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Detecting the Variability in Student Learning in Different Disciplines—A Person-Oriented Approach

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ABSTRACT
This paper examines disciplinary differences in the combinations of approaches to learning (i.e., learning profiles) among students, and how those combinations are related to academic achievement. In addition, the study focuses on how different learning profiles are related to students' self-efficacy beliefs in different disciplines. Data consist of HowULearn survey responses from 4,294 full-time students from six different disciplines. We used a person-oriented approach; that is, the latent profile analysis (LPA) with various functions. The results showed that it is possible to detect different learning profiles of students in different disciplines. The study highlights that students who struggle in almost every discipline have a dissonant learning profile or the deep unorganised profile. Therefore, special attention should be paid to identifying the students with dissonant learning profiles and to support them in recognising their own learning processes. Moreover, students' time and effort management skills should be fostered during university studies.

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Deep and surface approaches to learning; person-oriented method; self-efficacy; disciplines; academic achievement

Introduction

Institutes of higher education are constantly trying to find ways to enhance and support quality learning to improve learning outcomes. As part of such an effort, it is necessary to examine and understand disciplinary variation in student learning, more precisely their approaches to learning, because students' learning differs according to the discipline (Entwistle, 2009). Although student approaches to learning have been examined thoroughly in different disciplines (e.g., Entwistle, 2009; Entwistle & Ramsden, 1983; Kember et al., 2008; Vermunt, 2005), previous research has mainly focused on the relations between different variables and not on the learning profiles that emerge in different disciplines. Thus, research examining the disciplinary variance in learning profiles is still largely missing, especially in relation to academic achievement and self-efficacy.

There is also a continuing debate on how stable vs. variable students' approaches to learning are. There are studies suggesting that approaches are prone to change due to various contextual effects (e.g., Baeten et al., 2010; Coertjens et al., 2016; Koster & Vermunt, 2020; Vermunt, 2005), while others suggest that the approaches remain relatively stable across time and different contexts

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(e.g., Lietz & Matthews, 2010; Zeegers, 2001) and this may, thus, reflect a more typical way of studying across contexts with similar demands (Entwistle & McCune, 2004). Still, recent research highlights that on an individual level some approaches are more affected by the context and some are more stable (Postareff et al., 2018). Therefore, more research is needed on the different individual combinations of student approaches to learning in different disciplines but also on more generic, over disciplinary trends in approaches to learning. It is important to raise academics' awareness of specific needs inside the discipline as well as general awareness of successful studying in and outside their own discipline. The overall aim is, thus, to support teachers and academic developers to find the most effective ways to support students with different kinds of learning profiles and their academic achievement throughout the higher education institution.

The present study aims to explore whether it is possible to identify different study profiles across different disciplines using a person-oriented approach, which, compared to a variable-oriented approach, enables us to identify groups or types of individuals with similar attributes (Laursen & Hoff, 2006). Secondly, we explore how these study profiles are related to self-efficacy and academic achievement. There is previous evidence showing that students' self-efficacy beliefs influence the learning approaches they adopt (Coutinho & Neuman, 2008; Papinczak et al., 2008; Prat-Sala & Redford, 2010) and consequently self-efficacy beliefs play an important role when considering student learning in different disciplines.

Different Combinations of Approaches to Learning

Approaches to learning, as they are named and defined by researchers, usually refer to students' intentions concerning their studies and learning as well as their learning processes (e.g., Biggs, 2001; Entwistle et al., 2006; Entwistle, 1988, 2009). A *deep approach* refers to the intention to analyse and understand information through comprehending the bigger picture, focusing on underlying meanings and integrating new information with previous knowledge. A *surface approach* is characterised by a focus on memorisation, often resulting in a fragmented knowledge base where information is seen as fragmentary and unrelated (Entwistle, 2009). A recent qualitative study suggests that at its core, the surface approach entails unreflective studying rather than memorisation and repetition of knowledge (Lindblom-Ylänne et al., 2019).

A third approach, termed *organised studying*, refers to students' everyday practices in terms of how they manage and organise their studies and their time (Entwistle & McCune, 2004). It is therefore considered to be more of an approach to studying than an approach to learning (Entwistle, 2009; Entwistle & McCune, 2004), though in the present study we use the concept of approaches to learning to refer to deep and surface approaches and organised studying. Interestingly, at the individual level, the organised studying seems to be rather stable whereas deep and surface approaches to learning are more prone to variability (Postareff et al., 2018).

The various combinations of approaches to learning are expected to form a coherent whole in which the different theoretical elements fit together. However, previous research has shown that such combinations may inherently include degrees of conceptual incoherence or dissonance, meaning that the expected, theoretically coherent linkages between the approaches fail to appear (Cano, 2005; Lindblom-Ylänne, 2003; Lindblom-Ylanne & Lonka, 1999; Long, 2003; Meyer, 2000; Papinczak, 2009; Quinnell et al., 2012). For example, variable-oriented methods have provided strong evidence that the deep approach to learning is positively related to organised studying (e.g., Richardson, 2000). However, person-oriented methods make it possible to also detect students with an atypical combination of both a deep approach and an unorganised studying approach in different academic disciplines (Haarala-Muhonen et al., 2017; Parpala et al., 2010). Additionally, while research has shown that there is a strong negative correlation between the deep and surface approaches to learning, a person-oriented study conducted by Fryer and Vermunt (2018) found that Asian students are able to use both surface and deep approaches to learning either together or in a stepwise process. This indicates that both the deep and surface approaches to learning could be described as intermediate positions on the spectrum measuring student approaches to learning (Kember, 1996).

Approaches to Learning and Academic Achievement

A number of studies using variable-oriented methods imply that there is an association between students with a deep approach to learning and better learning outcomes (Minbashian et al., 2004; Entwistle et al., 2001; Hazel et al., 2002; Karagiannopoulou & Christodoulides, 2005; Prosser et al., 2000). However, results from several studies did not reveal relationships between the deep approach and academic achievement (Diseth, 2003, 2007a, 2007b; Gijbels et al., 2005; Karagiannopoulou & Milienos, 2015; Rytkönen et al., 2012). The use of person-oriented research techniques to study student approaches to learning increases understanding of these contradictory results. Some recent person-oriented studies highlight that it is the combination of using both the processes of a deep approach to learning and organised studying (time and effort management) that leads to better academic achievement (Karagiannopoulou et al., 2019; Ning & Downing, 2015). There is also evidence that students scoring high on measures for the deep approach to learning and low on organised studying are more likely to exhibit poor academic achievement when focusing on grade point average (GPA) (Haarala-Muhonen et al., 2017).

Self-Efficacy Beliefs and Approaches to Learning

Self-efficacy beliefs are defined as context-specific assessments of one's own ability to perform a task successfully (Bandura, 1997). The stronger the beliefs a person has about their competence, the higher their self-efficacy. Although self-efficacy is usually considered a context-specific construct, studies also suggest that it can be considered a general construct referring to an optimistic sense of personal competence and that it is closely associated with motivational variables and accomplishments (e.g., Chen et al., 2004; Luszczynska et al., 2005; Scholz et al., 2002). Many researchers have found a relationship between strong self-efficacy beliefs and students' deep approach to learning (Coutinho & Neuman, 2008; Papinczak et al., 2008; Prat-Sala & Redford, 2010). There is also evidence that students applying a surface approach to learning have lower self-efficacy beliefs (Papinczak et al., 2008; Prat-Sala & Redford, 2010). A number of researchers exploring the structural relationships between approaches to learning and self-efficacy have treated self-efficacy as an explanatory variable for approaches to learning (Fenollar et al., 2007; Liem et al., 2008; Phan, 2007). Thus, self-efficacy beliefs may be considered "expectancy constructs" because they are concerned with prospective confidence regarding whether a student will perform well on a task (Pintrich, 2003). A review by van Dinther et al. (2011) concluded that self-efficacy is vital to academic performance and that self-efficacy plays an important predictive and mediating role in relation to students' achievements, motivation and learning (see also Schunk & Pajares, 2002). Similarly, the present study treats self-efficacy as an explanatory factor in students' approaches to learning, i.e., the approach to learning that the student adapts is influenced by his/her self-efficacy beliefs.

Rationale for the Current Study

Research on student approaches to learning that combines both a person-oriented approach and disciplinary variance is still largely lacking. However, a person-oriented approach enables us to identify groups of students and typical and atypical types of individuals (Laursen & Hoff, 2006) studying in different disciplines, and thus, it helps us to understand effective studying and to develop tools to enhance quality learning in different academic disciplines. In the present study, we examine what combinations of approaches to learning (i.e., what learning profiles) emerge among students in different disciplines and how those combinations are related to academic achievement in different disciplines. In addition, the study focuses on students' sense of self-efficacy by treating it as an explanatory factor for students' approaches to learning. Following research questions were formulated: (1) What kind of student learning profiles can be detected in different disciplines? (2) How are different learning profiles related to self-efficacy beliefs in different disciplines? (3) How are different learning profiles related to academic achievement in different disciplines?

Material and Methods

Participants

The present study is part of a larger research project in which Scandinavian university students' approaches to learning were examined (Herrmann, Bager-Elsborg, & McCune, 2017; Herrmann, Bager-Elsborg, & Parpala, 2017). The present study focuses on disciplinary differences in students' approaches to learning, which have not previously been in focus in the project. Data in this study consist of survey responses from 4,294 full-time students. This particular study data were collected from students from the various disciplines at the School of Business and Social Sciences, including students at the Department of Law ($N = 615$, 14.3%), at the Department of Political Science ($N = 580$, 13.5%), the at Department of Psychology ($N = 523$, 12.2%), at the Department of Economics ($N = 1{,}761$, 41.0%), at the Department of Business Communication ($N = 599$, 13.9%) and at the Department of Business Technology ($N = 216$, 5.0%). The sample consisted of 62.5% Bachelor's degree students and 37.5% Master's degree students, of which 46.2% were men and 53.8% were women. The mean age was 23.9 (SD = 3.7, range = 18–54). The proportion of international students was 7.9%.

Responses were collected by means of an online-survey that had a response rate of 34%. Participation was voluntary and the study was performed in compliance with APA guidelines. Initial analyses showed that female students were slightly overrepresented in the sample as were younger students. An independent samples t-test showed that students' admission GPAs were higher in the group of responders ($M = 8.97$, SD = 2.03) than in the group of nonresponders [($M = 8.35$, SD = 2.14), t (7.042) = 13.7, $p < .001$]. Furthermore, university GPAs were higher among responders ($M = 7.18$, SD = 1.94) than among nonresponders [($M = 6.63$, SD = 2.26), t (9.834) = 14.0, $p < .001$]. The study complies with the Danish Code of Conduct for Research Integrity (2014) and was approved by The Danish Data Protection Agency.

Instruments

We used two sections, focusing on approaches to learning and self-efficacy beliefs, of the HowULearn questionnaire (previously named "Learn Questionnaire") (Parpala & Lindblom-Ylänne, 2012). The first part used in this study of the HowULearn instrument measures students' approaches to learning and was modified from the Approaches to Learning and Studying Inventory (ALSI, Entwistle & McCune, 2004). In addition, two items were modified and added from the Revised Learning Process Questionnaire (R-LPQ9; Kember et al., 2004). In HowULearn students are asked to describe how they had been studying in general in line with the original measurement instrument ALSI where students' approaches to learning were used to indicate a more typical way of studying across contexts with similar demands (Entwistle & McCune, 2004). HowULearn-questionnaire and scales of approaches of learning are widely used and validated in Finnish and international contexts (e.g., Cheung et al., 2020; Herrmann, Bager-Elsborg, & Parpala, 2017; Parpala et al., 2010; Postareff et al., 2018; Ruohoniemi et al., 2017; Rytkönen et al., 2012). The HowULearn questionnaire has also been translated into Danish and validated in the context of Danish higher education (Herrmann, Bager-Elsborg, & Parpala, 2017). The scales in the HowULearn measuring approaches to learning are Deep approach, Surface (unreflective) approach and Organised studying with four items each for a total of 12 items on the Likert-scale from 1 to 5. In this particular study, the reliability of the scales was measured using both Cronbach's alpha and Raykov's rho as the Alpha's limitations are well known (Cortina, 1993; Yang & Green, 2011), some of being, for example, the assumptions of uncorrelated errors and normality. The Deep Approach to Learning scale's (4 items, e.g., "I look at evidence carefully to reach my own conclusions about what I'm studying") Cronbach's alpha was 0.71 and Raykov's rho was 0.720. The Surface Approach to Learning scale's (4 items, e.g., "I am unable to understand the topics I need to learn because they are so complicated") Cronbach's alpha was 0.76 and Raykov's rho was 0.773. The third scale's, Organised Studying scale (4 items, e.g., "I am generally systematic and organised in my studies") Cronbach's alpha was 0.78 and Raykov's rho was 0.788.

Concerning students' self-efficacy, a scale in the HowULearn (Parpala & Lindblom-Ylänne, 2012) was constructed based on Pintrich et al. (1993) Motivated Strategies for Learning Questionnaire. Five items, using Likert-scale from 1 to 5, were modified to suit the academic discipline level of analysis rather than the course level of analysis. As it is applied here, self-efficacy refers to students' self-appraisal of their ability to master academic tasks, which includes their judgements about their ability to accomplish a task as well as their confidence in their skill to perform that task. Based on these items, a self-efficacy scale was computed (5 items, e.g., "I believe I will do well in my studies, as long as I make an effort") with Cronbach alpha being 0.830 and Raykov's rho being 0.831.

Data on students' university GPAs and admission GPAs were collected from the university administration. The Danish grading scale ranges from −3 (lowest) to 12 (highest). The descriptives of the whole sample, consisting of different disciplines are presented in Table 1 and concerning the correlations in Table 2.

Missing Values and the Calculation of the Summated Scales

The 12 indicator variables for approaches to learning contained between 32 and 82 (0.7% and 1.9%) missing values. There were 3,978 cases (92.6%) with no missing values, 236 cases (5.5%) with one missing value and the remaining 80 cases (1.9%) had between 2 and 12 missing values. We removed the data of respondents who had missing values for either seven or more of the approaches to learning variables or for more than two of the approaches to learning variables belonging to a particular scale (deep, surface or organised studying). This resulted in 4,267 cases, for which we calculated the average scores for the deep approach, for the surface approach and for organised studying. This strategy was chosen due to the low number of missing values and the rather similar mean values of the indicator variables related to a particular latent variable.

Self-efficacy scale averages were calculated for the data set of 4,267 cases based on a similar procedure: if there were missing data in three or more of the five indicator variables for self-efficacy, the data of the respondent were removed; otherwise, self-efficacy scale averages were calculated based on the available data. This resulted in 4,263 cases, which were used in the second analysis phase (with self-efficacy as a covariate).

There were GPA scores available for 4,213 out of the total of 4,267 respondents for whom we were able to calculate the average scores of approaches to learning.

Table 1. Descriptive statistics for the scales of the whole sample Herrmann, Bager-Elsborg, & McCune, 2017; Herrmann, Bager-Elsborg, & Parpala, 2017.

Scales	Mean	SD	α
Deep approach	3.6	0.63	.716
Organised studying	3.5	0.69	.770
Surface approach	2.6	0.83	.766
Self-efficacy	4.1	0.63	.830
GPA	7.2	1.90	

Table 2. Pearson correlations between approaches to learning, self-efficacy beliefs and academic achievement (Authors, 2017a).

Scales	1	2	3	4	5
1. Deep approach	1.000				
2. Organised studying	.255**	1.000			
3. Surface approach	−.246**	.054**	1.000		
4. Self-efficacy beliefs	.385**	.093**	−.458**	1.000	
5. Academic achievement (GPA)	.105**	.125**	−.255**	.265**	1.000

**$p < .01$.

Data Analysis

Our data analysis proceeded in three main phases. In the first phase, we performed latent profile analysis (LPA) to investigate whether distinct profiles in approaches to learning (i.e., distinct learning profiles) could be identified in the whole sample of students and within each individual academic discipline. This allowed us to assess whether the latent learning-profile structure differed across disciplines. In phase two, we examined the associations of self-efficacy beliefs and the learning profiles identified in the first phase. In this phase, self-efficacy was included as a predictor of class membership (learning profile) in a multinomial logistic regression analysis. In phase three, we included GPA as a distal outcome and examined differences among the learning profiles on the GPA variable. This procedure is described in detail in the article by Asparouhov and Muthén (2014).

In the first phase of the analysis, we assessed the number of latent learning profiles to retain by fitting the LPA models with two to seven latent profiles ($k = 2–7$). Decisions on the number of learning profiles to retain were based on examining the values of the Bayesian Information Criterion (BIC), with lower values indicating better model fit. We also examined entropy values, which reflect the degree of separation of the profiles. Higher entropy values indicate that the latent classes, i.e., learning profiles, overlap only slightly and are clearly separated.

Further, we assessed model fit using various different within-class covariance structures. The basic LPA model assumes that the observed variables are uncorrelated within each profile (i.e., that the class structure explains all the covariance among the variables). On the other hand, previous research has shown that approaches to learning are correlated in a consistent manner (Richardson, 2000), and we assumed that the LPA structure would not account for all the covariation among them. Because of this, we tested various different structures of within-class covariance, ranging from the commonly-used zero-covariance model to a model with freely estimated variance-covariance structures within each profile. Masyn (2013) addresses the estimation of within-class covariance structures.

Choices concerning the number of learning profiles and the within-class covariance structure were made based on the values of the BIC, on entropy values and on model parsimony: if two models were deemed to fit roughly equally well, the one with a simpler within-class covariance structure was favoured. BIC was chosen as an index of model fit as it can be used when comparing non-nested models (such as models based on different within-class covariance structures) and it has been shown to be an accurate criterion of model fit when the separation between the profiles is clear in LPA. Even though the entropy values are not an index of model fit as such, they convey information on how clearly the latent profiles could be distinguished from one another. To be useful in practice, the latent profiles need to be distinct enough from one another. Multivariate effect sizes for the difference between the latent profiles were quantified by calculating Mahalonobis distances.

The LPA models were estimated using MPlus 7.3 (Muthén & Muthén, 1998–2017). The default robust maximum likelihood estimator is used. To avoid local maxima, the final models were estimated based on 1,500 initial random starting values, with 500 values with the largest log-likelihoods chosen for the second optimisation step. A total of 100 iterations were performed during the first stage of the optimisation.

In the second phase of the analysis, the associations between the learning profiles and self-efficacy were examined. For this purpose, we used the R3STEP function available in MPlus 7, the use of which lets a variable can be specified as a predictor of the learning profile structure. This function is based on a three step analysis: (1) The most likely profile is specified for each student. (2) Measurement error in the latent profile variable is accounted for as specified in the work by Asparouhov and Muthén (2014). (3) Latent profile membership is predicted based on the specified auxiliary variable (in this case, self-efficacy). This results in a logistic regression model in which each latent profile in its turn functions as the reference profile with which the other profiles are compared. Obtaining a statistically significant result occurs when the log odds of belonging to a profile of interest differ from those of the reference profile.

Finally, in the last phase of the analysis, the GPAs within each latent profile were compared using the DU3STEP function of MPlus 7. This function monitors the shift in profiles. It first fits the LPA model, and after that compares the GPA means across the latent profiles, assuming unequal variances of the dependent variable (GPA) across profiles.

Results

To examine what kind of learning profiles can be detected, LPA was first conducted for the whole sample in order to find whether different subpopulations, i.e., learning profiles, could be detected across disciplines. If similar profiles would emerge across disciplines, the examination of the disciplinary differences would focus only on how these profiles are represented in different disciplines. However, the exploration of several different models showed poor model fit for the whole sample. Thus, latent profile models were fit separately to the data from each of the disciplines. This analysis revealed that a model with three latent profiles and a within-class covariance structure in which the covariances among the observed variables were freely estimated and constrained to equality across profiles was among the top three best-fitting models in five of the six academic disciplines. In Economics, we chose an otherwise similar model but with four latent profiles based on considerations of both model fit and model entropy values. The values of the BIC together with the entropy values for all the five best-fitting models are shown in Table 3.

In Law, Political Science and Psychology, the profile structures were highly similar. The profiles were made up of a combination of the deep approach and organised studying (Deep organised), a combination of the deep approach and unorganised studying (Deep unorganised I) and a profile in which the students scored high on all scales (Dissonant I). In these three disciplines, the most common profile was the Deep organised learning profile as over 60% of students belonged to this profile.

Table 3. The five best-fitting models for the disciplines

Business Communication				Law				Political Science			
Covariance structure	BIC	ΔBIC	Entropy	Covariance structure	BIC	ΔBIC	Entropy	Covariance structure	BIC	ΔBIC	Entropy
2b	3915	0	0.658	3b	4154	0	0.71	2d	3873	0	0.594
2f	3916	1	0.678	2e	4162	8	0.615	3b	3875	2	0.695
3b	3928	14	0.605	4b	4165	11	0.772	2b	3875	3	0.85
2d	3931	16	0.438	5b	4176	22	0.782	4b	3876	3	0.744
3f	3931	16	0.765	2b	4177	24	0.737	2f	3880	7	0.774

Psychology				Economics				Business Technology			
Covariance structure	BIC	ΔBIC	Entropy	Covariance structure	BIC	ΔBIC	Entropy	Covariance structure	BIC	ΔBIC	Entropy
4b	3458	0	0.754	3e	11657	0	0.489	3b	1432	0	0.855
2d	3458	0	0.501	4e	11678	20	0.551	4a	1432	1	0.789
3b	3461	4	0.739	4b	11687	30	0.664	2b	1433	1	0.948
3d	3461	4	0.663	4d	11688	31	0.663	2f	1435	3	0.993
5b	3466	9	0.786	5b	11690	33	0.706	3a	1436	4	0.735

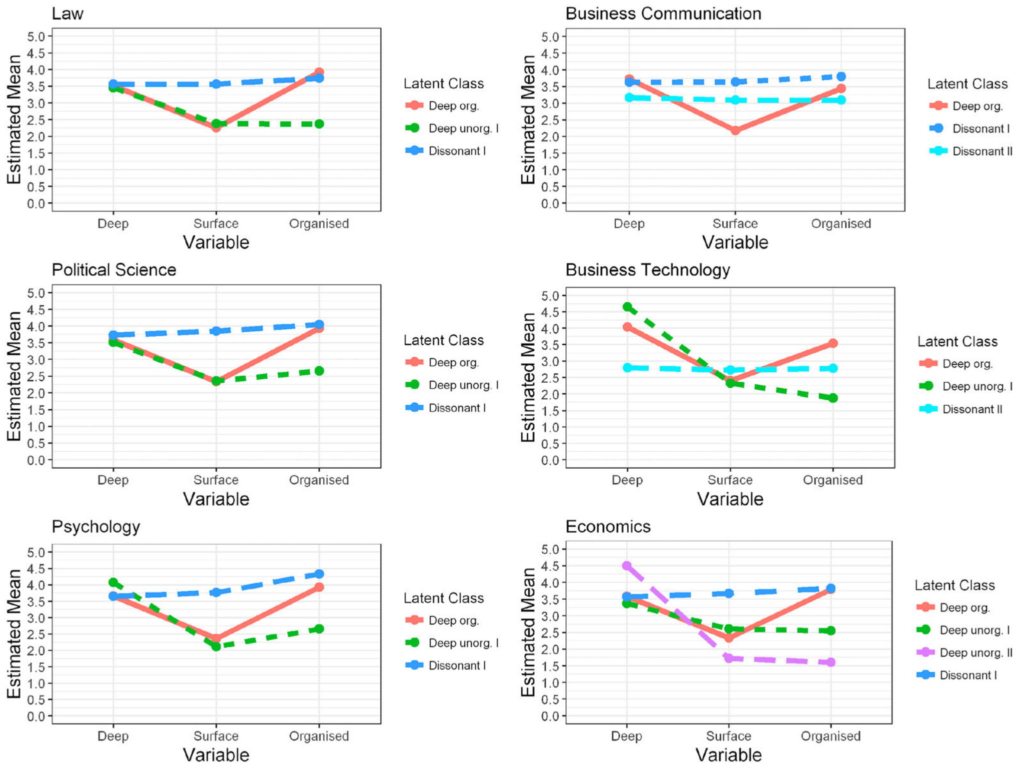

Figure 1. Learning profile (class) structures in the six academic disciplines.

The within-class correlation among the indicator variables were the following for the different academic disciplines: Law r(Deep, Surface) = − 0.144; r(Deep, Organised) = 0.135; r(Surface, Organised) = 0.024; Political Science r(Deep, Surface) = − 0.167; r(Deep, Organised) = 0.061; r(Surface, Organised) = − 0.026; Psychology r(Deep, Surface) = − 0.191; r(Deep, Organised) = 0.135; r(Surface, Organised) = − 0,064. The correlations between the different scales of approaches to learning were highly similar across disciplines, making it possible to label the profiles similarly across them.[1] Figure 1 illustrates the profile structures in all the disciplines.

In Law, 67% of students belonged to the profile Deep organised, 17% to Deep unorganised I and 16% to Dissonant I. Among students in Political Science, 61% belonged to the profile Deep organised, 33% to Deep unorganised I and 6% to Dissonant I. The students in Psychology fell into these profiles in a highly similar manner as 70% of them belonged to the profile Deep organised, 18% to Deep unorganised I and 12% to Dissonant I. The percentages of profiles in different disciplines are presented in Table 4.

The learning profile structure among those studying economics was only slightly different from the structures described above. The within-class correlation among the indicator variables were r(Deep, Surface) = − 0.078; r(Deep, Organised) = 0.146; r(Surface, Organised) = − 0.004. The solution with three different profiles did not fit the data from Economics. Instead, four different profiles emerged. Two profiles were very similar in nature in that they consisted of high scores on the deep approach and low scores on organised studying. The level of those scores in the dimensions was, however, different. There was a small group of students with very high scores on the deep approach and very low scores on organised studying. This profile was labelled as Deep unorganised

[1]Finding highly dissimilar within-class correlations across disciplines would have encouraged one to interpret the latent profiles as qualitatively different.

Table 4. Percentages of profiles.

Profiles	Business Communication %	Law %	Political Science %	Psychology %	Economics %	Business Technology %
Deep organised	63	67	61	70	53	82
Deep unorganised I		17	33	18	25	4.5
Deep unorganised II					1	
Dissonant I	16	16	6	12		
Dissonant II	21					13.5

II. However, only 1% of all students fell into this profile. The most common profile was Deep organised (53%). The second largest profile was Deep unorganised I (25%).

The profile structures in Business Communication and in Business Technology, were different compared to those that emerged for students in the first four disciplines. In Business Communication a group of students with higher scores on the surface approach and lower scores on the deep approach to learning compared to those of other student groups were found. This profile was labelled Dissonant II because the students' scores were all very near to average but still lower than the scores found in the Dissonant I. The largest profile in this discipline was again Deep organised (63%) and the second largest was Dissonant II (21%). The within-class correlations among the indicator variables were r(Deep, Surface) = − 0.032; r(Deep, Organised) = 0.149; r(Surface, Organised) = 0.029.

In Business Technology, in similarity with the Business Communication, the latent profile Dissonant II was found: the students belonging in this profile had average scores on all three scales measuring approaches to learning. However, among students in this discipline the pro Deep unorganised I was not detected. The most common profile in this discipline was again Deep organised (82%) and the second largest was Dissonant II (13.5%). The within-class correlations among the indicator variables were r(Deep, Surface) = − 0.110; r(Deep, Organised) = 0.107; r(Surface, Organised) = − 0.003.

Self-Efficacy Beliefs in Relation to Learning Profiles

Next the students' self-efficacy was examined in relation to different learning profiles separately in each discipline. The most consistent finding across all the disciplines was that having low self-efficacy increased one's probability of having one of the dissonant learning profiles. The probability of belonging in the Deep organised profile increased with increasing self-efficacy, but the differences between the Deep organised and Deep unorganised profiles were not statistically significant in any discipline other than in Economics. In the institute of Economics, the students belonging in Deep unorganised II profile were more likely to score higher on the self-efficacy measure than did students in the Deep organised profile.[2] Finally, among students in Business technology, those who reported low self-efficacy had an increased risk of membership in the Dissonant II profile; students in this discipline had the highest scores on the surface approach to learning. We present the results in the probability metric (Figure 2) as probabilities are more intuitive to understand than logarithms of odds ratios.

Differences in Academic Achievement

In general (across the disciplines), having the deep organised profile was more often related to having a high GPA compared to other profiles. However, slight differences between the disciplines were observed. Among students in Law, the GPAs of those with the profile Deep unorganised I were significantly lower than the GPAs of students with other profiles. In Political Science, students having

[2]This is perhaps not obvious looking at Figure 2. The use of the probability metric in Figure 2 reflects the sizes of the latent profiles: if the profile size is small to begin with, the probability of profile membership will remain low, no matter the value on the self-efficacy measure. This is the case with the latent profile Deep Unorganised II among students in Economics.

Table 5. The relation between the learning profiles and academic achievement in different disciplines.

	Business Communication		Law		Political Science		Psychology		Economics		Business Technology	
Profiles	*M*	SE	*M*	SE	*M*	SE	*M*	SE	*M*	SE	*M*	SE
Deep organised[a]	7.81[d**, e*]	0.09	7.59[b**]	0.10	7.63[d*]	0.11	7.99	0.11	7.34[b,c,d,**]	0.06	7.86	0.13
Deep unorganised I[b]			6.02[a**, d*]	0.31	7.29	0.14	7.82	0.25	5.61[a,c,**]	0.15	8.34	0.56
Deep unorganised II[c]									8.6[a,b,d,**]	0.31		
Dissonant I[d]	6.65[a,**]	0.27	7.17[b*]	0.24	6.79[a*]	0.22	7.14	0.39	6.07[a,c**]	0.1		
Dissonant II[e]	7.04[a*]	0.20									7.79	0.38

Notes: The letters indicate the statistically significant differences between the profiles. For example, [b] indicates that the mean differs significantly from profile b; [b,c,d,**] indicates that the mean differs significantly from b, c and d. Significances $^{**}p \leq .001$, $^{*}p \leq .01$.

the Deep organised profile had significantly higher GPAs than students in the profile Dissonant I, but no other differences were found. Surprisingly, in Economics students representing Deep unorganised II had significantly higher GPAs than all the other students, whereas students in profile Deep unorganised I had significantly lower GPAs than all the other students. The students in the profile Deep organised had significantly higher GPAs than did students in the profiles Dissonant I and Deep unorganised I. In Business Technology and in Psychology there were no statistically significant differences between the GPAs of students with different profiles. The results of the relation between the learning profiles and academic achievement in different disciplines are shown in Table 5.

Discussion

Learning Profiles in Different Disciplines

Our results showed that it was possible to detect different subpopulations, i.e., learning profiles, of students in different disciplines. We detected five different profiles (Deep organised, Deep

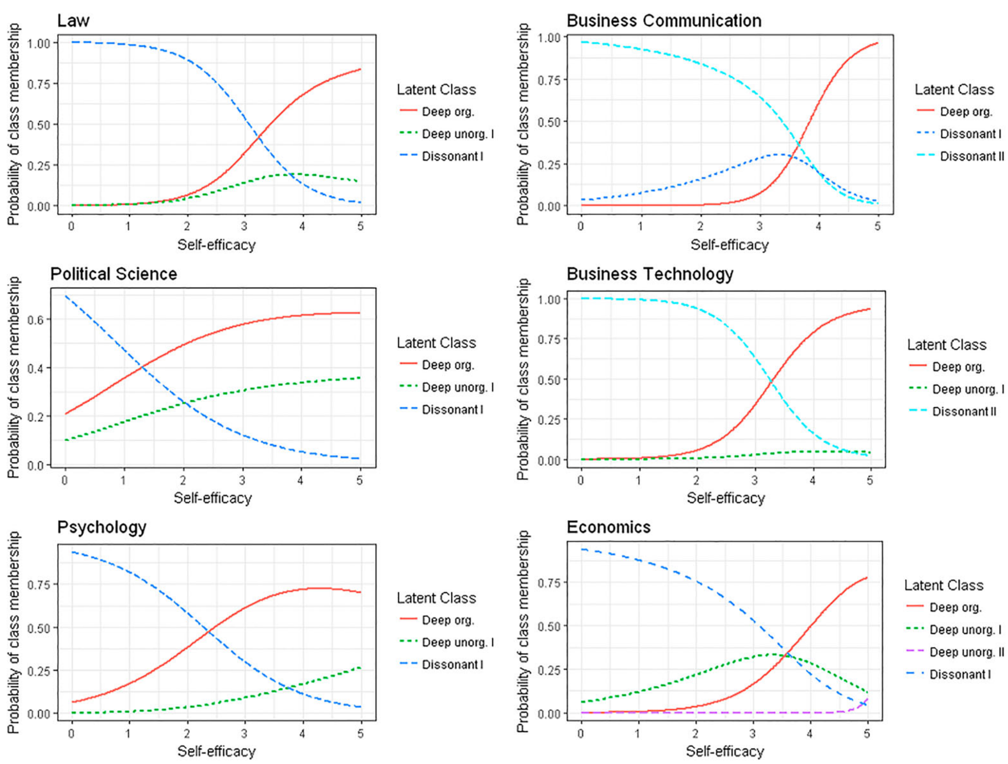

Figure 2. Probability of learning profile (class) membership as a function of self-efficacy scores.

unorganised I, Deep unorganised II, Dissonant I, Dissonant II). Each discipline had its own profile solution and no general solution for the whole data was found. As the correlations between the scales in the disciplines were similar, the learning profiles were labelled similarly, but they were differently represented in different disciplines. In general, we were able to detect students with typical and atypical combinations of approaches to learning. For example, the Deep organised profile is supported by the theory implying that the deep approach to learning and organised studying correlate strongly and positively with each other (e.g., Richardson, 2000). Identifying the profiles Deep unorganised I and Deep unorganised II was interesting because it supports the existence of a theoretically atypical combination of the deep approach to learning and organised studying, which has also been found in previous studies (Asikainen et al., 2020; Haarala-Muhonen et al., 2017; Parpala et al., 2010). The two dissonant profiles (high on all scales and close to average on all scales) are similar to the profiles High Quantity and Average found in a study by Fryer and Vermunt (2018). Similarly, two dissonant profiles, high and moderate, were found in a study by Karagiannopoulou et al. (2020). The profiles were represented differently in different disciplines (see Table 4). In Law, Political Science and Psychology three profiles emerged (Deep organised, Deep unorganised I and Dissonant I) but they were differently represented. For example, in Law and Psychology under 20% of students represented Deep unorganised I profile whereas in Political Science the percentage of students representing this profile was 33. In addition, in Economics three similar profiles were detected, but also one exceptional, small group of students representing Deep unorganised II profile. This profile should be carefully considered as there was only one percentage of students representing this profile. It was still very different from the other three, and thus, could not be included in the other profiles.

The profile solution was somewhat different in the two remaining disciplines. In Business communication, Deep unorganised profile was not detected as was the case in other disciplines. Moreover, in Business Technology the Dissonant I profile, detected in all other disciplines, did not emerge from the data.

To summarise, the Deep organised was the most common profile in every discipline which resembles the findings in previous research (Parpala et al., 2010). However, the second largest group of students represented Deep unorganised in Law, Political Science, Psychology and Economics. In Business Communication and Business Technology the second largest profile was Dissonant II with average scores on all the scales measuring approaches to learning. These results are being discussed more detailed below as we discuss the findings concerning the relations between learning profiles, self-efficacy and academic achievement.

Self-Efficacy in Relation to Learning Profiles in Different Disciplines

The examination of how students representing different learning profiles differed in their self-efficacy showed that in all disciplines students with Deep organised profile also had the highest self-efficacy. This is in line with previous research suggesting that strong self-efficacy beliefs are related to deep approach to learning (Coutinho & Neuman, 2008; Papinczak et al., 2008; Prat-Sala & Redford, 2010). On the other hand, students scoring high or average on all approaches to learning (profiles Dissonant I and Dissonant II) systematically had the lowest self-efficacy. This also resonated with previous studies suggesting that students applying a surface approach to learning have lower self-efficacy beliefs (Papinczak et al., 2008; Prat-Sala & Redford, 2010). In both these Dissonant profiles, the scores on surface approach were high which suggests that these students were struggling with forming a coherent understanding and reflecting on their studying, and this profile might thus resemble the profile previously labelled as Students applying a surface approach (Asikainen et al., 2020). It varied slightly from discipline to discipline in terms of which dissonant profile was associated with the lowest self-efficacy. Even though there were no statistically significant differences between students in Deep organised and Deep unorganised profiles, it was evident that students with the Deep Unorganised profile had lower self-efficacy beliefs. This suggests that the combination of deep approach and organised studying is especially important in terms of self-efficacy and successful studying.

Learning Profiles in Relation to Academic Achievement in Different Disciplines

Generally speaking, in three of the six academic disciplines included in this study, students in the Deep organised profile (that is, students scoring high in relating ideas, use of evidence and time and effort management) had systematically the highest level of academic achievement. This finding is in line with earlier research (Haarala-Muhonen et al., 2017; Karagiannopoulou et al., 2019; Ning & Downing, 2015) and highlights the importance of both organised studying and a deep approach to learning for successful studying, particularly in Business Communication, Law and Political Science. An exception to this was the Economics, in which a profile emerged that was not evident in the other disciplines: very high scores in relating ideas and use of evidence, but very low scores in time and effort management (Deep unorganised II). The profile correlated positively with high self-efficacy and good academic achievement. This profile in fact appeared to be quite distinct in many aspects. It appears that such economics students are highly engaged but may not deem organised studying to be an important component of their learning process. It might even be that they do not want to proceed in an organised and systematic way in their studies, but rather want to leave room for academic freedom and thought in their studies. It is noteworthy that students representing the Deep organised profile had the second highest level of academic achievement in Economics. This implies that the deep approach itself plays an especially important role in Economics in terms of academic achievement.

A more detailed examination of disciplinary differences in learning profiles revealed that in Law and Economics, students representing the Deep unorganised I profile had the lowest level of academic achievement. This was also the second largest profile in these disciplines. Previous research in the field of law supports this finding (Haarala-Muhonen et al., 2017). A longitudinal study on Finnish law students showed that students having high scores on the deep approach to learning and low scores on organised studying had the lowest grade point average and it took them the longest amount of time to graduate compared to students with high scores on both the deep approach to learning and organised studying (Haarala-Muhonen et al., 2017). In the present study, a similar result emerged in Economics, which is also a vocational discipline and rooted in practice. The results showed that students representing the Deep unorganised I profile (scoring high on the deep approach to learning and low on organised studying) had a lower level of academic achievement than students representing the Deep organised and Dissonant I profiles. One possible explanation for similar results in Law and Economics is that in both disciplines studying includes a combination of theory and practice. Especially in accounting, which is included in the economics studies in the participating university, students need to complete a number of practical exercises and simultaneously learn to understand the phenomena, resulting in a heavy workload (Scully & Kerr, 2014). Law students face a similar situation, as they need to solve legal problems and cases, which also requires an understanding of the issue at hand and competence in drawing conclusions (Haarala-Muhonen et al., 2017). Furthermore, a previous person-oriented study found that accounting students with high scores on the deep approach to learning and able to organise their studying succeeded in their studying (Duff, 2004). The present study supports the above findings by Duff (2004) and by Haarala-Muhonen et al. (2017) by implying that in disciplines rooted in practice the deep approach to learning in itself is not related to academic achievement; good time and effort management skills are also needed in these disciplines to ensure high academic achievement.

In Political Science and Business communication, students representing the Dissonant I profile had the lowest level of academic achievement compared to students representing other profiles.

Thus, the present study suggests that students scoring high on every approach to learning seem to struggle in their studies especially in these two disciplines compared to those representing the other profiles. There might be differing explanations for the emergence of such a profile. For example, students scoring high on all scales might have difficulties evaluating their own learning, and thus, they score high on each scale. On the other hand, it might be that such students score high on every scale because they have the intention to understand but not the means to do so. Or maybe the learning environment encourages the use of a surface approach to learning even though students would like to use a deep approach to learning and be more organised in their studying (Fryer & Vermunt, 2018). Nevertheless, the surface approach is more affected by the context than the other approaches (Postareff et al., 2018). In the present study, the items in the inventory measuring students' surface approach to learning are more focused on their inability to relate ideas and difficulties in understanding the content, in other words, their unreflective approach to learning (Lindblom-Ylänne et al., 2019). Therefore, the first explanation may well have more merit for the purposes of the present study, suggesting that students representing the profile might have difficulties with reflective learning and relating ideas more than with strategically changing their approaches to learning according to the demands of the learning environment. This is also in line with the result that students representing the Dissonant learning profile scored lowest also on self-efficacy beliefs.

Limitations of Study

The present study contains some limitations. Firstly, the study is based on the students' self-evaluations of approaches to learning. However, approaches to learning were measured by three scales, and the Cronbach's alphas were satisfactory. Moreover, the scales measuring approaches to learning have been validated and used in many studies and contexts (e.g., Asikainen et al., 2020; Ruohoniemi et al., 2017). These scales can also be used to measure students' typical way of studying (Entwistle & McCune, 2004), and therefore, the survey does not need to be administrated during a single course, for example. Secondly, the use of LPA and how the derived profiles are validated should also be considered. The learning profiles in the disciplines were supported by multiple criteria, both fit values (Table 1) as well as the previous research on learning profiles (e.g., Asikainen et al., 2020; Haarala-Muhonen et al., 2017; Parpala et al., 2010) which are important when deciding the final profile solution (Spurk et al., 2020). However, the profile Deep unorganised II in Economics is exceptional and requires a critical consideration. The Deep unorganised II was, however, also visually clearly emerging from the data in addition to model fit and was therefore kept as a separate profile. Moreover, one point of note is that even though the present study distinguishes between two dissonant profiles (Dissonant I and Dissonant II), the profiles appear quite similar in many ways and may, thus, not be treated separately in future research. The students scored similarly on the three measures for learning processes, and they differed only in how high they scored on those three dimensions. Finally, the use of GPA as a measure of achievement is somewhat questionable as it is only one, rather limited indicator of academic achievement. However, it is widely used as an indicator of the overall achievement.

Practical Implications in Different Disciplines

The result showing Dissonant learning profile being related to low scores on self-efficacy and lower academic achievement in many of the disciplines raises a question of how these students should be supported. Special attention should be paid to identifying students fitting the dissonant learning profiles and to support them in recognising their own learning processes and how such processes may be related to their self-efficacy as well. For example, Backhaus and Liff (2007) recommend that students' metacognitive awareness of their own learning processes and ways to self-monitor their own learning could be enhanced by having students complete an inventory regarding their approaches to learning as a means of making their learning styles more familiar to them. Similar examples have been reported in other institutions (Haarala-Muhonen et al., 2017; Parpala & Lindblom-Ylänne, 2012; Ruohoniemi et al., 2017). Moreover, monitoring and regulation strategy, in which students are explained how to assess their learning, has shown to improve academic achievement (de Bruin et al., 2017)

Moreover, in Law and Economics students representing the profile Deep unorganised had the lowest academic achievement. Thus, it is important to support students' abilities to manage their time and effort in these disciplines. Such support is also important because there is evidence that students scoring low on measures of organised studying experience more obstacles in their studies than do students with highly organised study skills (Hailikari et al., 2018). Academic staff could thus support students in their studying by, for example, explicitly communicating the time plan and goals of their lectures (Liborius et al., 2017) or by making curriculum changes to diminish the workload in studying (e.g., Haarala-Muhonen et al., 2017; Ruohoniemi et al., 2017). Several studies have also provided good examples of the fact that students' time and effort management skills may be fostered via different types of training, both face-to-face (Schmitz & Wiese, 2006) as well as web-based training (Bellhäuser et al., 2016).

Conclusion

On the basis of the present study, we conclude that although the majority of students belong to the profile Deep organised, which is also related to higher academic achievement in many of the disciplines, there are also students representing profiles which would require more support. For example, in Law and Economics profile Deep unorganised was the second largest profile with lower academic achievement and low levels of self-efficacy beliefs. In these disciplines students' ability to successfully organise and manage their time and effort at studying should be encouraged and supported, especially as organising skills may not be easy to develop (Postareff et al., 2018). This may also concern other disciplines rooted in practice but more research is needed. The present study also highlights that profile Dissonant I serves attention. This profile was related to lower academic achievement especially in Political Science and Business Communication, in which the very similar profile Dissonant II was the second largest profile and also struggling in studies. In the light of this profile, it would be very important to support students' ability to reflect on their own learning, relate ideas to one another and form a bigger picture. Moreover, the result implies that students scoring high on surface approach to learning, may score high on other scales as well (Fryer & Vermunt, 2018), indicating inability to reflect on own learning (Lindblom-Ylänne et al., 2019). Still, further research is definitely needed to better understand the Dissonant profile as well as to search the reasons why profiles are represented differently in different disciplines. This would require disciplinary-specific research using both quantitative and quantitative methods.

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