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A latent profile analysis of adult students' online self-regulation in blended learning environments

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ABSTRACT

Self-regulated learning (SRL) is crucial for academic success; therefore support, to enhance and maintain SRL skills is important. In blended adult education, the heterogeneity of adults creates diversity in SRL abilities, which makes it necessary to provide tailored support. Conducting latent profile analyses for a sample of 213 blended adult students, we identified three profiles, namely high, low, and moderate SRL profiles which prove differences in SRL strategy use and imply tailored SRL support. Through multivariate analysis of variance (MANOVA) and multinomial logistic regression, we further explore the differences in SRL between the profiles and the extent to which the students' personal background characteristics and achievement motivations predict their profile membership. The three profiles differ significantly in terms of the scores of all SRL subscales. Furthermore, only achievement motivation – more specifically, attainment and utility value – predicts profile membership. These results inform educational practice about opportunities for supporting and enhancing SRL skills. Anticipating attainment and utility value, time management, and collaboration with peers are all recommended. More specifically, teachers can, for example, use authentic tasks and examples during the learning process or be a role model regarding online interaction and information sharing.

1. Introduction

Blended learning environments combine face-to-face and online learning activities that are meant to complement each other (Boelens, Van Laer, De Wever, & Elen, 2015). These environments allow students considerable autonomy, which requires self-regulated learning (SRL) for individuals to succeed (Peverly, Brobst, Graham, & Shaw, 2003). Although blended learning environments are autonomous, tailored support for adult students in developing and maintaining their SRL skills should be provided. Since adult students are heterogeneous regarding their previous life, work, and educational experiences, they are diverse in their SRL skills (Barnard-Brak, Lan, & Paton, 2010), which makes a one-size-fits-all approach insufficient for supporting adult students. Optimisation and personalisation of the support of students is crucial for their learning (Authors, 2018b). To adjust the support they provide, teachers should have a clear perspective on students' current SRL. However, creating a rich assessment of adult students' SRL in blended learning environments is challenging because (1) existing research on the SRL of adult students in blended learning environments and how to support it is lacking, (2) research on SRL of students in contexts other than blended adult education is not generalisable to blended adult education due to the context specificity of SRL, and (3) in blended learning environments, teachers have limited time to observe their students individually. While blended learning environments allow for the individualisation of education and support, it can become challenging to provide individualised SRL support for each student considering the teachers' time and effort required to do so. The current study consequently examines how to support teachers in gaining information about their students' individual SRL needs in order to provide personalised support at an achievable level. More specifically, by means of latent profile analysis, the current study answers the question of which unobserved (latent) SRL profiles of blended adult students exist based on their level of self-regulation strategy use. To further integrate and account for the diversity of adult students, the current study also poses the question of whether students' background characteristics and achievement motivations can predict their SRL profile memberships.

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Finally, the study concludes with a discussion that addresses both the practical and scientific benefits of using the results from the current research to predict the SRL profile memberships of students.

2. Theoretical background

2.1. Self-regulation

Self-regulation is a process that is initiated by students in an effort to control their educational functioning in the following diverse areas: (1) the (meta)cognitive area, which represents the (meta)cognitive strategies used by students to efficiently learn and perform their tasks; (2) the motivational area, which includes strategies that students use to optimise their motivations and emotional reactions; (3) the behavioural area, which reflects the effort of students to persist and seek help during their tasks; and (4) the contextual area, which represents the activities of students to control and manage the (online) environment or classroom where their learning takes place (Pintrich, 2005). In each area, four phases occur – whether sequentially or not – in which students use diverse strategies aimed at acquiring knowledge and skills to improve themselves, their learning methods, and their learning environments (Pintrich & Zusho, 2007; Zimmerman, 2015). The first phase is the activation phase, which mainly transpires before the students' learning takes place. This phase prepares students to begin their learning and involves activities such as planning, goal setting, and galvanising perceptions of the self, task, and context. When learning actually begins, the second phase, namely the monitoring phase, serves a phase of awareness of the self, task, and context. This second phase shapes the third phase, which is the regulation phase. This phase includes strategies that help students learn and progress in their educational tasks. Finally, in the fourth phase, which is the reflection phase, students use strategies to look back upon the self, task, and context and decide on future behaviours and engagement (Pintrich, 2004; Pintrich & Zusho, 2007).

The level of self-regulation can be interpreted from a quantitative or qualitative point of view. Quantitatively, SRL is interpreted in light of its frequency as 'more is better' and refers to the amount of SRL or strategies used (e.g., Wormington, Henderlong Corpus, & Anderson, 2012). For example, Dörrenbacher and Perels (2016) and Abar and Loken (2010) have identified several SRL profiles (see Table 1) representing high, average, or low scores on all SRL subscales. These SRL scores can be interpreted as frequent, moderate, and seldom occurrences of SRL. However, while knowing how often students engage in SRL strategies is relevant and interesting, it is more important to gain insights into how the strategies are performed and, ultimately, if they are effective for the learning processes of students as indicated by the quality of SRL. An example of qualitative profiles is provided in the study of Ning and Downing (2015), who have found a cognitively oriented SRL profile and a behaviourally oriented SRL profile (see Table 1), both of which represent two types of SRL performance. Several other studies have determined that the use of some self-regulation strategies significantly influences students' academic achievements (e.g., Azevedo & Aleven, 2013; Dörrenbacher & Perels, 2016; Zimmerman & Martinez-Pons, 1986); thus, the qualitative view on SRL can inform teachers about the usefulness of certain SRL strategies for fostering the students' learning process. For example, using mastery or performance-approach self-talk as a motivational strategy (Schwinger & Stiensmeiser-Pelster, 2012), peer-learning strategies (Broadbent & Poon, 2015), help-seeking strategies (Sun, Xie, & Anderman, 2018) or, time and effort regulation strategies (Broadbent, 2017) is proven to have a positive effect on academic achievements.

Previous research on SRL profiles has mainly concentrated on university or college students in traditional face-to-face contexts (e.g., Dörrenbacher & Perels, 2016; Ning & Downing, 2015), with the exception of Barnard-Brak et al. (2010), who have focused on online students. Table 1 provides an overview of the SRL profiles found in these studies, all of which identify at least one high and one low SRL profile. Both Barnard-Brak et al. (2010) and Dörrenbacher and Perels (2016) have discovered an additional profile that was characterised with SRL scores between the high and low SRL profile scores. The other profiles had complex features or lent themselves to a specific aspect of SRL.

The profile with moderate scores on the SRL subscales included the most students in Barnard-Brak et al. (2010) and Dörrenbacher and Perels (2016) studies: 39% and 41% of the studies' samples, respectively. In Ning and Downing's (2015) study, the largest profile was the one with minimal self-regulators (31.9%). All of the studies demonstrate that higher SRL is positively associated with the academic achievements of students, and vice versa. In addition, in Barnard-Brak, Lan, and Paton's (2010) study, their 'super' and 'competent' SRL profiles did not differ from each other regarding the grade point average of students.

Despite these previous studies, there is a lack of research focusing on blended adult education. In this study, blended adult education is

Table 1
Overview of existing research on SRL profiles.

Profiles	Explanation	Studies
High SRL profile	Students who scored high on all SRL subscales.	Dörrenbacher & Perels, 2016; Ning & Downing, 2015; Barnard-Brak et al., 2010; Abar & Loken, 2010
Non- or minimal SRL profile	Students who scored low on all SRL subscales.	Dörrenbacher & Perels, 2016; Ning & Downing, 2015; Barnard-Brak et al., 2010; Abar and Loken (2010)
Average SRL profile	Students with SRL scores that were higher than the scores of the minimal SRL profile but lower than the high SRL profile.	Barnard-Brak et al., 2010; Dörrenbacher & Perels, 2016; Abar and Loken (2010)
Conflicting SRL profile	Students who scored low on time planning, procrastination (reverse coded) and self-evaluation but moderate on all other SRL subscales.	Dörrenbacher and Perels (2016)
Forethought-endorsing SRL profile	Students who scored higher on self-regulation strategies used in the proactive sense (e.g. goal setting and environment structuring) but scored lower on SRL strategies that came after the forethought phase (e.g. help-seeking, self-evaluation or time management).	Barnard-Brak et al. (2010)
Performance/reflection SRL profile	Students who scored higher on follow-up SRL strategies (e.g. help-seeking, self-evaluation and time management) but lower on proactive strategies (e.g. goal setting and environment structuring).	Barnard-Brak et al. (2010)
Cognitive-oriented self-regulated profile	Students who scored high on cognitive and metacognitive strategies but lower on behavioural strategies.	Ning and Downing (2015)
Behavioural-oriented self-regulated profile	Students who scored average and moderately high on subscales of behavioural strategies.	Ning and Downing (2015)

Table 2
Overview of studies regarding the relationship between background characteristics or achievement motivation and the use of SRL strategies.

Variable	Relationships	Example studies
Perceptions of task value	There seemed to be an association between the value that students attributed to their tasks or education and the extent to which they used SRL strategies.	Neuville, Frenay & Bourgeois, 2017; Pintrich & De Groot, 1990; Pintrich & Schrauben, 1992
Age	Older students seemed to show more SRL skills except for help-seeking.	Kizilcec et al. (2017)
Gender	Women seemed to use fewer strategies relating to strategic planning, elaboration and self-evaluation but reported higher levels of goal setting, task strategies and, in particular, help-seeking.	Kizilcec et al. (2017)
	No significant effect	Basol and Balgalmis (2016)
Prior educational level	Those with a bachelor scored lower in the use of strategies regarding strategic planning, self-evaluation and help-seeking in contrast to students with a degree lower than a bachelor. Students with a master's or PhD degree scored higher than students with a degree lower than a bachelor on goal setting, strategic planning and task strategies. As expected, students with a PhD reported stronger SRL skills but did not frequently seek help.	Kizilcec et al., 2017; Basol & Balgalmis, 2016
Occupation	Full-time students had lower SRL, especially for self-evaluation and task strategies. Working students were more engaged in goal setting, strategic planning and help-seeking but did not use many self-evaluation strategies.	Kizilcec et al. (2017)

conceptualised as education that is not provided by universities or colleges but by centres for adult education that organise their courses as a combination of face-to-face education in a classroom and online education at home. Thus, because blended learning environments are partly online, students are supposed to have 'regular' and 'online' self-regulation. The knowledge base regarding online self-regulation is still small. To the best of our knowledge, only Barnard, Lan, To, Osland Paton, and Lai (2009) have conducted a study in which they developed the Online Self-Regulated Learning Questionnaire (OSLQ) to specifically measure online SRL. Given the context specificity of SRL (Diseth, 2007; Schunk, 2001), studies outside the context of blended learning are not informative in describing online self-regulation. Broadbent (2017) has even found differences in the use of SRL strategies between students in an online environment and students in a blended environment. For instance, online students used more critical thinking and rehearsal strategies, while blended students use more help-seeking strategies. Because of these environmental influences, Barnard-Brak et al. (2010) have stated that replication of the research on SRL profiles in different contexts is needed.

2.2. Achievement motivation

To be a self-regulating student, individuals require both the skill and the will (Woolfolk, Winne, & Perry, 2000), meaning that without motivation to optimise and use SRL skills, education cannot be as effective (Dörrenbacher & Perels, 2016; Schwinger & Stiensmeiser-Pelster, 2012). Motivation – seen as the motor of students' engagement, effort, and persistence (Dörnyei & Ushioda, 2011; Jacot, Raemdonck, & Frenay, 2015) – has been operationalised in the literature in different ways, including the motivation to enrol (prior to the start of a training) (Carré, 2000; Deci & Ryan, 2000) or the motivation during the learning process that acts as a driver to continue one's education or achieve one's goals (Wigfield & Eccles, 2000). Since the focus of the current study is on profiling students according to their use of SRL strategies during the learning process, motivation during the learning process (i.e., achievement motivation) was used. Achievement motivation can be defined as the particular personal aspirations and goals of students that make them feel a need to achieve. These personal reasons provide the energy to persist and perform and in this way affect the students' learning behaviours. Achievement motivation can explain the students' task choices, persistence, and vigour in performing tasks (Eccles, Wigfield, & Schiefele, 1998). Wigfield and Eccles (2000) have developed the expectancy-value theory, which conceptualises achievement motivation as the students' expectations of success and values attributed to their blended learning education (Wigfield, 1994). This theory is applied to younger children in education in particular, but Bourgeois, de Viron, Nils, Traversa, and Vertongen (2009) have validated this theory and demonstrated its relevance for adult education. While expectations of success measure a future aspect, namely the probability in succeeding at a task by considering gains and losses (Eccles & Wigfield, 2002), ability beliefs measure the present beliefs about how well one will do on upcoming tasks. These ability beliefs are reflected in the self-efficacy concept of Bandura (1986), which is defined as 'people's judgements of their capabilities to organise and execute courses of action required to attain designated types of performances' (Bandura, 1986, p. 391). It is still unclear how self-efficacy as described by Bandura and outcome expectancy from the expectancy-value theory relate (Williams, 2010), but Bandura (1997) has argued that self-efficacy is more strongly predictive than is outcome expectancy (Kochoian, Raemdonck, Frenay, & Zacher, 2016). Furthermore, the value component of achievement motivation consists of (1) attainment value, which reflects the importance for the students of doing well at a task that allows positive enhancement of their self-concept (Jacot et al., 2015); (2) utility value, which refers to the usefulness or relevance of the task; and (3) intrinsic value, which indicates the students' enjoyment of or interest in the task (Wigfield & Eccles, 2000). Higher expectancy and values of students are associated with higher motivation to achieve (Shechter, Durik, Miyamoto, & Harackiewicz, 2011).

2.3. The link between motivation, background characteristics, and self-regulation

Achievement motivation has been shown to be a variable that significantly relates to SRL (Zusho & Edwards, 2011). For example, Barnard-Brak et al. (2010) have stated that people with higher self-efficacy beliefs more frequently enrol in autonomous environments such as blended environments that require SRL skills, because these students are more confident in themselves. However, Dunlosky and Rawson (2012) have contradicted this conclusion by stating that high self-efficacy may be an overestimation by students and could be accompanied by low SRL skills, which relate to underachievement. Overall, SRL students are associated with diverse motivational characteristics such as high self-efficacy beliefs (Zimmerman, 2015).

Regarding the subjective task value aspect of achievement motivation, Neuville, Frenay, and Bourgeois (2007) found in their study of university students that perceptions of task value played a crucial role in the SRL of students (see Table 2). The diverse studies of Pintrich are in line with this conclusion and state that motivational variables are supportive for the use of SRL strategies (e.g., Pintrich & De Groot, 1990; Pintrich & Schrauben, 1992).

In sum, students' achievement motivation and their self-regulation seem to be related (Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). This finding implies that students' level of achievement motivation could indicate the amount and kind of attention and support required. Previous studies (e.g., Authors, 2018; Carré, 2000) have already demonstrated that adults have diverse goals and reasons, and thus motivations, for beginning their education, which suggests that achievement motivations and use of SRL strategies are also diverse (Authors, 2018b; Barnard-Brak et al., 2010). This thought confirms the diversity amongst adult students in two critical aspects of success in blended education – namely achievement motivation and SRL – and also indicates the relevance of exploring the extent to which diverse achievement motivations predict the SRL of adult students in blended environments.

Furthermore, the heterogeneity of adult students makes it interesting and necessary to explore the differences in SRL regarding diverse student background characteristics. Due to their previous life, work, and educational experiences, adults seem to be self-directed and independent and thus able to learn in autonomous environments (Knowles, Holton, & Swanson, 2005). Table 2 provides an overview of some previous studies' findings regarding the differences in SRL strategy use across background characteristics. Kizilcec, Pérez-Sanagustín, and Maldonado (2017) conducted a study among students in massive open online courses and found differences in SRL use related to students' ages, genders, prior educational levels, and occupations. These kinds of results are scarce and because these previous studies were conducted in the context of fully online education, they encourage replication for studies in blended adult education, where research of both online and face-to-face SRL is needed.

3. Present research

Overall, our literature review clarifies that, since blended learning environments provide less social pressure, support, and structure to students in comparison with traditional face-to-face education (Wolters, Pintrich, & Karabenick, 2005), students are required to be autonomous in order to self-regulate (Ally, 2004; Woolfolk et al., 2000). According to this, SRL is especially important in blended learning environments, which requires teachers to gain insight into their students' SRL skills to be able to adapt their teaching methods and materials to provide students with tailored support (Dörrenbacher & Perels, 2016; Ning & Downing, 2015). Person-centred research that helps to develop homogeneous groups of students makes it easier for teachers to create supportive online and face-to-face environments that better address students' needs. Therefore, the first research question for the present study is '*What profiles can be identified for adult students in blended environments that are based on students' use of self-regulation strategies?*'. Considering previous research that has established the existence of multiple SRL profiles (e.g., Barnard-Brak et al., 2010; Dörrenbacher & Perels, 2016), we expect to find at least one profile with high scores for SRL and one profile with low scores for SRL.

Given the many studies that have demonstrated a link between achievement motivation and SRL (e.g., Neuville et al., 2007; Pintrich & Schrauben, 1992) and the evidence that individual differences create diversity in SRL (Barnard-Brak et al., 2010), the present study examines the effects of achievement motivation and personal background characteristics (e.g., gender, marital status, highest obtained degree, current educational level, and hours of work) on SRL strategy use. More specifically, the second research question that is explored is '*To what extent do achievement motivation and personal background characteristics of adult students in blended learning environments predict their SRL profile membership?*' Regarding achievement motivation, it is postulated that students with higher achievement motivations, which are indicated by high self-efficacy and high values attributed to their education, will have a profile with high SRL scores.

4. Methods

4.1. Context, participants, and procedure

In Flanders, the Dutch-speaking part of Belgium, there is a wide range of courses that are considered blended. Blended courses can differ from 5% online distance moments to 95% online distance moments supplemented with face-to-face, in-class moments. For the current study, participants were gathered by contacting all centres for adult education (CAEs) in Flanders, Belgium that provide some form of blended course. The institutions were asked to engage in the research, resulting in nine different CAEs that were willing to participate and numerous courses with different kinds of blends. We invited the participating CAEs to share a link to an online survey with students from all of their blended courses and, if possible, to provide time in class to fill in the survey together to ensure the certainty of the data. Before beginning the survey, students viewed an information page with a box at the bottom that they had to check if they agreed to voluntarily participate in the study. Making questions about personal information nonobligatory provided anonymity. This data gathering approach resulted in 349 adult student participants, of whom 213 completed the survey in its entirety. Since it is not possible to have exact information about the total population of students in a blended course in a CAE in Flanders, or about the total number of adult students who received (and saw) the invitation to the survey, no response rate can be presented. Of the 213 participating adults, 30% were men and 70% were women, with a mean age of 31.31 and a range between 18 and 56. Almost half of the students were unemployed (47.4%). Of the working students, the majority worked full-time (34.7%), and 17.8% had a part-time job. Most of the students lived with their partners and children (32.9%) or with their parents (24.9%). Others lived alone (14.6%), were single parents (6.1%), lived with their partners without children (19.2%), or cohabitated with others who were not their partner or parents (1.9%). Regarding the participants prior educational levels, 28.2% of students had a degree lower than secondary education, 22.5% had a secondary degree, and 49.3% had a higher educational degree. For current education, 46.9% were enrolled in a blended course in teacher education, 14.6% were in higher vocational adult education, 29.6% were in secondary adult education, and 8.9% were in Dutch-as-a-second-language education.

4.2. Instruments

An online survey was distributed to gather information on students' background characteristics, achievement motivation (self-efficacy and value), and online self-regulation. For background characteristics, the following variables were used: (1) gender (male or female), (2) age, (3) marital status (living alone without children, living alone with children, married or living together with partner without children, married or living together with partner with children, and living with parents or co-housing with friends or strangers), (4) highest educational level (lower than secondary education, secondary education, or higher than secondary education), (5) current educational level (Dutch as a second language, secondary adult education, higher vocational adult education, or teacher education), and (6) work status (unemployed, part-time, or full-time). Table 3 provides an overview of the different scales used to measure achievement motivation and online self-regulation. All scales were chosen because of their ability to sufficiently represent and measure the constructs in self-paced, online contexts and because there is evidence of their reliability and validity. For online self-regulation, we used Barnard et al.'s (2009) OSLQ because this is the only existing scale that has been designed for use in online learning. Barnard, Lan, To, Paton, and Lai (2009) have used this scale with a sample of 434 university students in blended education. Comparing the SRL subscales measured by the OSLQ with the four SRL phases proposed by Pintrich and Zusho (2007) (see Section 2.1), we concluded that the OSLQ covers

Table 3
Used scales to measure achievement motivation and online self-regulation.

Variable	Subscale (phase)	Amount of items + example	Cronbach's alpha
Achievement motivation	Self-efficacy[1]	5 items: "I can learn in distance moments without the presence of an instructor to assist me"	α = .774
	Attainment value[2]	4 items: "Blended learning will make me a more knowledgeable person"	α = .819
	Utility value[2]	3 items: "Being successful in blended education is useful for my promotion"	α = .853
	Intrinsic value[2]	3 items: "Blended education is interesting"	α = .935
Online SRL	Environment structuring[3] (Regulation)	4 items: "I know where I can study most efficiently for online courses"	α = .866
	task strategies[3] (Regulation)	4 items: "I read aloud online materials to fight against distractions"	α = .663
	time management[3] (Activation & Regulation)	4 items: "I allocate extra studying time for online courses because I know it is time-demanding"	α = .766
	help seeking[3] (Regulation)	4 items: "If needed, I try to meet my classmates face-to-face"	α = .592
	self-evaluation[3] (Monitoring)	4 items: "I summarise my learning in online courses to examine my understanding of what I have learned"	α = .745
	goal setting[3] (Activation)	6 items: "I set short time goals"	α = .810

Note: [1]measured by a scale of Artino and McCoach (2007), p. [2] measured by a scale of Chiu and Wang (2008); [3]measured by the OSLQ of Barnard et al. (2009).

all phases except the reflection phase (Jansen, van Leeuwen, Janssen, Kester, & Kalz, 2017). Upon examining the items measuring the time management scale, the scale seems to fit both the activation (e.g., making time schedules) and the regulation phase (e.g. allocating extra time). For self-efficacy, we used the measure reported by Artino and McCoach (2007), who developed and validated a self-reported measure of self-efficacy for learning within a self-paced, online learning context with 204 military and civilian adults. The items of the scale were adjusted slightly to measure the self-efficacy to learn during distance moments by replacing 'self-paced, online course' with 'distance moments'. Regarding the values, we used the scale presented by Chiu and Wang (2008) because it was developed on the basis of the prominent expectancy-value theory in the context of education (e.g., Battle & Wigfield, 2003; Eccles, 1984). This scale was validated in a web-based learning environment with 286 students who were enrolled in a web-based university course in Taiwan. The wording was slightly adjusted by changing 'web-based learning' into 'blended learning'. Finally, as suggested by Dörrenbacher and Perels (2016), all items were measured on a seven-point Likert scale ranging from one (*totally disagree*) to seven (*totally agree*) to provide detailed insights.

4.3. Data analysis

First, we established measurement models of key constructs by using confirmatory factor analysis. This step was necessary to ensure that subscale scores within the SRL framework could be distinguished and thus reported separately. In addition to SRL, the measurement model for achievement motivation – a possible key predictor of SRL profiles – was examined. To ensure that measurement models were appropriate, we tested the model fit by using several fit statistics. These statistics included the root mean square error of qpproximation (RMSEA), the standardized root mean square residual (SRMR), the Tucker-Lewis index (TLI), and the comparative fit index (CFI). The model fit was considered appropriate if the following criteria were met (Iacobucci, 2010): for the CFI and TLI, values close to or higher than 0.95 were preferred but values starting from 0.90 were considered acceptable; for the RMSEA and SRMR, values were preferably as low as possible but were considered acceptable below .08. However, we noticed that these guidelines could not be treated as strict rules due to their dependence on the complexity of the measurement models, the treatment of variables, and the number of factors (Marsh, Hau, & Wen, 2004).

Second, to group individuals into homogenous profiles with regard to their SRL, we performed latent profile analysis (LPA) (Vermunt & Magidson, 2002). Because the number of expected profiles was unknown, we conducted an exploratory analysis by investigating models for one to seven profiles. To obtain stable solutions, the variances were constrained to be equal across clusters (Scherer, Rohatgi, & Hatlevik, 2017). Using the statistical software MPlus7 (Muthén & Muthén, 2012), we generated several model fit criteria to help decide which latent profile model best fit the data. More specifically, the Bayesian information criterion (BIC) and akaike information Criterion (AIC) were checked, and smaller values for the BIC and AIC indicated a better model fit (Akaike, 1974; Schwarz, 1978). Furthermore, a significant *p*-value for the Lo-Mendell-Rubin likelihood ratio test implied that the k-profile model fit better than the model with k-1 profiles (Lo, Mendell, & Rubin, 2001). Next, the entropy was examined, which indicated the clear delineation of clusters. The entropy should have been as high as possible, with values larger than 0.70 already indicating an acceptable classification accuracy (Jung & Wickrama, 2008). Finally, the sizes of the profiles (profiles with less than 5% of the sample were not good) and their interpretability were used as further selection criteria (Marsh, Lüdtke, Trautwein, & Morin, 2009).

Third, multinomial logistic regression was conducted by using the profile membership as a dependent variable and achievement motivation and background characteristics as possible predictor variables. This activity was done to explore the predictive effects of achievement motivation and background characteristics for the SRL profiles.

5. Results

5.1. Measurement models

The model fit for the original online self-regulation learning scale was not satisfactory (RMSEA = 0.072; SRMR = 0.099; CFI = 0.821 and TLI = 0.795). After checking the modification indexes, the description of the items, and the factor loadings, which indicated a low factor loading for Item 6 of the subscale of goal setting and a large gap between the first two and last two items of the subscale of self-evaluation, the decision was made to delete Item 6 from the subscale of goal setting and split the self-evaluation subscale into two different subscales. Those two subscales were self-evaluation using peers (e.g., 'I discuss with my peers to see if what I learn differs from what they learn') and self-evaluation using strategies (e.g., 'I summarise what I have learned in online moments to check if I understand the content'). The Satorra-Bentler corrected chi-square difference test indicated that the model with two self-evaluation subscales fit the data significantly better than the model with only one self-evaluation subscale: SB-$\chi^2(30) = 233.899$, $p < .001$. Overall, the final model with seven subscales demonstrated an acceptable model fit: RMSEA = 0.047, SRMR = 0.060, CFI = 0.926, TLI = 0.913.

The original model for achievement motivation was satisfactory (RMSEA = 0.069, SRMR = 0.069, CFI = 0.937, TLI = 0.922), but the factor loadings were low for Items 1 and 5 of the subscale of self-efficacy. After checking the modification indexes and the description of the items in the subscale of self-efficacy, Item 1 was deleted and the model

Table 4
Means, standard deviations, and correlations of variables measuring online self-regulation and achievement motivation.

	1	2	3	4	5	6	7	8	9	10	11
1. Environment structuring	–	.33**	.54**	.30**	.44**	.45**	.14*	.19*	.41**	.45**	.27**
2. Task strategies		–	.56**	.22**	.34**	.38**	.12	-.12	.17*	.32**	.33**
3. Time management			–	.41**	.53**	.47**	.26**	-.03	.34**	.43**	.45**
4. Help-seeking				–	.35**	.45**	.65**	.08	.29**	.24**	.32**
5. Goal setting					–	.52**	.28**	.17*	.42**	.47**	.41**
6. Self-evaluation through strategies						–	.36**	.15*	.31**	.29**	.24**
7. Self-evaluation through peers							–	-.05	.15*	.19**	.29**
8. Self-efficacy								–	.38**	.20**	-.08
9. Interest value									–	.59**	.43**
10. Attainment value										–	.50**
11. Utility value											–
M	5.47	3.60	3.87	4.03	4.43	4.31	3.88	5.03	5.25	4.96	4.34
SD	1.13	1.25	1.35	1.17	1.20	1.50	1.68	1.22	1.35	1.08	1.57

Note. M = means; SD = Standard Deviation * $p < .05$; ** $p < .01$.

was tested again. This model fit improved some fit indices marginally (RMSEA = 0.073, SRMR = 0.059, CFI = 0.938, TLI = 0.920) and we decided to retain this model. Thus, the final model of achievement motivation consisted of four subscales, namely self-efficacy and attainment value with four items each and interest and utility value with three items each.

5.2. Descriptive statistics

Table 4 summarises the means, standard deviations, and correlations of the variables used. In particular, the subscales of achievement motivation and more specifically self-efficacy, interest, and attainment value, have tendencies towards high means. For online self-efficacy, the subscale environment structuring has the highest mean, while the subscales of task strategies, time management, and self-evaluation through peers have the lowest mean scores. All standard deviations are rather small, but the two subscales of self-evaluation and utility value show the highest range of values. The correlation matrix of the variables measuring students' SRL and achievement motivation demonstrates mainly weak (r = between 0.1 and 0.3) and moderate correlations (r = between 0.3 and 0.5). The correlations suggest that the SRL-related variables (1–7) are closely related to each other, and the same applies to the achievement motivation-related variables (8–11). Furthermore, the correlations suggest that there is an association between the SRL variables and the achievement motivation variables, especially the value (attainment, utility, and intrinsic) subscales. Table 4 presents the general correlational relationship among the variables.

5.3. Self-regulated learning profiles

To answer the first research question regarding the identification of SRL profiles, fit indices and criteria are used for the selection of the model with the optimal number of clusters (see Table 5). The Lo-Mendell-Ruben likelihood-ratio test indicates that the three-profile model ($p < .05$) fits the data better than the model with two profiles. Furthermore, the AIC and BIC are the lowest for the three-profiles model (AIC = 4712.64 and BIC = 4813.48), but entropy is highest for the two-profiles model (0.80). Furthermore, examining the cluster sample sizes and the theoretical interpretability of the clusters suggests that the three-profile model is optimal.

Table 5
Fit indices for different models with number of clusters ranging from 1 to 7.

Clusters	# of free parameters	BIC	AIC	Entropy	LMR-LRT
1	14	5115.59	5068.53	/	/
2	22	4876.00	4802.05	.80	p < .05
3	30	4813.48	4712.64	.79	p < .05
4	38	4807.00	4679.27	.81	p = .12
5	46	4797.66	4643.04	.82	p = .21
6	54	4804.10	4622.59	.85	p = . 75
7	62	4807.73	4599.33	.84	p = .14

The labelling of the profiles is based on the terminology of previous studies on SRL profiles (e.g., Abar & Loken, 2010). Fig. 1 shows the different profiles and their means for each self-regulation subscale. The first profile is called the 'low SRL profile' ($n = 34$), and students in this profile have the lowest scores for all subscales of online SRL. The opposite profile, namely the profile in which students score highest for all subscales of online SRL is called the 'high SRL profile' ($n = 53$). The third profile includes the most students ($n = 126$) and is called the 'average SRL profile'. Students in this profile are characterised by moderate scores on all online self-regulation subscales. When comparing the different profiles in terms of the trend in the scores for the various subscales, the high SRL profile shows a greater amount of time management in comparison to the other SRL subscales, while the low SRL profile demonstrates a low amount of time management. Furthermore, the amount of help-seeking is higher in the low SRL profile and lower in the high SRL profile compared to other SRL subscales. Finally, regarding self-evaluation, the results indicate that students with a low SRL profile evaluate themselves almost equally with the use of strategies as by involving peers. Students with average and high SRL profiles use more strategies to evaluate themselves than they use peers.

To further substantiate the significant differences in the means of the seven variables across profiles, a one-way MANOVA is used with all SRL variables as outcomes and the profile membership as the grouping variable. Based on Wilks' statistic, there is a significant effect of profile membership on the SRL of students: $\Lambda = .186$, partial-$\eta^2 = 0.569$, $F(14, 408) = 38.416$, $p < .01$. Tukey's HSD post-hoc tests suggests mean differences across all profiles in all SRL subscales (see Table 6).

A replication of the LPA with 10 randomly drawn samples of 150 participants reveals that only three samples could replicate the decision for three profiles. This observation testifies to the strong sample dependence of latent profiles (e.g., Meyer & Morin, 2016). Besides, the existence of different profiles for subgroups of students in our sample could also have been due to possible 'hidden' subgroups in the sample, which can be identified using background characteristics or contextual information to supplement the LPA. Therefore, achievement motivation and multiple background variables were included in the next step of the current study as possible predictors of the profile membership.

5.4. Predicting SRL profile membership

A multinomial logistic regression is conducted with self-efficacy and attainment, interest, and utility value as possible achievement motivational predictors of profile membership as well as age, gender, marital status, highest obtained degree, hours of work and current educational level as possible background characteristic predictors of profile

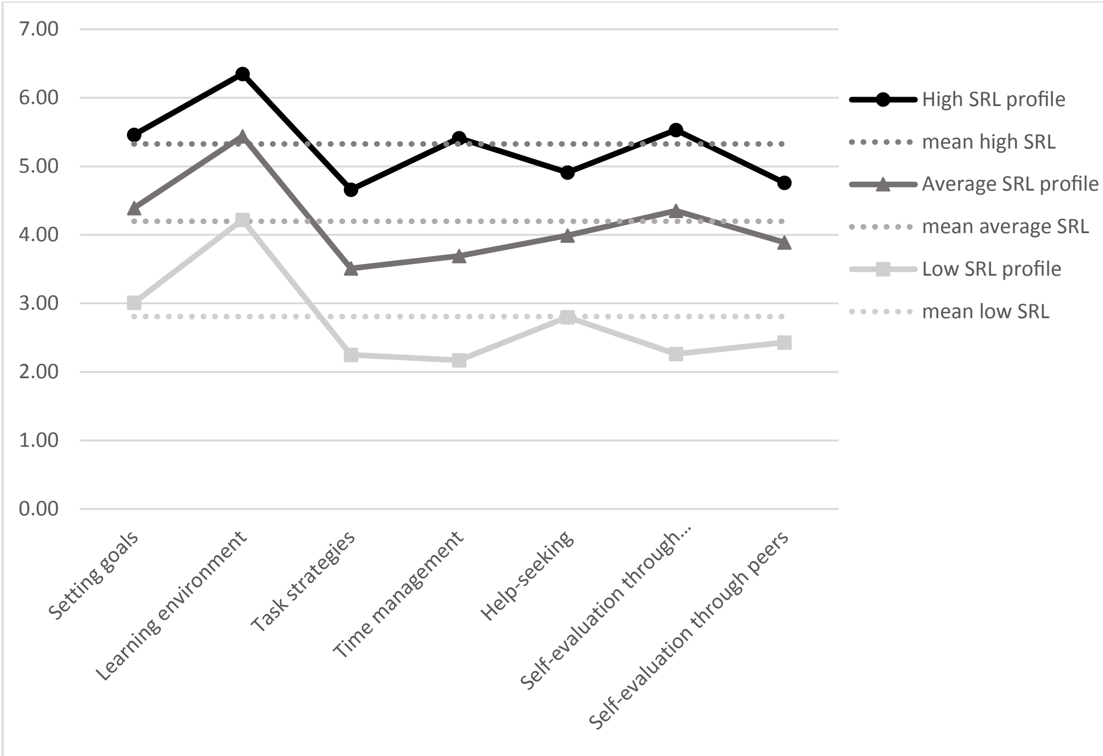

Fig. 1. SRL profiles of adult students in blended environments.

Table 6
Tukey HSD post hoc comparisons among the three profiles.

	Low SRL profile	Average SRL profile	High SRL profile
Variable	M (SD)	M (SD)	M (SD)
Setting goals	3.01 (.99)$_a$	4.39 (.88)$_b$	5.46 (.99)$_c$
Learning environment	4.22 (1.32) $_a$	5.44 (.88) $_b$	6.35 (.67) $_c$
Task strategies	2.25 (.84) $_a$	3.51 (.97) $_b$	4.66 (1.16) $_c$
Time management	2.17 (.67) $_a$	3.69 (.94) $_b$	5.41 (.79) $_c$
Help-seeking	2.80 (1.06) $_a$	3.99 (.93) $_b$	4.91 (1.02) $_c$
Self-evaluation through strategies	2.26 (1.24) $_a$	4.35 (1.10) $_b$	5.53 (1.03) $_c$
Self-evaluation through peers	2.43 (1.19) $_a$	3.89 (1.57) $_b$	4.76 (1.61) $_c$

Note: Means in the same row with different subscripts differ significantly at $p < .001$.

membership. This analysis are conducted to answer Research Question 2, which explores the extent to which achievement motivation and personal background characteristics of adult students predict their profile membership. The high SRL profile is used as the reference category. First, the likelihood of membership in the low SRL profile is compared to the membership in the high SRL profile. As shown in Table 7, negative significant effects are found for attainment value ($p < .01$; OR = 0.34) and utility value ($p < .01$; OR = 0.56). More specifically, as indicated by the odds ratios, membership in the low SRL profile is .34 and .56 times less likely for every one-unit increase in the attainment or utility value of students respectively. Second, comparison between the average SRL profile and the high SRL profile indicates that only the attainment value has a negative significant effect ($p < .05$; OR = 0.60). This indicates that when the attainment value of students increases by one, being a member of the average SRL profile is .60 times less likely than being a member of the high SRL profile. No significant

Table 7
Multinomial logistic regression results predicting profile membership.

		Low SRL profile vs. high SRL profile				Average SRL profile vs. high SRL profile			
			95% CI for Odds Ratio				95% CI for Odds Ratio		
		B (SE)	OR	Lower	Upper	B (SE)	OR	Lower	Upper
Background characteristics	Age	-.03 (.03)	.97	.92	1.02	-.04 (.02)	.96	.93	1.00
	Gender	.33 (.70)	1.39	.44	4.42	-.12 (.49)	.89	.40	1.98
	Marital status	.17 (.24)	1.18	.80	1.75	-.01 (.16)	.99	.76	1.27
	Highest educational degree	-.23 (.66)	.79	.27	2.33	.04 (.32)	1.04	.61	1.76
	Hours of work	1.80 (.97)	6.03	1.22	29.86	.70 (.60)	2.01	.75	5.39
	Current educational level	.77 (.56)	2.15	.85	5.42	.38 (.28)	1.46	.92	2.33
Achievement motivation	Self-efficacy	-.20 (.31)	.82	.49	1.36	-.25 (.20)	.78	.56	1.09
	Attainment value	−1.08 (.35)**	.34	.19	.61	-.51 (.25)*	.60	.40	.90
	Utility value	-.58 (.20)**	.56	.40	.78	-.18 (.13)	.84	.67	1.04
	Interest value	-.45 (.33)	.64	.37	1.10	-.37 (.26)	.70	.46	1.07

Note: *p < .05; **p < .01; reference category for gender is 'female'; for marital status is 'co-housing with friends or strangers'; for highest educational degree is 'higher than secondary education'; for hours of work is 'full-time'; for current educational level is 'teacher education'.

effects of any of the background characteristics, self-efficacy, or interest values on the profile membership of students were detected.

6. Discussion

The current study was intended to generate more information about adult students' SRL in blended courses, focusing on the online distance part of the blended-learning approach. Below, we first discuss the online SRL profiles that students represent when using technology to learn in their self-paced, online environments (RQ1). The impacts of self-efficacy and value on the online SRL profile membership of students are then discussed (RQ2). In this part, both students' self-efficacy to specifically learn in a self-paced, online environment and the value that students attribute to learning in a blended learning environment are used to discuss the concept of technology in education. We further discuss limitations and suggestions for future research, and conclude the discussion with practical implications regarding the use of blended learning environments and the accompanying technology to impact the students' learning and self-regulation. Following a person-centred approach, the present study sought to identify SRL profiles of blended adult students (RQ1) and explore the predictive effect of achievement motivation and student background characteristics on SRL profile membership (RQ2).

6.1. Self-regulation profiles (RQ1)

As expected, results of the LPA demonstrated the existence of at least two profiles which are called the high SRL profile and the low SRL profile. In addition, similar to the study by Abar and Loken (2010), the results identified a third SRL profile for students who scored higher than the low SRL profile on SRL strategy use but lower than the high SRL profile. We called this the average SRL profile, which applied to the most students and is comparable to the results of the studies of Barnard-Brak et al. (2010) and Abar and Loken (2010). These profiles mostly inform us about the quantity of the SRL strategy use of adult students, which refers to the amount of occurrences of a certain SRL strategy (e.g., Wormington, Henderlong Corpus, & Anderson, 2010). Applied to the current research, the profiles represent a high, average and low quantity of SRL strategy use (Abar & Loken, 2010). Since the least optimal profile, namely the low SRL profile, included the smallest number of students, the results are considered positive for blended adult education. This conclusion is in contrast with, for example, the study by Ning and Downing (2015), who developed SRL profiles with 828 final-year students in a university in Hong Kong where they found that the low SRL profile was the profile of most students. In this way, the present study disputes the statement of Lin and Huang (2013) that students have deficits in SRL and instead considers the present sample of adult students to be (relatively) high self-regulators.

These diverse profiles in SRL make it clear that adaptive learning environments, which try to meet students' needs by adjusting the presentation of educational material by using computers, are required. The profiles provide a starting point upon which this adaptive learning environment could be based (Özyurt & Özyurt, 2015). More specifically, while several authors (e.g., Dörrenbacher & Perels, 2016; Smit, de Brabander, Boekaerts, & Martens, 2017) have stated that SRL can be trained and supported, integrating online scaffolds into the adaptive learning environment would be beneficial for students' learning process. However, more information is needed to know which specific scaffolds to provide. A more in-depth look at the profiles indicated that the profiles differ from each other significantly regarding all subscales of SRL. When considering the overall mean SRL score for each profile, it is clear that all profiles scored higher than their mean on the subscales of goal setting and environment structuring. The latter seems logical since students in blended environments are pushed into finding a study area because they can learn partly outside the classroom in a self-chosen environment. However, the Authors (2018) found that blended adult learners mostly talked about the physical environment that they regulated. While blended learning environments provided students with the opportunity to regulate their blended context, they did not discuss regulating their online contexts during distance moments. Nevertheless, there are applications for adaptive media that could allow students to regulate their online contexts to their needs and desires (Truong, 2016). Furthermore, the finding that students of all three profiles used numerous goal setting strategies is positive since several authors have stated that setting goals positively relates to academic achievement (Lazowski & Hulleman, 2016; Schwinger & Otterpohl, 2017). For adults, setting goals is necessary because they mostly have busy life schedules related to their jobs, families, and other responsibilities in addition to education. Furthermore, the results indicate that for time management, only the high SRL profile students scored higher than their overall SRL mean. The statement by Abar and Loken (2010) that students with high SRL tend to study more material for a longer time than do students with less SRL could be a reason why individuals with a high SRL profile have a higher need to manage their time. The average and low SRL profiles used fewer time management strategies in comparison to their overall mean SRL, which could cause problems regarding goal achievement. In the autonomous environment of blended education in particular, students need to plan, manage, and control their time to meet their deadlines (Authors, 2018b). As the results of the current study suggest, the average and low SRL profile students tend to seek more help. This could be related to poorer time management, causing them to need help. Those with a low SRL profile, and to a lesser extent those with an average SRL profile, used help-seeking strategies in particular more than other SRL strategy subscales. This result demonstrates that students in the low SRL profile are more dependent on peers and teachers during their distance learning moments, which is reflected in the two self-evaluation subscales. In that area, students with a low SRL profile indicated using their peers more to evaluate themselves, while the average and especially the high SRL profile were more autonomous and independent students who evaluated themselves by using strategies. In terms of adaptive learning environments, the low SRL students would be best supported by integrating applications for intelligent tutor systems (Truong, 2016).

The findings of this part of the study indicate that students with a high SRL profile are better suited to blended learning environments where interaction with peers and teachers is more challenging (Authors, 2018b). Students in the average SRL profile are also suited for blended learning environments but will only do what is required to succeed.

6.2. Predictive role of achievement motivation and background characteristics (RQ2)

The focus on students is important in adjusting blended learning environments to make them more adaptive to the personal needs of individuals (Vandewaetere, Desmet, & Clarebout, 2011). More specifically, the achievement motivation of students is considered a crucial characteristic for developing adaptive instruction (Park & Lee, 2003). Results from the current study regarding the achievement motivation of blended adult students correspond to the study of Ning and Downing (2015) in that students with a high SRL profile have the highest achievement motivation. More specifically, attainment and utility value are predictive of the profile membership of students. These results indicate that the higher the attainment value of the students, the greater the chance that they are members of the high SRL profile group instead of being a member of the low or average SRL profile. In addition, the higher the utility value of students, the more likely it is that they are members of the high SRL profile group instead of being a member of the average SRL profile. This result means that a student with a high SRL profile attaches more importance to doing well on tasks in a blended learning environment than does a student with a low or average SRL profile, and the former also attributes more usefulness to his/her tasks in the blended environment than does an individual with a low SRL profile. Since students with high SRL think it is important to do well and that what they are doing is useful, they engage more and use more SRL strategies to reach their goals (Lazowski & Hulleman, 2016). Finally, in contrast with Neuville et al. (2007), results from the current study demonstrate no difference among students with a diversity of profiles regarding their thoughts about being able to learn in blended learning environments (self-efficacy) and their interests in this type of environment (interest value). Additionally, in contrast with several other studies (e.g., Kizilcec et al., 2017), the current study did not find any predictive effects related to learner background characteristics.

6.3. Limitations and future research

Although the present study offers important insights regarding diversity in blended adult students' SRL and the importance of value, several limitations must be addressed. First, replication of the LPA with 10 random samples of 150 participants provided evidence for the sample dependence of the latent profiles. This could have been due to 'hidden' subgroups in the sample, which may have depended on certain background variables. However, no relationships were found between background characteristics and the SRL profiles. Therefore, more research is needed that includes other possible important background characteristics (e.g., students' experience with blended learning) and also incorporates larger sample sizes. A larger sample size could potentially make it possible to identify more (or better established) profiles and lead to generalisable results for all blended adult students. Additionally, a larger sample size would allow for the inclusion of cross-loadings that could improve our model fit. Second, the cross-sectional nature of the present study design excluded changes in SRL and motivation over time. Self-regulated learning and motivation are dynamic variables and can be different for diverse tasks and educational programmes (Severiens, Ten Dam, & Van Hout Wolters, 2001). As such, there is a need for research that over time explores SRL of students in the same educational programme with the same tasks. Third, adult students' SRL was measured by self-reports. The resultant measures are therefore potentially unable to represent and judge the quality of students' SRL activities objectively. It could be that the students are unaware of performing certain strategies (e.g. activating prior knowledge) or that they did not indicate their behaviours as performing a certain strategy. Furthermore, the OSLQ (Barnard et al., 2009) had not been substantively used in previous research, which makes the current study relevant in validating the OSLQ for not only fully online education but also for blended education. However, the OSLQ still lacks crucial SRL concepts; such as motivation regulation (e.g., Richardson, Abraham, & Bond, 2012). In addition, according to a qualitative study on SRL, the Authors (2018b) have found that some SRL strategies such as peer learning, that are not included in the OSLQ seem important for blended adult students. In other cases, some SRL subscales may not be specific enough. For instance, task strategies can be further differentiated into rehearsal, elaboration, organisation, critical thinking, or metacognition. Future studies should therefore extend the SRL measures and strive to replicate our findings. Fourth, future research could include a new aspect, namely that of the teacher. It could be helpful to explore what impacts teaching style has on the SRL profiles of students. Fifth, since the current results only provide profiles that represent information concerning the quantity of SRL, it would be beneficial to gain more knowledge of the quality of the SRL of students through, for example, observational studies that explore how diverse adult students perform different SRL strategies and investigate the effects of using certain strategies. More specifically, the quantitative interpretation of SRL, namely 'more is better' (e.g., Wormington et al., 2012), is not necessarily true for SRL. Students who use a lot of SRL strategies may perform poorly because they use their SRL strategies in an inefficient way. Conversely, students who use few SRL strategies in an efficient way may perform well in their education. Furthermore, we believe that a next logical step in examining the latent profiles in greater depth would be to link them to measures of students' performance and learning. In line with this, the results indicate that 15% of the sample is still comprised of members of the low SRL profile. This is a high amount, meaning that more research is required regarding this specific group. Exploring whether this group is at risk of dropping out or is in fact still performing well will result in practically useful results. Sixth, when conducting future research, researchers should consider the type of blend of the courses to enhance comparability. Furthermore, it would be interesting to stress the computer-based and educational components in both the online distance moments and the face-to-face moments of the blended learning environment and compare these diverse learning moments. Finally, the non-significant relationship between self-efficacy and the SRL of students contradicts previous research. This result therefore requires more in-depth research on blended adult students' self-efficacy and whether or not the non-significant result has something to do with specific adult learner characteristics such as age, prior experiences, or having children.

6.4. Practical implications

The results of the current study could form a basis for creating adaptive learning environments that integrate scaffolds to enhance the SRL of students (Taub, Azevedo, Bouchet, & Khosravifar, 2014). The benefit of the blended learning environment in providing scaffolds is that the scaffolds can be implemented in both face-to-face and online environments (Nicol & Macfarlane-Dick, 2006). Overall, the findings prove that students have diverse SRL profiles, which implies that support should also be varied. Students characterised by a high SRL profile tend to need less support, but encouraging them to collaborate more with peers could benefit those individuals with a high SRL profile and students with average and low SRL profiles, who tend to seek help more regularly. Teachers could enhance peer learning by including more group work or by being a role model that shares information and efficient learning strategies in online forums. Students with low SRL profiles particularly require support to become more autonomous and independent. Encouraging these students to use more time management and self-evaluation strategies could be productive, and teachers could help these students manage their schedules by asking them to be transparent about their time via online planning. Self-evaluation could also be encouraged via online prompts, and tasks in which students have to evaluate themselves or create lists of possible strategies to evaluate themselves are options. Furthermore, since attainment and utility value are important predictors of SRL profile membership, teachers should demonstrate the use and personal value of their education to students. One means of doing this would be to get to know the students so that teachers could integrate authentic tasks and examples in the syllabus. In this way, teachers could anticipate the needs of students so the latter experience their education as useful when working on a task, which could help develop individuals' need to perform well to confirm their self-concept. For example, when teaching math in secondary adult education, it could be fun and interesting for adults working in the construction industry to bring blueprints from houses they are working on to apply their learned theories. Another example is that students in accounting classes in higher vocational adult education could bring their own paperwork or the paperwork of family or friends for practice. These types of activities could enhance student perceptions of the value of the course material (Neuville et al., 2007).

7. Conclusion

Self-regulated learning is a critical variable for success, especially in blended education. Although insight into adults' SRL in blended environments is crucial for enabling tailored support, research in this context is lacking. The present study fills this gap and expands the scientific literature on the SRL of blended adult students. The results of this person-centred study offer proof of the differences in SRL between adults in blended environments, because the findings indicate three SRL profiles, namely high, average and low SRL profiles. The distribution of students among the profiles seems optimal in that the most inefficient profile – the low SRL profile – contained the least number of students. This means that adult students in blended environments tend to be efficient enough to self-regulate their learning. Furthermore, the current study's results have helped to generate knowledge regarding the predictive effect of achievement motivation and individual background characteristics. More specifically, attainment and utility value were significant predictors of adult students' SRL profile membership, with higher amounts of attainment and utility value provoking more use of SRL strategies. Scaffolding the SRL of adult students in adaptive blended environments could provide means to enhance students' perceptions of the value of the course material. Getting to know the students and providing authentic tasks that are shaped by the students or adjusted to their personal situations is one example of boosting the perceived value of education that this study provides.

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