Exploring learner profiles among low-educated adults in second-chance education: individual differences in quantity and quality of learning motivation and learning strategies used

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Research Article

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Abstract

Research on learning strategies and learning motivation in different educational contexts has provided valuable insights, but in this field, low-educated adults remain an understudied population. This study addresses this gap by means of a person-oriented approach and seeks to investigate whether quantitatively and qualitatively different learner profiles can be distinguished among low-educated adults in second-chance education (SCE) by relating three key components of learning: learning motivation, regulation and processing strategies. 512 adult learners of six SCE-institutions filled in a Learning and Motivation questionnaire. Latent profile analysis shows the presence of motivational profiles differing both in quantity and quality (i.e., good-versus poor-quality and high-versus low-quantity motivational profiles) and regulatory profiles being distinct in the use of regulation strategies (i.e., self-regulated versus unregulated profiles). Mainly quantitatively different processing profiles were found among low-educated adults (i.e., active, moderate, inactive processing profiles). When integrating all three components of learning, analyses identified two more optimal motivational-learning profiles, combining good-quality motivation with a moderately-active use of self-regulation and processing strategies (i.e., good-quality motivation – self-regulated – active processing profile and good-quality motivation – moderate profile) and two more suboptimal profiles in which poor-quality or low-quantity motivation is combined with the inactive use of self-regulation and processing strategies (i.e., poor-quality motivation – unregulated – inactive processing profile, low-quantity motivation – unregulated – inactive processing profile). A fifth motivational-learning profile exhibits a pattern of poor-quality motivation combined with a moderately-active use of self-regulation and processing strategies.

1 Introduction

As lifelong learning is an important condition for employability, social inclusion and active citizenship, the European Council has been emphasizing the importance of adult learning for the last two decades (European Commission, 2001). However, a “Matthew effect” is apparent: those who are most in need of learning to improve knowledge and skills are least likely to find their way into adult education (Boeren, 2017). While the literature shows that good-quality motivation and good-quality learning strategies are important determinants of continued learning in adulthood (Klug et al., 2014; Pintrich & Groot, 1990; Weinstein & Hume, 1998), we may question whether both are adequately developed in adults who left regular secondary education early. Second-chance education (SCE) programmes are designed for this disadvantaged group of low-educated adults to obtain proof of secondary education and can represent an important starting point for lifelong learning.

Educational psychology research in the SCE-context is scarce. Existing research is primarily sociological in nature (e.g., Glorieux et al., 2011; Nordlund et al., 2013; Nordlund et al., 2015; Van Praag et al., 2017), rather than analysing the quality of learning processes, of which learning strategies and motivation are key components. Furthermore, compared to the scant empirical research undertaken among specific groups of adults, mainly generalizing theories on adult learning are available, considering adults a homogeneous group of learners (Knowles, 1980; Mezirow, 1995). This theorization may fall short in explaining learning processes among the targeted group in this research, as it overlooks these adults’ differences in prior educational pathways and therefore the potential associated individual differences in learning quality. Research in regular secondary and higher education contexts has repeatedly shown that regardless of age, individual learner differences exist (e.g., Vansteenkiste et al., 2009; Vermunt & Donche, 2017; Vermunt & Vermutten, 2004; Wormington et al., 2012).

Based on this existing body of research and given the variety of prior educational trajectories of SCE-learners, it can be expected that low-educated adults should not be considered a homogeneous group of learners, but learner profiles, differing in learning strategies and motivation, may be present. Therefore, a person-oriented approach, identifying these subgroups, is adequate (Bergman & Andersson, 2010; Magnusson, 1998). However, in person-oriented research, motivation and learning strategies have so far mainly been studied separately, rather than as an integrated whole. Yet literature points to the strong reciprocal relation between the two components, in which neither motivation nor learning strategies are the protagonist (e.g., Alexander, 2017). For this reason, the current study seeks to answer the question of which learner profiles exist among low-educated adults in SCE, based on learning strategies used and learning motivation, investigating both components, relative to each other. In what follows, we outline the theoretical framework guiding the empirical study and define how learning strategies and motivation are conceptualized.

1.1 Learning strategies

For almost 50 years, the Student Approaches to Learning (SAL) tradition has been investigating the qualitatively different ways students learn (Biggs, 2003; Lonka et al., 2004; Marton, 1976; Marton & Säljö, 1976; Schmeck, 1988). Early models in the SAL-field found ample evidence for a dichotomous conceptualization of a study-approach, deep versus surface (Biggs, 2003; Entwistle et al., 2003). Adherents of the SAL-tradition advocate that qualitative differences in learning are associated with qualitatively different learning outcomes (Biggs, 1979). Departing from the notion that learning is a complex phenomenon consisting of different aspects, the learning patterns model (LP-model) subsequently emerged (Vermunt & Donche, 2017; Vermunt & Vermutten, 2004), comprising a cognitive, regulative, affective-motivational and epistemological component. By doing so, the LP-model bridged work in the SAL-field with early Self-Regulated Learning (SRL) research (Vermunt & Donche, 2017; Vermunt & Vermutten, 2004). Empirical research, mainly in the context of higher education, has shown that relationships between the different components in this model yield four qualitatively distinct learning patterns (Vermunt & Donche, 2017; Vermunt & Vermutten, 2004). Learning strategies, or how students use regulation and processing strategies whilst studying, are central to this model. Processing strategies refer to those strategies to cognitively process learning content and which directly lead to learning outcomes, such as knowledge, understanding and skills. Metacognitive regulation strategies are used by
the learner to manage the learning process and have an immediate impact on cognitive processing strategies and thereby an indirect influence on learning outcomes (Vermunt & Donche, 2017). The four learning patterns each have their own logical combination of processing and regulation strategies and therefore differ in their quality. Students tending toward a meaning-oriented learning pattern process learning content in a deep way, by seeking connections between learning materials or approaching learning materials with a critical eye, they combine these deep processing strategies with a high degree of self-regulation strategies. Students with a reproduction-oriented learning pattern process learning content rather in a surface manner, by memorising material and getting lost in details, these students usually prefer strong external regulation by the learning environment. Students with an application-oriented learning pattern prefer to make connections to concrete situations or previous practical experiences when learning and prefer both self- and external regulation strategies. Finally, according to the LP-model, students can be identified lacking any regulation strategies and using few to none processing strategies and whom the model labels as the undirected learning pattern. The former two patterns are considered good-quality patterns, as they are more often positively related to performance, while the latter patterns are considered poor-quality learning, as they are found related with negative academic performance (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004).

The four learning patterns emerged from variable-oriented research and their dimensions should rather be considered as prototypical. Yet person-oriented research has shown that students can be more versatile and engage in specific combinations of processing and regulation strategies, which constitutes their relatively unique ‘learner profile’ (Donche & Van Petegem, 2009). Person-oriented studies drawing on the LP-model found homogeneous groups based on the combination of processing and regulation strategies used. These studies generally found distinct profiles in quality, labelled self-regulated/meaning-oriented/constructive/deep profiles versus externally regulated/undirected/reproduction oriented/surface profiles (Donche & Van Petegem, 2009; Slaats et al., 1999; Van Petegem et al., 2005; Vanthournout et al., 2009; Vermetten et al., 2002; Wierstra & Beerends, 1996). Studies also identified profiles differing in the quantity of learning strategies used. The flexible/versatile profile retrieved in some of these studies is characterized by high scores on both self- and external regulation, as well as high scores on deep and surface processing strategies (Donche & Van Petegem, 2009; Slaats et al., 1999; Vanthournout et al., 2009; Wierstra & Beerends, 1996). In some of the studies also an inactive/passive/unregulated profile was found, scoring low on all processing strategies and self- and external regulation (Slaats et al., 1999; Van Petegem et al., 2005; Vermetten et al., 2002). All studies, except the one conducted by Slaats et al. (1999) among secondary vocational education students, took place in higher education and therefore, differ significantly from the population studied in the present study.

1.2 Learning motivation

Learning motivation is conceptualized in this study according to Deci and Ryan's (2000) Self-Determination Theory (SDT), a widely used motivation theory that addresses why people initiate and persist in learning and which succeeds in explaining study success in different academic contexts. According to SDT, motivation is a multidimensional concept, delineated on two axes. On the one hand, statements can be made about the quantity of motivation, the other axis is a continuum representing the quality of motivation. Since quality within SDT is understood as the degree to which behaviour is self-determined, SDT refined the traditional dichotomy between intrinsic and extrinsic motivation, by further distinguishing between four motivational regulations. Motivation is situated at the lower end of the continuum, which is the same as a lack of motivation. Next on the continuum are various forms of extrinsic motivation. The least self-determined form of extrinsic motivation is external regulation. This behaviour is initiated by external pressure, such as rewards or power. Introjected regulation refers to behaviour that is self-imposed, such as behaviour to avoid guilt or boost the ego. The third and most self-determined form of extrinsic motivation, is identified regulation. It refers to behaviour that is posed because the learner finds it valuable. At the very top of the continuum is intrinsic motivation which refers to behaviour that stems from personal choices, values, interest or pleasure. External regulation and introjected regulation fall under the heading of controlled motivation within SDT because in both cases there is pressure to set the behaviour. Identified regulation and intrinsic motivation are both forms of autonomous motivation, because in both cases, the learner self wants to set the behaviour, without internal or external pressure (Deci & Ryan, 2000). Unlike other motivation theories, SDT argues that high levels of motivation are not necessarily associated with desired outcomes, when the motivation is of poor quality (Deci & Ryan, 2000; Vansteenkiste et al., 2006). For this reason, SDT conceptualizes motivation in a theoretically more fine-grained way to make statements not only about quantity but also about quality of motivation.

Although initially a variable-oriented approach was commonly used within SDT, many studies meanwhile have adopted a person-oriented approach. A crucial argument for this approach is typically that learners may have a combination of motives to learn, resulting in a personal motivational profile (Vansteenkiste et al., 2009). Based on the SDT-framework, four profiles can be expected: two motivational profiles that are distinct in quantity and where beneficial (i.e., internal regulation and identified regulation) and more disadvantageous motivational drives (i.e. introjected regulation, external regulation and amotivation) co-occur in higher or lower degrees (a high-quantity versus low-quantity profile), and two profiles that are distinct in terms of quality, that is a good-quality profile with high scores on beneficial and low scores on disadvantageous motivational regulation types and amotivation or a poor-quality motivational profile with an opposite motivational pattern (Vansteenkiste et al., 2009).

Person-oriented studies using the SDT-framework have identified different types of motivational profiles depending on the motivational scales that were included. The studies differ in whether composite scores for autonomous and controlled motivation were used, or analyses were carried out at the level of motivational regulation types. In these studies, amotivation was not consistently included as a motivational variable. Hence, the person-oriented SDT-research relevant to this study, differs in number of motivational profiles found: two to five profiles were retrieved. The results of profiling studies distinguishing between four profiles, were aligned with the theoretical expectations, described. In most of these studies, a high-versus low-quantity motivational profile and a good-versus poor-quality profile were identified (Cents-Boonstra et al., 2019; Hayenga & Corpus, 2010; Henderlong et al., 2016; Kusurkar et al., 2013; Liu et al., 2009; Rothes et al., 2017; Vansteenkiste et al., 2009; Wormington et al., 2012; Zhang & Lin, 2000).
2020). Studies retrieving five profiles, in addition to the above division, also found a moderate profile (Ullrich-French & Cox, 2009; Wang et al., 2016) or a distinct amotivational profile, when including amotivation as well (Haerens et al., 2010). The types of the motivational profiles found in the studies identifying three profiles are not consistent. Typically, these studies found two of the four expected motivational profiles, supplemented by a ‘moderate profile’ (Boiché et al., 2008; Kong & Liu, 2020; Ntoumanis, 2002; Ratelle et al., 2007). Among studies that retrieved two profiles, there was often a division into good-versus poor-quality (Fin et al., 2017; Pugh, 2019) or high-versus low-quantity (Yli-Piipari et al., 2009). Most of these studies identified a good-quality motivational profile, which was, as theoretically expected, consistently linked to several optimal learning outcomes, such as performance and use of good-quality learning strategies (e.g., Cents-Boonstra et al., 2019; Henderlong et al., 2016; Kusurkar et al., 2013; Vansteenkiste et al., 2009). As these studies took place in a variety of educational contexts, we can expect, based on the research discussed, that motivational profiles among low-educated adults in SCE will also differ in quantity and quality.

1.3 Interplay of learning strategies and motivation

As learning is inherently a multidimensional construct, several learning theories, including the LP-model, have incorporated a learning strategies and motivational component (Alexander, 2017; Pintrich, 2004; Vermunt & Donche, 2017). Recently, increasing research has been exploring the interrelatedness of processing and regulation strategies as conceptualized by the LP-model and motivation as conceptualized by SDT. These studies generally found a positive relationship between autonomous motivation and self-regulation and the use of all processing strategies, in particular deep processing strategies. Controlled motivation was most often associated with surface learning strategies, such as memorising and analysing and external and lack of regulation, whereas amotivation was positively related to lack of regulation and negatively to the use of all processing strategies (Catsyssse et al., 2015; Donche et al., 2013). However, these studies are variable-oriented in nature and thus not seeking to identify learner profiles who can be described by their specific repertoire of learning motives and learning strategies used. In addition, research has also focused on integrated person-oriented studies seeking associations between motivation, regulation and cognitive processing strategies. Although this body of research often varies in conceptual definitions of learning strategies and motivation, and thus also differs from the present study in terms of theoretical frameworks used, they do point at the existence of motivational-learning profiles (Cano & Berbén, 2009; Heikkilä et al., 2011; Heirweg et al., 2019; Liu et al., 2014; Liu et al., 2021).

2 Present Research

This study seeks to understand the quantitatively and qualitatively different ways in which low-educated adults in SCE learn, by considering learning as an integrated whole of motivation, metacognitive regulation and cognitive processing strategies. Beyond the variable-oriented tradition that both LP-model and SDT long have known, this person-oriented research seeks to investigate naturally occurring subgroups among low-educated adults, based on their unique repertoire of learning strategies and learning motives. This study not only contributes to scarce theorization about learner profiles of low-educated adults, but also bridges two theoretical frameworks (LP-model and SDT), that provided substantial empirical evidence about qualitative and quantitative differences in learning and motivation (Vansteenkiste et al., 2009; Vermunt & Donche, 2017).

Before investigating the presence of different motivational-learning profiles based on underlying dimensions of learning strategies and motivational drives, for reasons of internal validity, it is appropriate to explore their expected variable-oriented interrelationships. We question whether previously found associations between the motivational subscales and subscales for cognitive processing and regulation, also occur within the specific SCE-context, in which the associations between these learning components are unexplored. Based on previous variable-oriented research we expect autonomous motivation to be positively associated with self-regulation and (deep) processing strategies and controlled motivation to be positively associated with surface processing strategies and external and lack of regulation. Amotivation is expected to be positively related to lack of regulation and negatively with all processing strategies. In a first step, we want to juxtapose the reciprocal associations between motivation, regulation and cognitive processing strategies found in the SCE-context with expectations based on theory and previous research (RQ1 – variable-oriented). Based on the insights of the former step, we aim to distinguish learner profiles among SCE-learners. In the person-oriented part of this study, we first explore for each of the separate components of learning, which motivational, regulatory and processing profiles can be identified (RQ2 – person-oriented). Based on earlier findings, we expect motivational, regulatory and processing profiles to be distinct in terms of quantity and quality. For each of the components we expect to find at least two profiles, differing in quantity (high-quantity versus low-quantity) or in quality (good-quality versus poor-quality) and a maximum of five profiles in which all profiles from the quadrant are present, potentially complemented by a moderate profile. For the third research question, we explore whether motivational-learning profiles can be distinguished, examining the unique integration of learning motivation, regulation and processing strategies among subgroups of SCE-learners (RQ3 – person-oriented).

3 Methodology

3.1 Context, participants and procedure

The present study was conducted in six institutions for adult education in Flanders (northern part of Belgium). After the approval of the Ethics Committee for the Social Sciences and Humanities (SHW_21_56), the principals of different institutions for adult education were contacted. Both rural \((n = 3)\) and urban \((n = 3)\), as well as smaller \((n = 3)\) and larger \((n = 3)\) institutions for adult education were selected to compile a heterogeneous sample of participants. We took a random sample of students who were enrolled in SCE in a general track (25.49%) or vocational track (53.63%) or both at the same time (20.88%). Depending on the availability of class time to complete the questionnaire, either an online (34.96%) or a paper and
pencil version (65.04%) was used. In both cases, an informed consent form explaining the purposes of the study and use of personal data, preceded the survey. In case of the paper and pencil questionnaire, the same member of the research project was present to ensure uniformity of the administration procedure. Three participants present at the time of survey registration decided not to participate in the study. This approach resulted in 512 adult participants of which 68.36% identified themselves with the female gender, 31.42% with the male gender and 0.22% with another gender. Median age was 25 (\(M = 29, SD = 11.01\)), ranging from 17 to 76. At the time of survey administration 77.13% of the participants was unemployed, 0.90% was retired and 21.97% had a parttime or fulltime job. About half of the participants had a mother (51.60%) and, or father (52.19%) born in Belgium and 63.03% had Dutch as their native language. The mother and, or father of respectively 50.86% and 54.16% of the participants successfully finished compulsory secondary education. As for students’ preliminary trajectory in secondary education, 44.44% pursued vocational education, 13.71% took a general track, 33.33% combined general and vocational education and 8.51% took classes at a special needs institute.

### 3.2 Instrument and measurement

Students’ motivation and learning strategies were measured by means of the LEarning and MOtivation questionnaire (LEMO) (Donche et al., 2010). This 49-item self-report inventory includes 15 items measuring learning motivation based on SDT (Deci, & Ryan, 2000) and 34 items measuring regulation and processing strategies, as conceptualized by the LP-model model (Vermunt, 1998). All items were measured on a seven-point Likert scale to reduce ceiling effects (Cramer & Howitt, 2004). Items ranged for motivation from one (totally disagree) to seven (totally agree) and for regulation and processing strategies from one (never) to seven (always).

For reasons of data quality, before undertaking any further analyses, observations with an incorrect answer to the bogus items included in both sections of the questionnaire (motivation: “The sun is purple”; regulation and processing strategies: “I am paid biweekly by leprechauns”), were deleted (27.54%) (Curran, 2016). To test construct validity, a separate confirmatory factor analysis (CFA) was undertaken for the subscales of motivation, processing strategies and regulation strategies. CFAs resulted in an acceptable fit (Byrne, 2010; Hu & Bentler, 1999): motivation (CFI = .92, RMSEA = .08, SRMR = .06); regulation strategies (CFI = .87, RMSEA = .08, SRMR = .07); processing strategies (CFI = .91, RMSEA = .06, SRMR = .06).

Table 1 provides an overview of the scales (13) used after validation and for each of these scales the highest loading item and corresponding Cronbach's alpha. Since Cronbach's alpha is sensitive to the number of items per scale and rather few items per scale were used, a cut-off of .60 is considered adequate (Cortina, 1993). Each scale was created by averaging the scores on the items.
### Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Subscale</th>
<th>Number of items + example</th>
<th>Cronbach's alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>Autonomous motivation</td>
<td>“I am motivated to study…”</td>
<td>α = .89</td>
</tr>
<tr>
<td></td>
<td>Intrinsic motivation</td>
<td>3 items: “... because I enjoy studying.”</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Identified motivation</td>
<td>3 items: “... because I personally think it is valuable.”</td>
<td>α = .74</td>
</tr>
<tr>
<td></td>
<td>Controlled motivation</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Introjected motivation</td>
<td>3 items: “... because I will feel bad about myself if I don't do it.”</td>
<td>α = .72</td>
</tr>
<tr>
<td></td>
<td>External motivation</td>
<td>3 items: “... because others (parents, friends, teachers...) oblige me to do so.”</td>
<td>α = .75</td>
</tr>
<tr>
<td></td>
<td>Amotivation</td>
<td>3 items: “Honestly, I don't know; I feel like I'm wasting my time in school.”</td>
<td>α = .70</td>
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<tr>
<td>Processing strategies</td>
<td>Stepwise/Surface processing</td>
<td></td>
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<td></td>
<td>Analysing</td>
<td>4 items: “I analyse the separate components of a theory step by step.”</td>
<td>α = .73</td>
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<tr>
<td></td>
<td>Memorising</td>
<td>4 items: “I list the most important facts and then memorise them.”</td>
<td>α = .66</td>
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<td></td>
<td>Deep processing</td>
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<tr>
<td></td>
<td>Relating &amp; Structuring</td>
<td>4 items: “I relate specific facts to the main issue in a chapter or article.”</td>
<td>α = .71</td>
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<tr>
<td></td>
<td>Critical processing</td>
<td>4 items: “I try to be critical of the interpretations of experts.”</td>
<td>α = .66</td>
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<td></td>
<td>Concrete processing</td>
<td>4 items: “With the help of the theories presented in a course, I devise solutions to practical problems.”</td>
<td>α = .72</td>
</tr>
<tr>
<td>Regulation strategies</td>
<td>External regulation</td>
<td>6 items: “I use the instructions and the course objectives given by the teacher to know exactly what to do.”</td>
<td>α = .70</td>
</tr>
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<td></td>
<td>Self-regulation</td>
<td>4 items: “In addition to the syllabus, I study other literature related to the content of the course.”</td>
<td>α = .69</td>
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<td></td>
<td>Lack of regulation</td>
<td>4 items: “I notice that the study instructions that are given are not very clear to me.”</td>
<td>α = .78</td>
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</tbody>
</table>

### 3.3 Data analysis

To explore variable-oriented relationships between the variables included in this study (RQ1), Pearson correlations were calculated. To answer the person-oriented research questions in this study (RQ2, RQ3), we used a latent profile analysis (LPA), a model-based cluster analysis approach to fit a series of models with a different number of classes and by comparison to retain the model with the optimal number of significantly distinguishable profiles (Harring & Hodis, 2016; Pastor et al., 2007). LPA can be employed in different ways to identify homogeneous groups, ranging from an exploratory to a purely confirmatory approach, where there are clear hypotheses about the number and size of the profiles (Spurk et al., 2020). Based on the theoretical framework central to this study, as well as previous person-oriented research in this field, we expected 2 to 5 profiles to emerge. Typically, LPA uses several information criteria to evaluate how many groups best describe the data (Howard et al., 2016). However, as multiple information criteria can point to different conclusions, Akogul and Erisoglu (2017) state that subjective decision-making might arise. To overcome this problem, we used Saaty’s (1990) Analytic Hierarchy Process (AHP), in which different model fit criteria (AIC, AWE, BIC, CLC, and KIC) are mathematically combined into a composite relative importance vector (C-RIV) and with the highest value representing the model with the most optimal number of profiles (Akogul & Erisoglu, 2017). Within LPA, often multiple maxima exist for the estimation of the log-likelihood parameter, indicating the best-fitting profile solution. To strive for a global maximum value, different starting values were used to replicate the optimal log-likelihood estimate (Berlin et al., 2014). For LPA, inspection of missing data, outliers and normality of the distributions is recommended (Berlin et al., 2014; Vermunt & Magidson, 2002). With a listwise-deletion solution up to 25% of the observations would have to be removed, therefore single imputation was used (tidyLPA, Rosenberg et al., 2018). As extreme outliers might bias the final profile solution, multivariate outliers were identified and removed, using Mahalanobis distance. This resulted in the removal of 17 cases (4.58%) with a p-value smaller than 0.001. A visual inspection of histograms and computation of skewness, showed that the motivational scales external regulation and amotivation were not normally distributed and were therefore, log-transformed (Curran-Everett, 2018). The scales found to be relevant in the analyses for RQ2 (> 50% explained variance, Milligan & Cooper, 1985) were combined to re-examine through LPA which motivational-learning profiles could be identified.
(RQ3). For reasons of interpretability, key variables were standardized by rescaling to z-scores. All analyses were carried out in R (R Core Team, 2022), making use of the packages mclust (Scrucca et al., 2016) and tidyLPA (Rosenberg et al., 2018).

4 Results

4.1 Variable-oriented associations between motivation, regulation and processing strategies (RQ1)

To understand the relationships between the variables under study and to examine, for reasons of internal validity, whether these relationships, although in a totally different setting, converge or diverge from theoretical expectations, correlations were estimated (Table 2). The most noteworthy correlations are discussed, using the operational definitions in the work of J. Cohen (1988) for interpreting the correlation coefficients.

Within both theoretical models, we note relationships between the variables that are theoretically logical. The SDT-continuum can be recognized in the simplex pattern of the motivational regulation types. Adjacent motivational regulation types correlate more strongly (e.g., internal and identified regulation) and become weaker and negative when we move along the SDT-continuum (Ratelle et al., 2007). As for the LP-model, as expected, the mutual correlations within the deep, as well as within the surface processing strategies, are strong and only a weak to moderate association exists between the deep processing strategies and the surface processing scale memorising. A strong relationship, however, is found between the deep processing strategy relating & structuring and the surface processing strategy analysing. There is, in other words, a distinction, albeit not as clear as theoretically expected, between deep and surface processing strategies. Within the metacognitive regulation strategies, self- and external regulation correlate moderately, meaning that there is an association, but at the same time, both regulation strategies are sufficiently distinct. As expected, there is no relationship between the scale lack of regulation strategies on the one hand and self- and external regulation strategies on the other. As expected, lack of regulation strategies is not or only weakly associated with all processing strategies and the scale external regulation strategies is strongly correlated with the surface processing strategies analysing and memorising. Less expected are the weak to moderate relationships between external regulation strategies and the deep processing strategies. For the self-regulation strategies we observe the expected strong associations with all deep processing strategies, but also less-expected, strong and moderate associations with the surface processing strategies analysing and memorising, respectively. The observed correlations between processing and regulation strategies are mostly in line with the theoretical expectations in the LP-model, but are challenging to interpret at some points. This may be an indication of the specific use of learning strategies by the targeted group of SCE-learners in this study.

From Table 2, we can also derive the following relationships between the SDT-constructs and those of the LP-model. As expected, internal and identified motivational regulation are positively correlated with self-regulation strategies and all cognitive processing strategies, but not particularly with deep processing strategies, and weakly negatively correlated with lack of regulation strategies. The moderately positive correlation with external regulation strategies is somewhat unexpected. Between introjected motivational regulation, external motivational regulation and amotivation on the one hand and processing and regulation strategies on the other, we find only weak correlations. We do not clearly find the expected relationships between introjected and external motivational regulation, external regulation strategies and the surface processing strategies analysing and memorising. Although weak, there is an expected positive association between amotivation and lack of regulation strategies. Again, we can conclude that the associations are partially congruent with theoretical expectations, possibly indicating at some points divergent patterns among low-educated adults in SCE.

All of the analysed variables, except for the less self-determined forms of motivation (i.e., external regulation and amotivation), obtained mean scores that are above the range of the scales.
Table 2

Correlations and descriptive statistics

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<td>Motivational regulation types</td>
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<td>Autonomous motivation</td>
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<td>1. Internal regulation</td>
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<td>.43***</td>
<td>.22***</td>
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<td>1.26</td>
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*p < 0.05, **p < 0.01, ***p < 0.001

4.2 Motivational, regulatory and processing profiles (RQ2)

To identify motivational, regulatory and processing profiles, we conducted a LPA. Guided by theoretical expectations, we tested the sample for 2 to 5 latent profiles by means of the AHP-approach (Akogul & Erisoglu, 2017). The fit criteria and C-RIV for the estimated profile solutions are presented in Table 3. We can conclude that four motivational, two regulatory and five processing profiles can be distinguished.
Table 3
Fit indices used for the AHP to select the optimum model varying in number of latent profiles (2 to 5)

<table>
<thead>
<tr>
<th>N profiles</th>
<th>AIC</th>
<th>AWE</th>
<th>BIC</th>
<th>CLC</th>
<th>KIC</th>
<th>C-RIV</th>
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<td>4245.56**</td>
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<td>0.2518*</td>
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</tbody>
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* Optimum model according to the composite relative importance vector (C-RIV)

** Indicates the best fitting model according to this information criterion.

Figures 1, 2 and 3 display the identified motivational, regulatory and processing profiles, respectively. As for the motivational profiles (Fig. 1), we found, in line with theoretical expectations, a distinction between quantity and quality of motivational regulation types. The first profile (18.08%) was labelled low-quantity, as this group of participants is characterized by relatively low levels of all motivational regulation types, except for amotivation. The poor-quality profile (16.67%) has relatively the lowest levels of internal and identified regulation and the highest levels of external regulation and amotivation, whereas the good-quality profile (40.11%) exhibits the opposite pattern. The high-quantity profile (25.14%) has relatively high scores on all motivational regulation scales, except for amotivation. For introjected regulation ($\eta^2 = 0.29$), the four-profile solution explains a substantial amount of variance (> 50%) in the motivational regulation scales.

For the variables measuring regulation strategies, a two-profile solution proved most optimal. Both profiles have an average level of lack of regulation, with the profiles being distinct in their scores on self- and external regulation strategies: relatively high versus relatively low. As the two-profile solution explains only sufficient variance in the self-regulation scale ($\eta^2 = 0.62$), the profiles were labelled self-regulated (62.15%) versus unregulated profile (37.85%).

For the processing scales, the five-profile solution yielded the most optimal results. Of the profiles found, 4 of 5 are quantitatively distinct, scoring either relatively high or low on all processing strategies. We labelled these profiles active (21.47%), moderately-active (49.15%), moderately-inactive (19.21%) and inactive profile (4.80%). The fifth profile was labelled deep profile (5.37%), because of its relatively low levels of surface processing strategies (analisysing and memorising) and relatively high levels of deep processing strategies (critical processing, relating & structuring, and concrete processing). Except for the memorisation scale ($\eta^2 = 0.37$), a substantial proportion of the variance in the variables (> 50%) is explained by the five profiles. Participants are not evenly distributed across profiles, with the moderately-active profile comprising the largest and the inactive and deep profiles the smallest proportion of participants.

4.3 Motivational-learning profiles (RQ3)

To explore whether motivational-learning profiles can be identified, we conducted an LPA, including only nine of the motivational, regulatory and processing scales that were found to be relevant dimensions (RQ2) (> 50% of the variance explained by the profiles, Milligan & Cooper, 1985). By including only variables capable of identifying individual differences, we also obtained a more parsimonious solution. Based on the fit criteria and the C-RIV (Table 4), we retained the five-profile solution.
**Indicates the best fitting model according to this information criterion.**

Figure 4 displays these five motivational-learning profiles. For the processing strategies there is little variation in quality of strategies used: the mean scores are either relatively high, moderate or low for all processing scales across profiles. In other words, homogeneous subgroups of learners can only be discerned in the quantity of processing strategies used, not in quality. For this reason, the cognitive processing component in the different profiles was labelled active, moderate and inactive. Profiles are distinct in the extent to which they use self-regulation strategies. We added self-regulated and unregulated to the labels of those profiles standing out in the presence or absence of self-regulation strategies. A distinction in quality was made for the motivational component in the profiles. For each of the profiles, we either see relatively higher levels of good-quality, combined with relatively lower levels of poor-quality motivational regulation types, or vice versa. The motivational component in the triangle-profile was labelled low-quantity profile, as the mean scores for the various motivational regulation types were all below zero. The identified motivational-learning profiles are more difficult to relate to the theoretical frameworks of the current study, but reflect unique combinations of motivation and learning strategies and represent, therefore, homogeneous subgroups of SCE-learners. The good-quality – self-regulated – active processing profile (22.60%) can be seen as the most optimal learner profile among SCE-learners. These adult learners have the most qualitative learning motivation, use self-regulation strategies most often and are most active in using processing strategies. However, these learners do not distinguish between good- and poor-quality processing strategies. The largest group was labelled the good-quality motivation - moderate profile (40.96%) and consists of adults exhibiting relatively good-quality motivation, but who do not stand out for the self-regulation and processing strategies they employ. Two suboptimal profiles were distinguished. These subgroups are notable for the limited use of both self-regulation and processing strategies. One of these profiles stands out for the relatively highest scores on amotivation and external motivational regulation and was therefore labelled poor-quality motivation – unregulated – inactive processing profile (12.71%). The other profile was named low-quantity motivation – unregulated – inactive processing profile (8.47%), because of its relatively low scores on all motivational regulation types. The fifth profile deviates most from theoretical expectations, since in this subgroup poor-quality motivation is associated with moderate to active use of self-regulation and processing strategies and was labelled poor-quality motivation – moderately-active profile (12.25%).

## 5 Discussion And Conclusion

As learning processes of low-educated adults are an understudied terrain, the current study aimed to explore learner profiles in SCE, differing in the quantity and quality of learning motivation, regulation and processing strategies used, departing from the SDT- and LP-framework. For reasons of internal validity and to support the interpretation of the person-oriented part of the study, variable-oriented associations between the motivational, regulation and processing scales were first investigated (RQ1). To identify homogeneous profiles, being unique in their repertoire of learning motives, regulation and processing strategies used (RQ2), as well as in their combinations of these three components (RQ3), LPA was used.

LPA for the separate components of learning revealed for the motivational component four profiles representing the expected theoretical quadrant and thus, profiles differing not only in the quantity of motivation, but also in quality (Deci & Ryan, 2000; Vansteenkiste et al., 2009). The good-quality profile found in this study also emerged in most of previous person-oriented SDT-research and contained in this study the largest proportion of the participants, followed by the high-quantity motivational profile. Building on previous person-oriented research linking SDT-profiles to learning outcomes (e.g., Cents-Boonstra et al., 2019; Henderlong et al., 2016; Kusurkar et al., 2013; Vansteenkiste et al., 2009), we can argue that suboptimal motivational profiles were also identified, namely the poor-quality and low-quantity motivational profile.

For the regulation and processing strategies, mainly profiles differing in quantity were found. These profiles are in line with the flexible/versatile profiles and inactive/passive/unregulated profiles found in former LP-research (Donche & Van Petegem, 2009; Slaats et al., 1999; Vanthournout et al., 2009; Van Petegem et al., 2005; Vermuten et al., 2002; Wierstra & Beerends, 1996). Contrary to these previous person-oriented research results, mainly found in higher education, we hardly identified any profiles being distinct in the quality of processing strategies used. Only a small proportion of the participants (5.37%) was classified in the deep processing profile. Previous person-oriented studies advanced as a possible explanation for these quantitative profiles, that they may represent strategic or flexible learners who consciously use a broad range of learning strategies to meet the expectations of the learning environment (Vanthournout et al., 2013). We question whether this strategic learner hypothesis holds true for the targeted group of low-educated adults in this study, whom we hypothesise to be rather inexperienced learners. An alternative explanation is found in the developmental hypothesis put forward in the review study by Vermunt and Vermuten (2004). As learners acquire more learning experiences

<table>
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<th>N profiles</th>
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</table>

* Optimum model according to the composite relative importance vector (C-RIV)
throughout their educational careers, they seem to make a more clear distinction between deep and surface processing strategies and thus to develop as a learner. Vanthournout et al. (2009) found empirical evidence for this developmental hypothesis, where in a longitudinal study in higher education, flexible profiles seemed to further evolve into meaning directed/deep profiles differentiating more clearly between deep and surface processing strategies. This developmental hypothesis may hold true for the group of SCE-learners who often did not have had a trouble-free prior educational trajectory and where further development in learning strategies is possible. For this reason, we labelled the profiles active versus inactive profiles. Inactive profiles hardly use any processing strategies, active profiles considerably use a broad range of processing strategies, but do not distinguish between deep and surface processing strategies. Another interpretation given by Vermunt and Vermetten (2004) is the context hypothesis, suggesting that it is not development that explains the lack of differentiation in strategies used, but the educational context. Variable-oriented studies reviewed by Vermunt and Vermetten (2004) showed that the expected factor pattern diverges in very specific learning contexts or is less clearly defined in the starting period in a new educational context, as a period of change and acclimation is warranted. As the SCE-context diverges from the context of higher education, in which most LP-research took place, and the modular educational system is new to most of the SCE-learners, also this context hypothesis might explain the mainly active and inactive regulatory and processing profiles found in this study.

Results show that among SCE-learners, profiles can also be identified making unique combinations of motivational regulation types and regulation and processing strategies. In the motivational-learning profiles identified in this study, however, a deep processing profile was no longer present and only profiles were distinguished differing in the quantity of self-regulation and processing strategies used. For the motivational component, motivational-learning profiles mainly differed in the quality of motivation. In line with previous SDT-research (Deci & Ryan, 2000), we conclude that two more optimal and three more suboptimal profiles were, therefore, distinguished. As mentioned, the motivational-learning profiles of the current study are more difficult to compare with motivational-learning profiles found in previous research, as the theoretical frameworks and research contexts differ (Cano & Berbén, 2009; Heikkilä et al., 2011; Heirweg et al., 2019; Liu et al., 2014; Liu et al., 2021). Yet, results show that patterns found in this study are very similar to the motivational-learning profiles among primary school students, found by Heirweg et al. (2019). The cognitive and self-regulatory component in these profiles are also solely distinct in quantity and not in quality and where the active profiles are combined with more optimal and the inactive profiles with more suboptimal motivational drives. Given the younger age group in the study by Heirweg et al. (2019), this result again might point to motivational-learning profiles that are more common among less experienced learners and adding support to the developmental hypothesis advanced in LP-research (Vermunt & Vermetten, 2004).

The results raise new interesting hypotheses pointing toward the need for longitudinal research. The results for the regulatory and processing component of learning indicate limited differentiation in strategies used. Longitudinal research could provide an answer to the question of whether and how the different profiles are variable across time and whether variability is mainly present in the motivational, regulatory or cognitive component of learning. In addition, intervention-based research can offer further insights on how to promote good-quality regulation and processing strategies in low-educated adults. Learning strategies may not only develop through gaining more learning experiences, but can also be promoted by the educational learning environment (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Since the most optimal regulation and processing profiles found in this study still do not distinguish between good-quality and poor-quality learning strategies, we expect instruction to have a role to play here as well. An interesting further avenue is also to relate SCE-profiles with input and output characteristics. We currently do not know whether the profiles found are also homogeneous in terms of background characteristics of SCE-learners and whether the assumed optimal and suboptimal profiles also differ in learning outcomes, such as achievement or risk of dropping out (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Finally, qualitative research can be informative as to why the merely quantitative distinctions in processing and regulatory profiles have been found. We postulated that the strategic learner hypothesis may not hold true for the targeted group of SCE-learners, but further research is needed to investigate this assumption. In-depth qualitative data can provide insight into the expectations set by learning environments in this context and how this may trigger the specific use of processing and regulation strategies by SCE-learners. This would also support the context hypothesis (Vermunt & Vermetten, 2004) and might provide valuable insights for educational practice.

Despite the fact that the results show that interpretable learner profiles can be distinguished among SCE-learners, this study faces certain limitations. Although self-report measures are appropriate for making explicit educational psychological aspects of learning, such as motivation and learner preferences for (meta)cognitive strategy use, profiles found, nevertheless, remain the result of respondent’s self-assessment, which requires a certain degree of metacognition of the participant (Pekrun, 2020). The active and inactive profiles found may indeed indicate a limited distinction between different regulation and processing strategies used, but may as well be the result of consistently high or low scoring of the corresponding items in the questionnaire. Self-reporting supplemented by more online measures, may further unravel this potential bias in the measurement process. In addition, the self-report instrument used is not flawless. The LEMO-questionnaire (Donche et al., 2010) was developed and validated in upper secondary and higher education contexts and is clearly capable of identifying learner profiles, but may not be the most optimal measurement technique for this population. A significant proportion of observations based on bogus items was removed to retain the most high-quality data, which may have biased the results. To conclude, this study draws upon two theoretical frameworks (SDT and LP-model) that previously have been found to be capable of identifying qualitative and quantitative differences in motivation, regulation and processing strategies and their interrelationships. We may question, however, whether other dimensions of learning and motivation are also present in SCE-learners. Qualitative research can uncover the specificities of this understudied research context.

To conclude, our study succeeded in identifying quantitatively and qualitatively different learning and motivational profiles among low-educated adults in SCE. By drawing on theoretical frameworks that have proved valuable and the exploration of learner profiles in a new research context,
results show that low-educated adults differ in the quantity and quality of their learning strategies and motivation and thus should not be considered a homogeneous group of learners. Therefore, the present study not only contributes to scarce theorization of low-educated adults’ learning, but also generates important hypotheses for future research.

**Declarations**

**Statements and Declarations**

- **Author contributions**
  All authors contributed to the study concept and design. Data collection and analyses were performed by Bea Mertens. The first draft of the manuscript was written by Bea Mertens and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

- **Ethics declarations**
  The authors declare no competing interests.

- **Disclosures**
  - Funding information is not applicable / No funding was received.
  - Research was approved by the Ethics Committee for the Social Sciences and Humanities (SHW_21_56).

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  - Adult learning
  - Learning strategies
  - Motivation
- Most relevant publications in the field of Psychology of Education
  - No previous publications

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- Transition to higher education
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Most relevant publications in the field of Psychology of Education


References


**Figures**
Figure 1

Z-scores for motivational regulations of the four-profile solution
Figure 2

Z-scores for regulation strategies of the two-profile solution
Figure 3

Z-scores for processing strategies of the five-profile solution
Figure 4

Z-scores for motivation, regulation and processing strategies of the five-profile solution