090	4 < 3
5	34	4812.93	4915.29	4807.68	−2372.46	0.988	3	.030	5 > 4
6	40	4725.90	4846.33	4719.73	−2322.95	0.978	3	.133	6 < 5
7	46	4670.86	4809.35	4663.77	−2289.43	0.977	1	.707	7 < 6

Note. $n = 150$; The LMR test compares the current model with a model with k - 1 profiles. AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-Adjusted BIC; LMR = Lo-Mendell Ruben Likelihood Ratio Test.

Table 6
Descriptive statistics (mean and standard deviation) of the five SRL profiles for online SRL activity, and the Bonferroni corrected post hoc *pairwise comparisons among the profiles.*

Online SRL activity variable	Low completion-no activity$_a$ (n = 4, 3%)	Medium-completion low activity$_b$ (n = 13, 9%)	High completion-medium activity$_c$ (n = 92, 61%)	High completion-high activity$_d$ (n = 31, 21%)	Full completion-very high activity$_e$ (n = 10, 7%)
1. Completion rate	11.88 (15.02)$_{bcde}$	72.69 (12.76)$_{acde}$	98.61 (3.49)$_{ab}$	99.52 (2.25)$_{ab}$	100 (0.00)$_{ab}$
2. Watch time	3.00 (5.35)$_{bcde}$	50.00 (19.89)$_{acde}$	64.15 (11.17)$_{abde}$	112.61 (16.39)$_{adce}$	170.10 (24.82)$_{abcd}$
3. On time rate	1.00 (1.15)$_{bcde}$	8.69 (2.84)$_{acde}$	15.14 (1.26)$_{ab}$	15.65 (0.71)$_{ab}$	15.80 (0.42)$_{ab}$
4. Rewind actions	1.25 (1.89)$_{de}$	17.00 (18.23)$_{de}$	15.37 (13.46)$_{de}$	79.16 (20.78)$_{adce}$	160.90 (32.08)$_{abcd}$
5. Revisit actions	0 (0)$_{de}$	0.46 (1.13)$_{de}$	1.01 (1.43)$_{de}$	6.90 (1.04)$_{abc}$	7.30 (0.67)$_{abc}$

Note. Subscripts A–E indicate significant differences ($p < .05$) from other profiles according to the Bonferroni corrected *post hoc* tests. Interpretational guidance: 1 = mean percentage of watched videos (0–100); 2 = total minutes watching videos (total length without repeating portions was 54 min); 3 = high score (16) means that a student completed every video on time, 4 = all deliberate rewind actions; 5 = high score (8) means that a student revisited already completed videos after at least 6 h at least once.

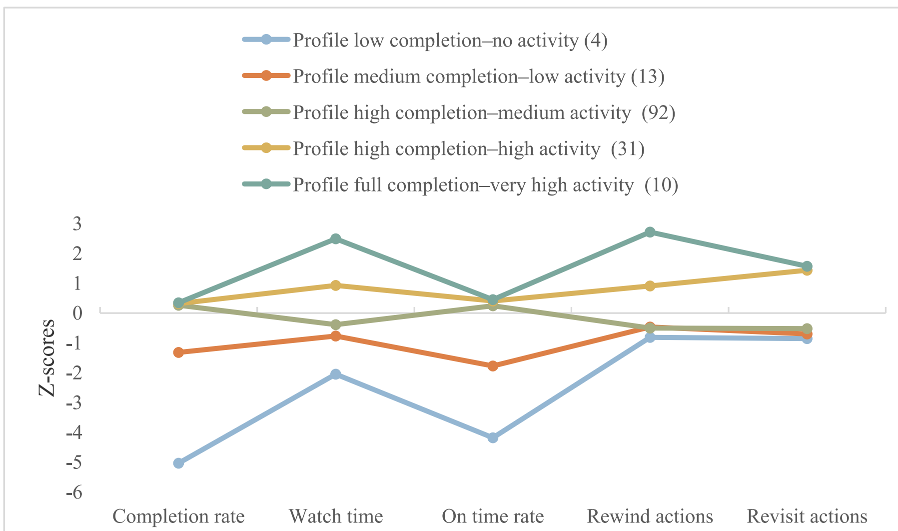

Fig. 1. Comparison of SRL profile (n) online SRL activity variables in z-scores.

Table 7
Descriptive statistics (mean and standard deviation) of the five SRL profiles in the pre- and post-tests.

Variables	Low completion-no activity$_a$ (n = 4, 3%)	Medium completion-low activity$_b$ (n = 13, 9%)	High completion medium-activity$_c$ (n = 92, 61%)	High completion-high activity$_d$ (n = 31, 21%)	Full completion-very high activity$_e$ (n = 10, 7%)
Self-regulated learning pre-test					
Metacognition before	2.56 (1.26)	3.88 (1.38)	3.03 (1.25)	2.74 (1.06)	3.25 (1.01)
Metacognition during	3.42 (1.09)	4.47 (0.99)	3.93 (0.95)	3.81 (1.05)	4.17 (0.64)
Metacognition after	2.44 (0.99)	3.69 (1.39)	2.92 (1.19)	2.96 (1.24)	3.55 (1.22)
Persistence	3.35 (1.54)	4.90 (1.03)	4.44 (1.25)	4.33 (1.26)	4.68 (0.87)
Help seeking	2.75 (0.89)$_{be}$	5.06 (0.98)$_a$	4.57 (1.17)	4.63 (1.28)	5.33 (0.96)$_a$
Time management	4.13 (1.05)	4.56 (1.14)	4.21 (1.31)	3.76 (1.28)	4.18 (0.94)
Motivation pre-test					
Intrinsic goal orientation	4.25 (0.46)	4.38 (1.18)	3.95 (1.18)	3.76 (1.20)	4.10 (0.84)
Extrinsic goal orientation	4.50 (1.67)	5.03 (1.36)	4.73 (1.31)	4.73 (1.26)	5.05 (1.24)
Task value	4.13 (1.81)	4.31 (1.90)	3.98 (1.46)	3.95 (1.59)	4.14 (1.52)
Expectancy: self-efficacy	5.00 (0.89)	4.58 (1.22)	4.74 (1.17)	4.77 (1.13)	4.86 (0.78)
Cognition pre-test					
Prior knowledge	7.67 (1.53)	8.35 (2.13)	9.23 (1.75)	9.26 (1.70)	9.72 (1.80)
Cognition *post-test*					
Learning outcomes	16.50 (3.58)	13.69 (5.25)$_{cde}$	18.54 (5.84)$_b$	18.97 (4.64)$_b$	22.78 (5.65)$_b$

Note. Subscripts A-E indicate significant differences ($p < .05$) from other profiles according to the Bonferroni corrected post hoc tests for the pre-tests, and Hochberg's GT2 correction for the post-test. Interpretational guidance: Likert-item range for the SRL and motivation tests was 1–7. Maximum score for the prior knowledge test was 14.50, and for the learning outcomes test 30.

For a full description of the SRL profiles, we provide the profile means and standard deviations on the scales of the SRL and motivation pre-test, the prior knowledge pre-test, and the learning outcomes post-test in Table 7. Fig. 2 visualizes the differences between the profiles based on standardized *z*-scores for these variables. The zero line represents the mean score for all the students for that particular variable. The included variables were used to answer research questions 2 and 3.

In addition, we assessed differences between students' pre-test SRL profiles with a one-way MANOVA, with SRL profile membership as the independent variable and the student-level pre-test variables (i.e., self-reported SRL, self-reported motivation, and prior knowledge) as dependent variables. After assessing the equality of covariances using the Box's M test and homogeneity of variances using Levene's test, we performed separate non-parametric Kruskal–Wallis tests for the student-level pre-test variables due to violation of assumptions. We found a significant different distribution across SRL profiles ($p = .011$) for *help seeking*, but not for the other variables (*p* ranges from .105 to .987). Only significant Kruskal–Wallis tests were followed up by Bonferroni corrected pairwise comparisons, and results are provided in subscripts in Table 7.

3.2. Relating self-regulated learning profiles to learning outcomes

To answer the second research question about differences amongst the SRL profiles for learning outcomes, we conducted a one-way ANOVA with the learning outcomes test as the dependent variable and SRL profile membership as a factor. First, homogeneity of variance amongst SRL profiles was checked using Levene's test. This showed that the variances for the learning outcomes test were equal, $F(4{,}144) = 1.48$, $p = .211$. We found a significant effect of SRL profile membership on learning outcomes, $F(4, 144) = 4.02$, $p = .004$; partial $\eta^2 = 0.10$. Hochberg's GT2 test was used for *post hoc* comparisons, as the sample sizes for the profiles varied greatly (Field, 2018). *Post hoc* comparisons indicated significantly ($p < .05$) lower means for students in the profile *medium completion–low activity* in contrast with students in the profiles *high completion–medium activity*, *high completion–high activity*, and *full completion–very high activity*. All other comparisons were not significant. Means and standard deviations of the learning outcomes test are provided in Table 7.

3.3. Predicting self-regulated learning profile membership

To answer the third research question about which student-level variables predict SRL profile membership, we conducted a multinomial logistic regression with the scales of the SRL and motivation questionnaire pre-tests and the prior knowledge test as predictors and profile membership as the dependent variable (e.g., Vanslambrouck et al., 2019). We removed the SRL profile *low completion–no activity* from the analysis due to missing values that lead to an even smaller sample size than the original $n = 4$. We set the profile *medium completion–low activity* as the reference category, as this sample had the lowest completion rate and SRL activity that contrasted best with the other SRL profiles. Results of the multinomial logistic regression analysis are provided in Table 8. The nonsignificant model fit indicates that the full model does not predict profile membership better than the intercept-only model. In combination with nonsignificant likelihood tests in which the predictive value of the independent variables is tested for membership of the profile *medium completion–low activity* in comparison with membership of the other profiles, this leads us to conclude that none of the predictors in the model predict profile membership.

4. Discussion and conclusions

By taking a *person-centered approach* to online SRL activity trace data from a secondary education FL course, we aimed to show differences in students' SRL that can be used to guide further research on tailored SRL support according to individual differences in SRL skills. We asked (1) which SRL profiles can be identified according to students' online SRL activities, (2) if these SRL profiles differ in learning outcomes, and (3) if self-reported motivation, self-reported SRL, and prior knowledge predict SRL profile membership. In line with previous research in higher education, We found five distinct online SRL profiles from low completion and no activity to full completion and very high activity. We also found that some of these SRL profiles significantly differed in learning outcomes. However, we found no student-level predictor variables to explain SRL profile membership. We interpret the results of the research questions through a detailed description of the similarities and differences between these SRL profiles.

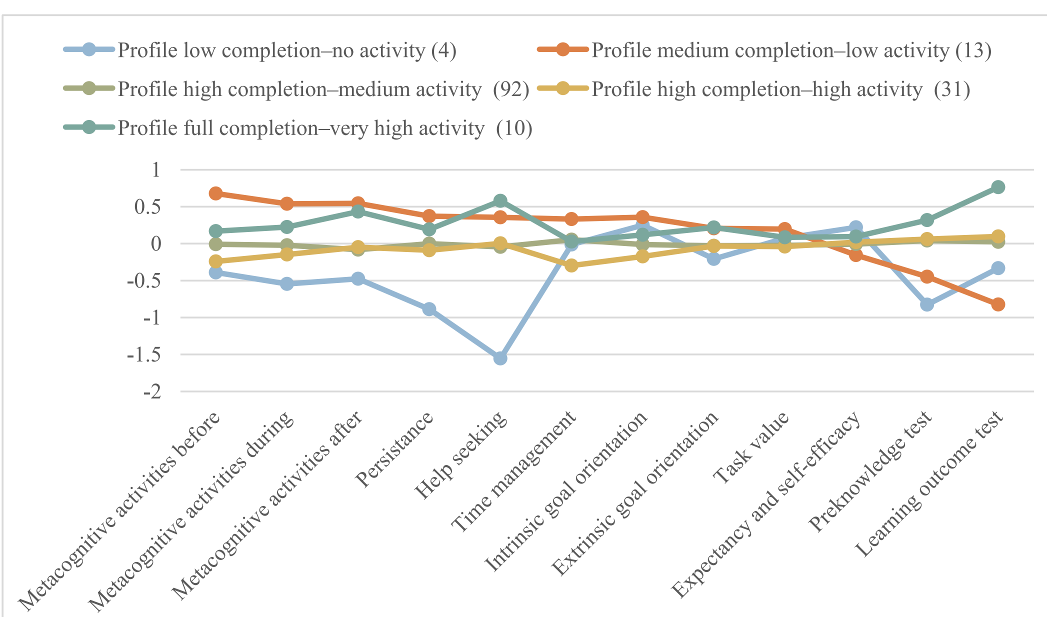

Fig. 2. Comparison of SRL profile (n) pre-test and post-test measurements in z-scores.

Table 8
Results of the multinomial logistic regression predicting SRL profile membership.

Variables	Profile *medium completion–low activity* (*n* = 12) vs. Profile *high completion–medium activity* (*n* = 87)			Profile *medium completion–low activity* (*n* = 12) vs. *high completion–high activity* (*n* = 29)			Profile *medium completion–low activity* (*n* = 12) vs. *full completion–very high activity* (*n* = 9)		
	B	SE	*p*	B	SE	*p*	B	SE	*p*
Self-regulated learning pre-test									
Metacognition before	-.32	.40	.426	.78	.47	.097	.58	.60	.332
Metacognition during	-.41	.60	.494	.35	.65	.589	.72	.80	.364
Metacognition after	-.23	.40	.560	.24	.46	.608	.61	.58	.295
Persistence	-.50	.48	.300	.26	.52	.613	.25	.63	.691
Help seeking	-.22	.34	.518	.11	.37	.766	.50	.49	.314
Time management	.32	.43	.453	.21	.48	.663	.44	.66	.503
Motivation pre-test									
Intrinsic goal orientation	-.51	.51	.294	.69	.56	.217	.31	.72	.665
Extrinsic goal orientation	.26	.38	.408	.40	.41	.320	.57	.49	.245
Task value	.32	.36	.340	.42	.40	.295	.08	.52	.877
Expectancy: self-efficacy	.40	.37	.321	.44	.42	.293	.45	.55	.421
Cognition									
Prior knowledge test	.22	.20	.272	.23	.23	.308	.48	.30	.114

Note. The profile *medium completion–low activity* served as the reference group. Pseudo R^2 = 0.19 (Cox & Snell), 0.22 (Nagelkerke), 0.10 (McFadden). Model χ^2 (33) = 248.19, p = .699.

4.1. Online self-regulated learning activity profiles: similarities and differences

The profile *low completion–no activity* was the smallest group of students (3%), who did not follow instructions and engaged very little in watching the instructional videos. The students in this profile scored 6.0 (out of 10) points in the learning outcomes test. This is comparable to a C grade, and it was not statistically different to other profiles. As the sample size of the profile *low completion–no activity* was small, we cannot draw general conclusions about the relationship between their average learning outcomes and SRL skills. In contrast to previous research in which the majority of students were found to belong to a highly selective or even non-user group, this group was particularly small in our study (Broadbent & Fuller-Tyszkiewicz, 2018; Kovanović et al., 2015; Ning & Downing, 2015). This could be due to a difference in educational level (secondary vs. higher education), a more binding educational context (e.g., stricter secondary school culture of following homework instructions), or the incentive that was given to students to complete the instructional videos (e.g., a few extra credits on their final mark; see Radhakrishnan, Lam, & Ho, 2009).

The profile *medium completion–low activity* comprised a small group of students (9%) who struggled to complete all the instructional videos (73%) and generally failed to complete half of the instructional videos before the deadline. This could be an indication of insufficient planning skills in these students, but further research with a broader view on SRL skills (e.g., planning) is needed to confirm this hypothesis. Their average watch time was slightly shorter than the total length of the instructional videos and was significantly different from all of the other profiles. On average, the students in this profile scored 5.1 (out of 10) points in the learning outcomes test, which is comparable to an F grade. This score, which indicates a fail grade, was statistically different from the learning outcomes of students from the three profiles with high to full completion. This is in line with previous research that also found that students who were less active in regulating their learning achieve worse learning outcomes (Bannert, Reimann, & Sonnenberg, 2014; Jovanović et al., 2017).

The profile *high completion–medium activity* included the majority of students (61%), who generally completed all the instructional videos and completed them before the face-to-face class. The students in this profile generally scored 6.6 (out of 10) points in the learning outcomes test, which is comparable to a B grade. They also seem to be able to plan well and persist in their online learning activities (i.e., sufficient completion and on time rate). Similarly to students in the profile *medium completion–low activity*, they performed few monitoring activities (i.e., rewind and revisit actions). In this respect, this group shows behavior comparable to the selective SRL profiles in previous studies, in which students seem to do only the minimum to pass the course (cf. Barnard-Brak et al., 2010; Jovanović et al., 2017; Kovanović et al., 2015). Similarly, other studies found that the majority of the students were clustered in an SRL profile that can be described as average SRL behavior (Abar & Loken, 2010; Vanslambrouck et al., 2019).

The profile *high completion–high activity* was the second-largest subgroup of students (21%), who also generally completed all the instructional videos and before the deadline. The students in this profile generally scored 6.7 (out of 10) points in the learning outcomes test, which is comparable to a B grade. Only a few students did not complete a few portions of the instructional videos. In contrast to students in the *medium completion–low activity* profile, they performed significantly more rewind and revisit actions, and thus also spent significantly more time watching the instructional videos. These results are similar to previous research that also found a profile of students who performed more SRL activities, but achieved as well as competent regulators in terms of learning outcomes (Barnard-Brak et al., 2010).

The profile *full completion–very high activity* consisted of a small proportion of the students (7%), who fully completed each portion of the instructional videos. The average students' score of 7.8 (out of 10) points in the learning outcomes test, which is comparable to an A grade, was not statistically different from the learning outcomes of students in the profiles *high completion–medium activity* and *high completion–high activity*. Students from the profile *full completion–very high activity* performed significantly more rewind actions and thus spent more time watching than students from all other profiles. In addition, students from this group revisited the instructional videos significantly more than students in profiles with low to medium SRL activities. Therefore, the profile *full completion–very high activity* is comparable to the super regulators profile described in previous research (Broadbent & Fuller-Tyszkiewicz, 2018).

4.2. Theoretical implications

One contribution of the current study is that it offers several nuances to the scientific debate about the quantitative interpretation of SRL activities. One of the supposed benefits of FL is that students in the online pre-class learning phase can revisit content and re-watch instructional videos without restrictions (Abeysekera & Dawson, 2015; C. K. Lo, Hew, & Chen, 2017; Lundin, Bergviken Rensfeldt, Hillman, Lantz-Andersson, & Peterson, 2018). On the one hand, previous research found that more SRL behavior leads to better learning outcomes (e.g., You, 2016). In our study, we indeed found that students from the profile *medium completion–low activity* undertook significantly fewer SRL activities than students from the profiles *high completion–high activity* and *full* *completion–very high activity* and achieved significantly worse learning outcomes. In contrast, however, students from the profiles *high completion–high activity* and *full completion–very high activity* did not receive higher learning outcomes than students in the *high completion–medium activity* profile. On the other hand, it has been suggested in previous research that students with poorer SRL skills may undertake more but inadequate SRL activities and students with better SRL skills may undertake fewer but more efficient SRL activities (Vanslambrouck et al., 2019; Wormington et al., 2012). In our study, we found that students from the profile *full completion–very high activity* performed significantly more SRL activities than students from the profiles *high completion–high activity* and *full completion–very high activity*, but achieved similar learning outcomes. Although there is no conclusive evidence for the discussion, our results suggest that the first interpretation does exclude the second interpretation.

Our study expands the current knowledge about *person-centered approaches* to online SRL behavior to eighth-grade secondary education. Moreover, we used practically relevant and commonly provided variables from an authentic learning context and found results comparable to previous research in higher education (Jovanović et al., 2017; Kovanović et al., 2015; Maldonado-Mahauad et al., 2018). It is for future research to confirm that our proposed method of relating behavioral data to SRL activity was accurate by testing it on a larger scale and in different subjects and educational levels within secondary education.

4.3. Practical implications

As we found no student-level variables that significantly predicted profile membership, our findings provide no concrete leads on how to tailor SRL support in FL environments. However, our results can still aid practitioners of FL in tailoring their SRL support in FL environments. For example, teachers and researchers may want to focus their SRL support on students in the profile *medium completion–low activity* in particular, as they generally failed to pass the course. This group of students failed to watch more than three-quarters of the instructional videos, and for approximately half of the time also not before the deadline. It seems that this group could benefit from specific SRL support in the forethought phase, such as goal setting, strategic planning, and self-motivational beliefs. This can be achieved by instruction in the classroom (e.g., Ness & Middleton, 2012) or by personalized online prompts focused on the forethought phase (e.g., Lehmann et al., 2014).

Another example relates to the students in the profile *low completion–no activity*. Previous research indicates that insufficient SRL skills can lead to non-compliance (Eriksson, Adawi, & Stöhr, 2017). Although we did not measure the complete set of SRL skills of the students (e.g., how they regulate their own learning outside the online learning environment), their online SRL behavior could be used as a starting inference. The SRL of this group of students could, for example, be supported by enhancing their intrinsic motivation to watch and interact with the videos. Due to the small sample size of this subgroup, it was not possible in the current study to clarify if, for example, low (self-reported) motivation or low (self-reported) SRL skills are underlying factors that could explain this behavior. However, external motivators such as extra credits seemed insufficient in persuading this group to engage in the homework activities. Supporting the intrinsic motivation of these students seems a requirement for them to engage in SRL activities (cf. Lehmann et al., 2014). Furthermore, this small sample of students was also quite negative about seeking help from their teacher or peers and thus seems to prefer learning on their own. Further research could reveal whether it helps to specifically teach the students from this profile the value and usefulness of help-seeking activities (cf. Karabenick & Gonida, 2018). However, as this group generally scored a sufficient grade, it is also possible that these students' SRL skills are adequate and that they learned just enough by attending classes, or that they studied other offline available learning materials (e.g., their textbook).

Moreover, students from the profile *high completion–high activity* scored almost the same as those from the profile *high completion–medium activity* in the learning outcome and prior knowledge tests and demonstrated comparable *on time* and *completion* rates. However, what stands out is that the students from the former profile performed significantly more rewind and revisit actions and thus spent more time on the online learning activities, but achieved as highly as the majority of students in the latter profile who performed fewer of these monitoring activities (cf. Barnard-Brak et al., 2010). On the one hand, one could argue that the students from the profile *high completion–high activity* need all these SRL activities to score as highly as the students from the other profile. On the other hand, one could argue that, while their behavior does not lead to higher learning outcomes, students who seem to perform SRL activities excessively often could benefit if their self-efficacy, efficiency, confidence, or merely the quality of their SRL activities is supported.

4.4. Limitations and directions for future research

Previous research has found that students' self-reported motivation, self-reported SRL skills, and prior knowledge are related to differences in students' SRL (Abar & Loken, 2010; Kizilcec et al., 2017; Ning & Downing, 2015; Sun et al., 2018; Vanslambrouck et al., 2019; Yang et al., 2018). However, none of the self-reported SRL scales, self-reported motivation scales, and prior knowledge variables predicted profile membership.

First, it is possible that other predictive variables that we did not measure may play a role. For example, there is modest evidence that students' SRL is related to their socio-economic background, which in turn could affect students' online SRL activities (Muijs & Bokhove, 2020). In addition, students' anxiety levels could also predict students' online SRL activities (Broadbent & Fuller-Tyszkiewicz, 2018). More research in secondary education is needed to determine how we can predict SRL behavior on the basis of student-level variables, which in turn can guide the design of SRL support.

Second, the lack of prediction could be due to the higher accuracy of predicting SRL behavior by SRL behavior measurements than by self-reports (Li et al., 2020; Rovers et al., 2019; Wang, 2019). While we used online behavioral data to find SRL profiles, we used self-reports to measure self-reported SRL and motivation. It could therefore also be possible that the Dunning–Kruger effect plays a role, such that students with poor SRL skills tend to overestimate their SRL ability (Kruger & Dunning, 1999). This is especially likely given the relatively young student population in the current study.

Third, the measurement of prior knowledge had low reliability, which could mean that these differences may not have been optimally measured. We therefore advise treating this variable with caution. Although our measurement of prior knowledge was of a similar nature to that in other studies (e.g., Taub et al., 2014; Yang et al., 2018), we advise careful consideration of the reliability of measuring prior knowledge and suggest exploring different methods of including this variable in multinomial logistic regression analyses to predict profile membership of secondary education students. For example, Ning and Downing (2015) used prior academic performance (i.e., GPA) as an indication of cognitive ability and prior knowledge, while Sun et al. (2018) asked students to report on their highest level of similar course content prior to the course, in addition to the measurement of pre-class homework grades as an indicator of prior domain knowledge.

Finally, we acknowledge that the following limitations may have an impact on the generalizability of our results. Although the participating school is generally representative of urban secondary schools in the Netherlands, more research is needed to reduce the possible bias of differences in schools that may affect students' differences in online SRL behavior (for example caused by school-wide SRL training in the school's curriculum). Moreover, as the subsample sizes of the profiles *low completion–no activity* and *full completion–very high activity* are quite small, we have to be cautious with our interpretations of these profiles. More research with larger subsample sizes is needed to determine, for example, whether the extraordinarily high SRL activity of students in the profile *full completion–very high activity* is related to prior knowledge (Taub et al., 2014; Yang et al., 2018) or improved learning outcomes (Jovanović et al., 2017, 2019).

In addition, the ratio of student numbers in the profiles could possibly be affected. First, it may be affected by a novelty effect, as the FL method and the use of the online learning environment was new for the students. Although this does not explain the differences in SRL behavior between students, as it was new for all the participants, it might have caused more students than would otherwise have been expected to be included in SRL profiles with higher completion rates just because it was new and interesting for them. Second, we provided a small number of extra credits to students for watching the instructional videos to reduce non-compliance that would lead to a decrease in our sample size. This incentive was the same for every student and is common in this natural educational context. It is likely that the same SRL profiles would have been found without this external incentive. However, it could be an explanation for the very small sample size of the *low completion–no activity* profile.

4.5. Conclusions

Broad academic consensus has been reached on the importance of sufficient SRL support in the development of SRL skills (Muijs & Bokhove, 2020; Quigley, Muijs, & Stringer, 2018). Previous research has shown that one effective way to implement this is by supporting students' SRL in an FL context (e.g., (van Alten et al., 2020); Lai & Hwang, 2016; Moos & Bonde, 2016; Yılmaz et al., 2018). However, less is known about the extent to which SRL support should be personalized to students' differences in SRL skills. By taking a *person-centered approach*, the current study revealed clear differences in SRL behavior amongst secondary education students in an ecologically valid FL context. These differences are also related to differences in learning outcomes, as students in the profile *medium completion–low activity* failed in the learning outcomes test and scored significantly worse than those in the profiles with higher SRL activity. The differences in online SRL behavior, which are related to differences in learning outcomes, suggest that, compared with one-size-fits-all SRL support, personalized SRL support could be an important improvement for learning environments which aim to support students' SRL.

Credit author statement

David C.D. van Alten, Conceptualization, Methodology, Investigation, Resources, Writing – original draft. Chris Phielix, Conceptualization, Methodology, Writing – review & editing, Supervision. Jeroen Janssen, Conceptualization, Methodology, Writing – review & editing, Supervision. Liesbeth Kester, Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

None.

Acknowledgments

This research was supported by funding from the Dutch Ministry of Education, Culture and Science, (grant number OCW/PromoDoc/1065001).

Appendix. Analyses on the impact of two types of self-regulated learning support

The data from this study originate from a previously conducted quasi-experiment. The learning materials (both online and offline) were exactly the same for all the students, except for one difference in the online instructional videos. The content of the video was similar, but a total of 75 students received video-embedded SRL support, while the other 75 students received no SRL support. Here, we provide a detailed analysis to determine whether these two types of support affected SRL behavior in the current study.

First, we checked whether there was a difference in prior knowledge for educational levels, which would have required us to take this into account in later analyses. Participating students were enrolled in two educational levels: senior general ($n = 21$) and pre-university level, which consists of *atheneum* level ($n = 119$) and *gymnasium* ($n = 10$) level (which includes Latin and Greek as compulsory courses). We found a significant main effect of class level (independent variable) on prior knowledge as the dependent variable in an ANOVA, $F(2, 138) = 3.74$, $p = .026$, partial $\eta^2 = 0.05$. Subsequently, we found no significant main effect of SRL support variant (independent variable) on prior knowledge as the dependent variable in an ANOVA, $F(1, 139) = 2.43$, $p = .121$, partial $\eta^2 = 0.02$. This indicates that the students with different prior knowledge were equally distributed over both types of SRL support.

Second, we checked *a priori* differences in the SRL support variant in self-reported SRL and motivation. We found no significant difference between the two SRL support variants (independent variable) in a MANOVA including the 11 SRL and motivation self-reported pre-test scales as dependent variables, $F(10, 138) = 1.33$, $p = .221$; Wilk's $\Lambda = 0.912$, partial $\eta^2 = 0.09$. Therefore, the students from both SRL support variants did not differ in relevant *a priori* measurements.

Third, we analyzed the possible impact of SRL support on students' actual online SRL behavior. We performed a MANOVA with *completion rate*, *on time rate*, *rewind actions*, and *revisit actions* as dependent variables, SRL support variant as the independent variable, and class level as the controlling factor given the differences in prior knowledge for class level. *Watch time* was omitted from the analysis because of a very high correlation ($R > 0.95$, $p < .01$) with rewind actions and the problem of multicollinearity. We excluded nine students due to non-compliance, as they did not watch at least 70% of the instructional videos (cf. van Alten et al., 2020). For the students in the SRL support group, non-compliance indicates that they were not sufficiently exposed to our intervention, which hinders a fair comparison of the impact of the SRL support variant. We found no significant difference between the two SRL support variants for the online SRL activity variables, $F(4, 134) = 2.26$, $p = .066$; Wilk's $\Lambda = 0.937$, partial $\eta^2 = 0.06$. Overall, we conclude that the difference in SRL support in the offering of the course material did not significantly affect SRL behavior.

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