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Nature vs nurture: learning conceptions and environment as precursors to learning strategy patterns and their outcomes

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ABSTRACT

Much of formal higher education research on learning experiences has focused on processing strategies and outcomes, however, less attention has been paid to their precursors. This study employed Biggs' 3P model to examine the contributions of learning conceptions (as part of learning patterns (LPs) research; construction of knowledge, intake of knowledge) and perceptions of learning environment (appropriate workload, good teaching) as Presage factors affecting both (stepwise, deep) processing and (self-, external, lack of) regulation strategies (Process), which collectively affect outcomes (Product; generic skills, satisfaction, and end-of-term grade). Psychology students ($n = 242$) in second and third year attending a major state-supported university completed the Inventory of Learning Styles, the Course Experience Questionnaire and student satisfaction of teaching scale. Fully-forward latent-variable SEM was undertaken according to the stages of the 3P model. Though some relationships in part reflected meaning-directed (construction of knowledge predicting deep processing and self-regulation) and reproduction-directed (intake of knowledge predicting stepwise processing and external regulation) LPs, several associations did not support traditional learning patterns (construction of knowledge predicting external regulation, intake of knowledge predicting lack of regulation). The results warrant the continued investigation of these relationships between learning components of LPs using more robust research designs and analyses. A positive learning environment (appropriate workload) predicted deep processing and negatively predicted lack of regulation. Deep processing positively predicted achievement while lack of regulation negatively predicted all outcomes. Learning conceptions and learning environment simultaneously had large effects on learning strategies and outcomes, indicating the importance of supporting their development. A separate Latent Profile Analysis of Presage variables revealed three subgroups: Inactive, Passive-Idealist and Environment Driven; none of which revealed a preference for either construction or intake of knowledge. Learning environment positively associated with achievement. Theoretical and practical implications are discussed.

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Introduction

Student processing strategies and their effects on outcomes have been studied extensively (e.g., Dinsmore & Alexander, 2012; Lizzio et al., 2002; Vermunt & Donche, 2017), but what leads students to adopt these strategies in the first place?

Two established theories that describe students' use of processing strategies are Students' Approaches to Learning (SAL; Biggs, 1999; Entwistle & Tait, 1990; Marton & Säljö, 1976) and Learning Patterns (LPs; Vermunt, 1998; Vermunt & Donche, 2017). In the SAL research tradition, students adopt learning approaches (e.g., surface or deep) in response to their specific learning context (Biggs, 1999; Entwistle & Tait, 1990; Marton & Säljö, 1976). Educators are hypothesised as affecting SAL through course experiences (Asikainen & Gijbels, 2017; Lizzio et al., 2002; Ramsden, 1991). Students' prior learning experiences have also been shown to meaningfully impact students' use of processing strategies (Martínez-Fernández & Vermunt, 2015). Learning Patterns theory examines students' processing and regulation strategies (together known as learning strategies; Vermunt & Donche, 2017) at a general level, posited as being influenced by both the learning context and previous learning conceptions. Learning conceptions describe students' beliefs about learning developed over previous learning experiences (Vermunt & Donche, 2017). Though teachers have less control over students' current learning conceptions, they can be developed across learning experiences (Vermunt & Vermetten, 2004).

Researchers (e.g., Richardson, 2011) have called for the rapprochement of the two theories. Using Biggs' (1993) 3P model, the current study draws upon and tests both theories simultaneously by examining learning environments and learning conceptions (Presage) and their cascading effects on learning strategies, from a learning patterns perspective (Process), and outcomes (Product). Building on previous work that investigated effects of course experience on learning patterns (Law & Meyer, 2011) and SAL using the 3P model (Diseth, 2007; Diseth et al., 2006; Lizzio et al., 2002), these precursors – i.e., the learning environment and learning conceptions – serve as the foundation for the current study from which to examine the learning experience both deeply (by considering processing and regulation strategies, learning conceptions, course experience, and outcomes) and broadly (across the stages of the 3P model). Intervention strategies are informed by the expected and unexpected pathways in fully-forward (where all paths from Presage to Process, and both Presage and Process to Product are tested simultaneously with no paths removed to improve fit) latent-variable SEM analysis for the overall group. Furthermore, person-centred analyses (i.e., Latent Profile Analysis; Magidson & Vermunt, 2004) are conducted on Presage variables to inform practical strategies for different subgroups.

Theoretical frameworks

Learning patterns

Learning patterns (LPs; Vermunt & Donche, 2017) are characterised as embodying specific aspects of four learning components: learning conceptions, orientations (and motivations), processing strategies, and regulation strategies. Learning conceptions are mental models and beliefs students hold about learning informed by previous experience.

These affect approaches to studying (Richardson, 2011), including learning strategies (processing and regulation strategies; Vermunt & Donche, 2017). A large-scale principal component analysis on the Inventory of Learning Styles (ILS; Vermunt, 1998), measuring aspects of each learning component suggested four LPs. Students employing a *meaning-directed* LP construct knowledge, view learning tasks as their own, process information deeply, adopt self-regulation strategies (monitor progress, test, reflect, adjust habits) and are motivated by personal interest. With a *reproduction-directed* LP, students intake knowledge from the teacher through memorisation and analysing (stepwise processing), respond to external sources of regulation, and are motivated by demonstrating their success to themselves and others. Students following an *undirected* LP have ambivalent motivation, conceive learning as cooperative and stimulating, lack regulation and do not adopt specific processing strategies. The *application-directed* LP involves adopting a concrete processing strategy, conceiving learning as use of knowledge and being motivated by vocation. Studies have replicated some of these relationships using logistic regression (e.g., Vanthournout et al., 2012), person-centred (e.g., Heikkilä et al., 2011) and path analyses (e.g., Martínez-Fernández & Vermunt, 2015). A cross-cultural study (Vermunt et al., 2014b) of eight samples including the original sample (Vermunt, 1998), found that an application-directed LP was only present in the original sample. Furthermore, in all samples, concrete processing loaded strongest on the meaning-directed LP. Another LP, passive-idealistic, has often emerged (Vermunt et al., 2014a; Vermunt & Donche, 2017) containing all learning conceptions, but no learning strategies.

Higher achievement and higher quality learning outcomes are generally associated with the meaning-directed LP (Donche et al., 2014; Martínez-Fernández & Vermunt, 2015), while lower quality outcomes are usually exhibited by those employing an undirected LP (Donche et al., 2014; Vermunt, 2005). The other two learning patterns have reported mixed relationships with outcomes (Vermunt & Donche, 2017).

Relationships between learning components of the ILS along with effects on outcomes have been tested in many higher education contexts. Belgian engineering students' regulation and processing strategies were studied longitudinally, finding that deep processing and self-regulation predicted each other across three time-points (meaning-directed LP; De Clercq et al., 2013). Loyens et al. (2008) found that Dutch fourth-year university psychology students' self-regulation predicted deep, stepwise and concrete processing, while external regulation predicted stepwise processing, lending support to the existence of meaning-directed and reproduction-directed learning patterns. Martínez-Fernández and Vermunt (2015) found that in Spanish and Latin American undergraduates, construction of knowledge, deep processing and their effects on students' effort predicted achievement, while intake of knowledge negatively predicted achievement. Less common in LPs research are the effects of students' perceptions of the teaching environment.

LPs are not stable psychological traits but learning dimensions that are more holistic and multidimensional than SAL (Vanthournout et al., 2013). Students might not clearly differentiate between use of LPs and are influenced by context (e.g., disciplinary differences, course experience; Vermunt & Vermetten, 2004). In comparison, SAL theorises that deep and surface approaches to learning are adopted in reaction to specific contexts (Biggs, 1993) and does not consider regulation, nor learning conceptions explicitly.

The Course Experience Questionnaire (CEQ; Ramsden, 1991; Wilson et al., 1997) has been widely used (Lizzio et al., 2002; Richardson, 1994; Yin & Wang, 2015) to report the contextual demands students face according to their perceptions of the learning environment. Law and Meyer (2011) examined the relationships between course experience, learning patterns, and outcomes (satisfaction and expected achievement) within secondary students in Hong Kong. Controlling for age, gender, prior academic performance and area of study, multiple regression path-analysis and partial correlations were used, testing one outcome at a time. The undirected LP associated with lower expected achievement. Generic skills correlated with external regulation and all learning conceptions. Good teaching correlated with construction of knowledge. LPs mediated the effects of appropriate workload on expected achievement, though results on which LPs were unclear due to modelling limitations. A fully-forward model separating out the different learning conceptions, processing and regulation strategies within LPs could overcome previous limitations; allowing for all paths to be tested simultaneously, and clearer identification of relationships.

3P Model

Biggs' (1993) 3P model describes classroom learning in three sequential stages, Presage, Process and Product. The Presage stage involves teaching context (e.g., curriculum, teaching methods and workload) and student context (e.g., prior knowledge, motivations and abilities). These variables feedforward to the Process stage, which considers task processing, including learning strategies (traditionally SAL, e.g., surface or deep approach to learning; Biggs, 1999). The Presage and Process lead into the Product stage (outcomes). The 3P model allows for the integration of additional learning components described by learning patterns research such as learning conceptions (Presage) and metacognitive regulation strategies (Process) to be studied alongside students' course experience and processing strategies in a fully-forward manner.

Results on SAL learning strategies and their effects on achievement using the 3P model in higher education have been inconclusive. Lizzio et al. (2002) analysed the learning experiences of undergraduate students, finding that good teaching more strongly predicted outcomes than prior achievement. Both deep and surface strategy predicted achievement. Diseth et al. (2006) tested the effects of CEQ on SAL, and subsequently, SAL on exam grades for undergraduate psychology students. Good teaching and appropriate workload predicted deep approach positively, and surface approach negatively. Neither learning approach predicted examination grade. Incorporating learning patterns theory (Vermunt & Donche, 2017) provides a different magnification to investigate the effects of learning conceptions and learning environment, on both current and ongoing processing and regulation strategies, and outcomes.

Person-centred perspectives on learning patterns

Person-centred approaches to analyses have clarified how subgroups of students differentiate between the reporting of different scales of the ILS. Fryer and Vermunt (2018) investigated the structure, development of and movement between subgroups of Japanese undergraduate students on (self, external and lack of) regulation, processing strategies (Trigwell & Ashwin, 2006) and GPA. Three of four subgroups reported similar levels of regulation strategies within the subgroup, suggesting that students did not readily differentiate based on regulation strategy. Heikkilä et al. (2011) identified three subgroups in Finnish university students based on processing and regulation strategies: non-academic students, self-directed students and helpless students. Differences were found in deep understanding, self-regulation and lack of regulation. Non-academic and helpless subgroups reported similar profile shapes but different levels (for a discussion on profile shapes and levels: see Morin & Marsh, 2015) with higher lack of regulation and lower levels of self-regulation. The self-directed subgroup reported a contrasting shape on regulation and deep understanding scales compared to other subgroups. Vanthournout et al. (2013) investigated students undergoing teacher-training in Belgium on processing strategies finding four subgroups: deep approach, surface approach, all-low and all-high. Despite the above mixed results, Vermunt and Vermetten (2004) previously reported higher education students experienced more differentiated use of learning patterns. The reviewed work has primarily focused on Process variables. Given the focus of this study on the precursors to learning strategies and outcomes, a person-centred analysis on Presage variables could inform potential interventions in guiding students in particular subgroups towards adopting specific learning strategies and achieving outcomes.

The current study

The interplay between contextual factors (i.e., course experience) with learning conceptions and their effect on students learning strategies and outcomes remains to be clarified. The current study builds on the work presented to this point by testing a fully-forward model based on 3P principles (Biggs, 1993) using latent SEM. Specifically, forward linkages between course experiences and learning conceptions (Presage), processing and regulation strategies (Process) and achievement, generic skills and student satisfaction (Product) are tested. These results illuminate potential pathways for interventions supporting achievement and other important outcomes. As this was an initial attempt at using fully-forward latent-variable SEM analysis with ILS and CEQ constructs, potential limitations on construct validity along with limited sample size amplified model complexity concerns. The authors needed to be selective in which variables to include in the model. With support in the literature (e.g., Martínez-Fernández & Vermunt, 2015; Richardson, 2011) for learning conceptions as precursors to learning strategies, the learning orientations component was removed. As findings regarding the application-directed LP are inconsistent (e.g., Vermunt et al., 2014a), and due to the current research context (psychology students), it was not included. Furthermore, Stimulated Education and Cooperative Learning conception scales were not considered as they do not traditionally associate with any processing strategies (Vermunt & Donche, 2017). With a focus on students' perception of the teaching environment, CEQ Independence, Clear Goals and Appropriate Assessment scales, and were removed. The research questions and hypotheses of the SEM analysis centre around the remaining constructs of the ILS and CEQ. Subsequently, a person-centred analysis with the Presage variables examined subgroup structure. The findings suggest theoretical and practical implications overall and for individual subgroups.

Research questions

The following research questions and hypotheses guided the study.

RQ1) How do the learning environment and learning conceptions (Presage) affect learning strategies (Process) and outcomes (Product)?

Hypothesis 1a: Construction of knowledge would predict both self-regulation and deep processing (meaning-directed LP; Vermunt & Donche, 2017). Intake of knowledge would predict both external regulation and stepwise processing (reproduction-directed LP; Vermunt & Donche, 2017).

Hypothesis 1b: The learning environment (e.g., appropriate workload, good teaching) would positively predict meaning-directed LP components (e.g., deep processing; Diseth et al., 2006; Lizzio et al., 2002), and negatively predict undirected LP components (e.g., lack of regulation; Law & Meyer, 2011).

Hypothesis 1c: Learning strategies of the meaning-directed LP (e.g., deep processing and self-regulation) would positively predict outcomes (Product; Donche et al., 2014; Martínez-Fernández & Vermunt, 2015) while learning strategies of the undirected LP (e.g., lack of regulation) would negatively predict outcomes (Product; Donche et al., 2014; Vermunt, 2005; Vermunt & Vermetten, 2004).

RQ2) How do learning conceptions and perceived learning environment differ among students? In the person-centred analysis,

Hypothesis 2a: Subgroups will demonstrate clear preferences for particular learning conceptions over others (greater expected differentiation in higher education students; Vermunt & Vermetten, 2004).

Hypothesis 2b: Subgroups with higher construction of knowledge, good teaching and appropriate workload will present higher achievement (Vermunt & Donche, 2017).

Methods

Participant context, procedure, data collection and instruments

Participants were undergraduate psychology students ($n = 242$) in their second and third years of study, attending their spring semester courses at a major state-supported university in Spain. The majority were female (80.2%), enrolled in their second year (58.7%), and aged between 19 and 25 (96.3%). Participants received a booklet containing the questionnaires, which they completed at a single time during regular class time. The booklet contained the 36-item CEQ (Wilson et al., 1997), the 120-item ILS (Vermunt, 1998), and a 5-item measure on Satisfaction (Grace et al., 2012). All items were measured on a 5-point Likert scale from 1 (‘never or rarely true of me’) to 5 (‘always or almost always true of me’). Participants provided written consent for access to their end-of-term grades. Participation was voluntary, and students could opt-out at any time. Ethical clearance was obtained from the university.

Analyses

M*plus* 7.0 (Muthén & Muthén, 2014) was used for Latent SEM analyses (RQ1) and Latent Profile Analysis (LPA; RQ2; Magidson & Vermunt, 2004). R v3.5.3 was used for all other analyses (RQ1 & RQ2). Missing data (<1%) were handled by Maximum Likelihood Estimation in M*plus* and imputation using multiple imputed chain equations in R.

For Confirmatory Factor Analysis (CFA) and latent SEM, fit indicators included Comparative Fit Index (CFI) >.90/.95 (McDonald & Marsh, 1990), and Root-Mean-Square Error of Approximation (RMSEA) <.08/.05 (Browne & Cudeck, 1992) representing acceptable and good fit respectively, while Square Root Mean Residual (SRMR) <.08 indicated good fit (Hu & Bentler, 1999). Small, medium and large educational effects were given by $|\beta| \geq .05/.10/.25$ respectively (Keith, 2015).

LPA investigating subgroups based on the learning environment and learning conceptions was undertaken. One to six subgroups were tested. Three information criteria were used to assess model fit: AIC (Akaike's Information Criterion; Akaike, 1987), BIC (Bayesian Information Criterion; Schwartz, 1978) and sample-size adjusted BIC. An elbow, or minimum in BIC was regarded as the most useful criterion (Nylund et al., 2007) for determining number of subgroups. Posterior probabilities derived by the model were summarised by an entropy criterion, where values closer to one indicate a better fit (Celeux & Soromenho, 1996). A minimum subgroup size of 10% of the sample also guided model selection. Consistent with previous person-centred research, and that LPA is a mean-based approach, entire scales were used.

Scale and item refinement for latent SEM

The authors strived to obtain a theoretically sound yet parsimonious model. The final model was organised using the 3P framework (Figure 1). Presage variables contained the students' perceptions of the learning environment (CEQ: Good Teaching, Appropriate Workload) and learning conceptions (ILS: Construction of Knowledge, Intake of Knowledge). Process variables included (ILS: Self-, External, Lack of) Regulation and (ILS: Deep, Stepwise) Processing. Product variables included Generic Skills, Satisfaction and Achievement (end-of-term grades). All variables were regressed onto dummy-variable control variables: Gender (Female = 0, Male = 1) and Year (Second-year = 0, Third-year = 1). The variables within each stage (i.e., Presage, Process, Product) were allowed to correlate.

Almost all previously reviewed variable-centred research on Presage variables used path-analysis models with manifest (and not latent) variables, or models which are not

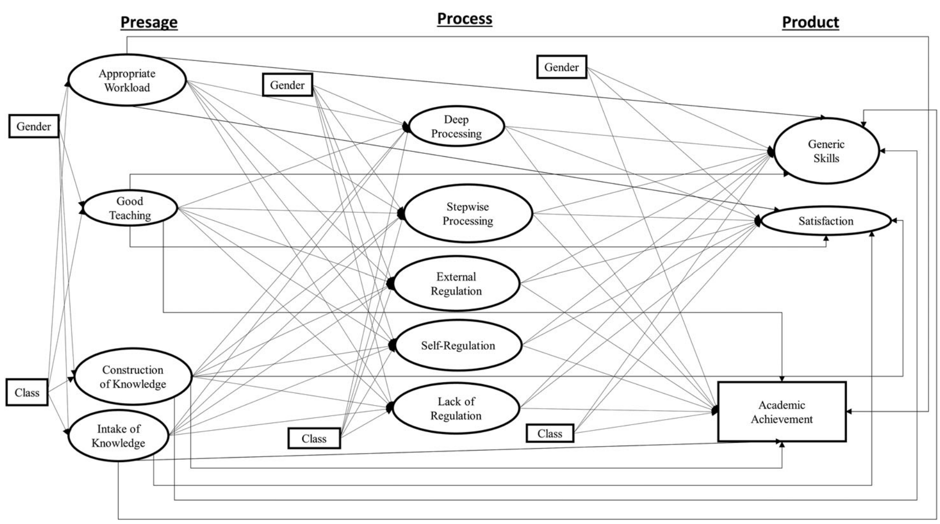

Figure 1. Fully-forward 3P model.

Table 1. Highest loading item of scales.

Scale	Highest Loading Item (Number of items)
Presage	
Appropriate Workload	The workload is too heavy.(3, reversed)
Good Teaching	Teaching staff here work hard to make subjects interesting.(4)
Construction of Knowledge	I should try to think up examples with the study materials of my own accord.(4)
Intake of Knowledge	I should repeat the subject matter on my own until I know it sufficiently.(3)
Process	
Deep Processing	I try to see the connection between the topics discussed in different chapters of a textbook.(4)
Stepwise Strategy	I memorise definitions as literally as possible.(4)
External Regulation	When doing assignments, I train myself thoroughly in applying the methods dealt with in a course.(3)
Self-Regulation	I add something to the subject matter from other sources.(3)
Lack of Regulation	I notice that I have trouble processing a large amount of subject matter.(3)
Product	
Generic Skills	The course has improved my written communication skills.(4)
Satisfaction	Overall, I would recommend this course to others.(4)

fully-forward. Constructs discussed in this study cannot be measured directly, so latent variables should be used with SEM (Kline, 2005). Due to the more stringent model requirements (i.e., latent variables), the use of a fully-forward 3P model and the considerable number and diversity of the variables, several steps were taken to reduce model complexity, while safeguarding the validity of the intended collative constructs and answering the research questions.

In addition to reducing the number of variables, item removal for the remaining variables followed guidelines from Hair et al. (2010): (1) Latent variables could be described meaningfully by four items, with three items being acceptable if other latent variables have more than three, and (2) All standardised CFA loadings should be >.50. Each scale separately underwent repeated single-factor CFAs where the lowest loading item was removed each time, until four items remained, or three if loading minimums were not met. The lowest standardised loading over all remaining items in the model was .48 (next lowest >.53). Table 1 presents highest loading, and number of items for each scale. Composite reliabilities (Raykov's ρ) of scales were acceptable ($\rho > .60$; Tseng et al., 2006) except for Lack of Regulation which was marginal ($\rho = .59$).

Results

Descriptive statistics, correlations and composite reliabilities of scales are presented in Table 2. Correlations were generally consistent with theory and previous research, demonstrating relationships with well-known learning patterns and their relationships with learning environment and outcomes.

Latent SEM analyses

CFA of the model resulted in acceptable to good fit (CFI = .92; RMSEA = .035, 90% CI [.028, .041]; SRMR = .053). Significant, meaningful effects from latent SEM analysis and variance explained (R^2) of each variable are presented in Figure 2. From Presage to Process, Appropriate Workload predicted Deep Processing ($\beta = .22$, moderate, $p < .05$,

Table 2. Correlations, descriptive statistics, reliability.

	AW	GT	CoK	IoK	DP	SP	ER	SR	LoR	GS	Satis	Ach
Appropriate Workload	–											
Good Teaching	.16*	–										
Construction of Knowledge	.03	.04	–									
Intake of Knowledge	−.05	.15*	.19**	–								
Deep Processing	.20**	.17**	.22***	.05	–							
Stepwise Processing	−.07	.09	.08	.49***	.09	–						
External Regulation	.03	.14*	.31***	.33***	.38***	.27***	–					
Self-Regulation	−.01	−.02	.22***	−.05	.49***	.04	.21**	–				
Lack of Regulation	−.39***	−.05	.09	.20**	−.07	.16*	.13*	..03	–			
Generic Skills	.11	.47***	.08	.08	.17**	.10	.05	.11	−.17**	–		
Satisfaction	.25***	.63***	.13*	.11	.19**	.07	.14*	.05	−.23***	.52***	–	
Achievement	.15*	.08	.10	−.08	.26***	−.11*	.05	.08	−.28***	.05	.20**	–
Mean	2.71	2.77	4.15	3.17	3.44	2.89	3.36	3.70	2.62	3.31	3.30	0(Z)
SD	.87	.79	.59	.83	.82	.97	.80	.87	.88	.82	.87	1(Z)
Raykov's ρ	.69	.78	.74	.64	.78	.79	.71	.64	.59	.75	.88	–

Note: ***$p < .001$,**$p < .01$,*$p < .05$. Scales measured 1–5 except for Achievement.

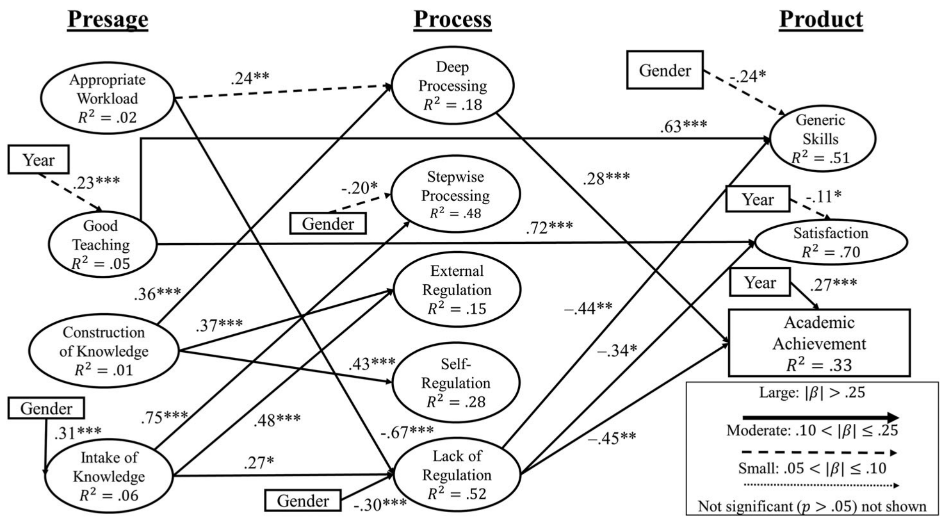

Figure 2. Significant (*$p < .05$, **$p < .01$, ***$p < .001$) paths. Gender: Female = 0, Male = 1. Year: Second-year = 0 and Third-year = 1.

Hypothesis 1a), and Lack of Regulation ($\beta = -.67$, large, $p < .001$, Hypothesis 1a) negatively. Construction of Knowledge predicted both Deep Processing and Self-regulation ($\beta = .28/.49$, large, $p < .001$, Hypothesis 1b). Intake of Knowledge predicted both Stepwise Processing and External Regulation ($\beta = .38/.73$, large, $p < .001$, Hypothesis 1b). However, Intake of Knowledge also predicted Lack of Regulation ($\beta = .27$, large, $p < .05$), and Construction of Knowledge predicted External Regulation ($\beta = .23$, moderate, $p < .01$).

From Process to Product, Deep Processing predicted Achievement ($\beta = .51$, large, $p < .01$; Hypothesis 1c), and Lack of Regulation negatively predicted Generic Skills, Satisfaction and Achievement ($\beta = -.41/-.29/-.48$, large, $p < .05/.05/.01$, Hypothesis 1c). From Presage to Product, Good Teaching predicted Generic Skills and Satisfaction ($\beta = .64/.74$, large, $p < .001$).

Third-year students reported higher levels of Good Teaching ($\beta = .23$, moderate, $p < .001$), Satisfaction ($\beta = .11$, moderate, $p < .05$) and Achievement ($\beta = .26$, large, $p < .001$). Second-year students reported higher External Regulation ($\beta = -.16$, moderate, $p < .05$). Females reported greater levels in Lack of Regulation ($\beta = -.28$, large, $p < .001$). Males reported a greater Intake of Knowledge ($\beta = .24$, moderate, $p < .01$).

Person-centred analyses

Person-centred results describe how subpopulations of students differentiate between their learning conceptions and their perceived environment. LPA indicator values on the Presage variables (Good Teaching, Appropriate Workload, Construction of Knowledge and Intake of Knowledge) are presented in Table 3. BIC and SABIC presented elbows and minimums with the three-subgroup solution. AIC presented the sharpest elbow at three subgroups. Entropy supported four subgroups, though the three-subgroup solution presented medium entropy (Clark & Muthén, 2009). Based on these results a three-subgroup solution was selected. Profiles and mean values are presented in Table

Table 3. Latent profile analysis of presage variables.

Subgroups	1	2	3	4	5	6
AIC	1905.535	1879.522	**1855.822 (elbow)**	1854.615	1854.975	1855.290
BIC	1933.447	1924.878	**1918.623 (elbow)**	1934.860	1952.665	1970.425
SABIC	1908.088	1883.670	**1861.566 (elbow)**	1861.955	1863.910	1865.821
Entropy	–	.58	.61	.72	.69	.70
Smallest Subgroup (% of sample)	–	42%	27%	8%	2%	2%

Note: AIC: Akaike Information Criteria; BIC: Bayesian Information Criteria; SABIC: Sample-size Adjusted BIC.

Table 4. Mean subgroup and one-way ANOVA with covariate data.

	Inactive (*n* = 66) Mean (SD)	Passive-Idealist (*n* = 69) Mean (SD)	Environment Driven (*n* = 107) Mean (SD)	*ANOVA p*	*F*	R^2
Good Teaching	2.17 (.52)	2.38 (.40)	3.33 (.42)	<.001	171.5	.59
Appropriate Workload	2.52 (.64)	2.19 (.63)	3.14 (.62)	<.001	51.34	.30
Construction of Knowledge	3.59 (.50)	4.18 (.44)	4.04 (.49)	<.001	28.05	.19
Intake of Knowledge	2.89 (.50)	4.03 (.43)	3.54 (.45)	<.001	107.8	.47
Year 2 (Year 3)	34.8% (65.2%)	31.9% (68.1%)	48.6% (51.4%)			
Male (Female)	27.3% (72.7%)	11.6% (88.4%)	20.6% (79.4%)			

4 while standardised means are shown in Figure 3. Students reported similar levels of the two conceptions in all subgroups (Hypothesis 2a). Guided by previous research, subgroups were labelled Inactive (low values on all scales; Vermetten et al., 2002), Passive-Idealist (high conceptions, low on learning environment; Vermunt & Donche, 2017), and Environment Driven (high learning environment, low conceptions) making up 27%, 29% and 44% of the sample respectively. Environment Driven subgroup had higher Achievement than the Passive-Idealist subgroup ($p < .05$; Hypothesis 2b).

ANOVA testing of each Presage variable demonstrated that the three subgroups were significantly different ($p < .001$; Table 4). Variance explained varied from .19 to .59.

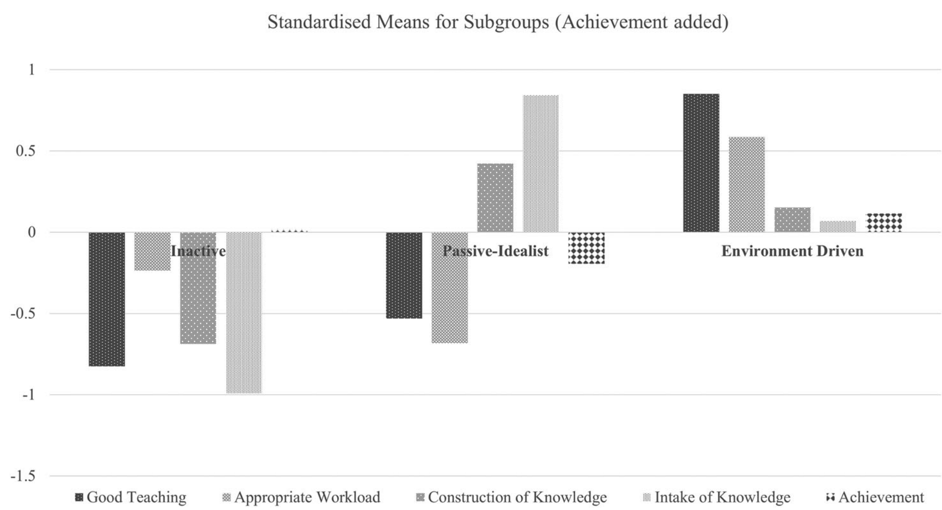

Figure 3. Standardised subgroup profiles: Inactive, Passive-Idealist, Environment Driven. Achievement not analysed.

MANOVA was used to test the explanatory power of the three subgroups (Wilks' Lambda = .32, $p < .001$, df = 4, $F = 128.51$, $R^2 = .68$), explaining a substantial amount of variance.

Discussion

Latent SEM analysis confirmed relationships mirroring well established LPs (Hypothesis 1a). Construction of Knowledge predicting Self-regulation and Deep Processing are indicative of a meaning-directed LP, while Intake of Knowledge predicting External Regulation and Stepwise Processing affirm a reproduction-directed LP.

The learning environment through Appropriate Workload predicted Deep Processing positively and Lack of Regulation negatively (Hypothesis 1b). Furthermore, Deep Processing (meaning-directed LP) positively predicted Achievement, whereas Lack of Regulation (undirected LP) negatively predicted all of Generic skills, Satisfaction and academic Achievement (Hypothesis 1c).

The person-centred analysis revealed three subgroups whose measured learning conceptions (Construction of Knowledge, Intake of Knowledge) differed by less than half a standard deviation (refuting Hypothesis 2a). Those in the Environment Driven subgroup, perceived a better learning environment and demonstrated greater achievement (Hypothesis 2b).

Implications for theory

From Presage to Process variables, both expected and unexpected relationships were found. Predictions that mirrored established learning patterns (meaning-directed and reproduction-directed) were confirmed. Intake of Knowledge however also predicted Lack of Regulation. Students may resort to a Lack of Regulation when insufficient external regulation is provided leading to dissonance and hence lower Achievement (Vermunt & Vermetten, 2004). Similarly, Construction of Knowledge also predicted External Regulation. Donche et al. (2013) found that discovery-oriented teaching strategies that were expected to promote Deep Processing and Self-regulation also led to External Regulation and Surface Processing. The assessments and teaching activities may cause friction between their intended regulation approach and learning conception.

In perception of teaching environment, the effect of Appropriate Workload on Deep Processing was confirmed (Diseth et al., 2006), while a negative effect on surface/Stepwise Processing (Lizzio et al., 2002) was not observed. Good Teaching also had large effects on Generic Skills and Satisfaction directly, though Good Teaching did not significantly affect Achievement in this study (Lizzio et al., 2002; Vanthournout et al., 2012). Deep Processing predicted Achievement (Martínez-Fernández & Vermunt, 2015; Vanthournout et al., 2012) using ILS and other instruments (Diseth et al., 2006; Lizzio et al., 2002), however, Self-regulation did not.

From person-centred analyses, intra-subgroup means of Construction of Knowledge and Intake of Knowledge were similar, suggesting that students may not have a dominant learning conception. This suggests that students can remain undifferentiated between LPs in university, diverging from Vermunt and Vermetten (2004). The subject context (psychology) might play a role, where both learning conceptions and their resulting learning strategies are viewed as relevant. For example, in the Model of Domain Learning (Alexander, 2003), surface processing is employed more often during acclimation stages and diminish, giving way to deep processing as competence is gained.

Shape differences comparing learning conceptions scores relative to learning environment scores were observed. The difference in Achievement between Environment Driven and Passive-Idealist subgroups further explained the variable-centred results. The Passive-Idealist subgroup reported greater Intake of Knowledge, which through Lack of Regulation, led to lower Achievement. Appropriate Workload for the Environment Driven subgroup, which in variable-centred results suggested greater Deep Processing, lead to higher Achievement.

Overall, the results suggest two converging pathways to promote higher achievement. Appropriate Workload (course experience) and Construction of Knowledge (learning conceptions) both predicted Deep Processing, which then predicted Achievement. However, Intake of Knowledge (likely due to insufficient External Regulation) and (in)Appropriate Workload converge on Lack of Regulation to negatively predict Achievement. The results support Richardson's (2011) assertion that both learning conceptions and environment play meaningful roles in determining processing strategies and outcomes.

Implications for practice

Practical implications are suggested through adaptations of the learning environment targeted at developing specific CEQ and ILS constructs. One means of intervention strongly supported by past research (Vermunt & Vermetten, 2004) is undertaking process-oriented instruction, directed at promoting the meaning-directed LP.

Vermunt (1998) characterised conceptions of learning (and learning patterns generally) to be stable, yet still malleable. For example, Vermunt and Vermetten (2004) found that the stability of learning patterns decreased in the presence of innovative teaching methods. Vermetten et al. (1999) found that there was both an individual-bound and context specific component in the use of learning strategies, paralleling the posited dominating influences in the Passive-Idealist and Environmental Driven subgroups respectively found in this study.

Regarding regulation from external sources, classrooms can vary from strongly teacher-regulated to loosely teacher-regulated, where a learning environment with more regulation will support students in shifting away from a lack of regulation (Vermunt & Vermetten, 2004). While this provisional solution may weaken the pathway towards lower Achievement, will students self-regulate or lack regulation when left to their own devices? Students should be supported with specific activities such as identifying and targeting conceptions, promoting reflection, challenging misconceptions and providing feedback, which have been shown to promote Deep Processing and Self-regulation (Lonka & Ahola, 1995). Students in the Passive-Idealist subgroup should be offered additional (External) regulation by the teacher (Vermunt & Vermetten, 2004) to minimise Lack of Regulation. Students' workload should be monitored and adjusted accordingly to compensate for the dissonance/friction (Vermunt & Vermetten, 2004) and reduction in study pace (Lonka & Ahola, 1995) students may experience.

Assessments should be constructively aligned (Biggs, 1993) with learning outcomes which require deep processing. However, practitioners should note that introducing 'active learning' or promoting 'more engagement' alone might be insufficient to support deep processing in learning (Gijbels et al., 2009).

Vermunt and Vermetten (2004) encouraged a holistic approach (targeting the cause, not the symptom) including promoting Construction of Knowledge. Vermunt (1995) promoted reflection on learning processes in undergraduate psychology students in the Netherlands by linking their preconceptions about studying and diagnoses of their own method of learning to individually tailored teaching. This resulted in a shift away from reproduction-directed and undirected LP variables towards the meaning-directed LP. Such an approach in this and similar contexts may yield fruitful results, especially for students in the Environmental Driven subgroup.

These interventions are likely to benefit the Inactive subgroup, leveraging the feedback and feedforward loops proposed by Vermunt and Donche's (2017) and 3P models.

Limitations and future directions

The results presented in the study should be treated with caution. All measures except Achievement were obtained through self-report and from one domain of study. Using the same (refined) items in other geographic and subject contexts would examine external validity of the results. The marginal Lack of Regulation scale may need revision.

Although the 3P framework facilitates a fully-forward model, the self-reported data is cross-sectional and collected in one wave. The 3P model (Biggs, 1993) and learning patterns model of student learning (Vermunt & Donche, 2017) indicate that the processes are bidirectional. The regression coefficients and correlations provide a single snapshot of the connections between tested constructs, and thus may be artificially inflated compared to those observed longitudinally. The findings in this study are, however, theoretically meaningful and empirically consistent with cross-sectional correlations in longitudinal studies on some LP variables (e.g., De Clercq et al., 2013; Fryer & Vermunt, 2018), and warrant further testing. Longitudinal studies with multiple waves could further confirm these relationships and investigate development over time (e.g., Process and Product variables could be modelled to impact future learning conceptions). Future studies could examine the use of the 4P model (Price, 2013) where the first 3P stage is split between Presage (e.g., student/teacher characteristics, social/institutional/professional contexts) and Perceptions (e.g., learning environment and conceptions).

Going forward, the authors encourage a shift away from mean-based multiple regression and path-analysis techniques. The variable-centred analysis of the proposed model indicated acceptable fit suggesting that a latent approach to learning patterns and course experience research is possible. These variables cannot be directly measured and are formed from a collection of indicators. A larger sample size could allow for latent-variable SEM to be conducted separately on each of the subgroups obtained from LPA to compare connections between subgroups. Finally, a larger sample and refinement of the items could help improve the entropy criterion and demonstrate more heterogeneity between the subgroups.

Conclusion

A cross-sectional dataset measuring undergraduate psychology students' responses of the ILS, CEQ and a satisfaction measure underwent fully-forward latent SEM using the 3P framework (Biggs, 1993). The effects of course experience and learning conceptions on learning strategies (processing and regulation), and subsequently on outcomes (Achievement, Satisfaction and Generic Skills) were studied. Several consequential relationships found in learning patterns research were replicated (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Appropriate Workload and Construction of Knowledge both predicted Deep Processing which served as an intermediary to predict Achievement positively, while (in)Appropriate Workload and Intake of Knowledge both predicted Lack of Regulation, which negatively predicted all outcomes. These two pathways highlighted the pivotal roles that both learning conceptions and the learning environment play in the learning experience. Intake of Knowledge predicted Lack of Regulation, suggesting the traditional boundaries between learning patterns may be blurred when insufficient regulation is provided (Vermunt & Vermetten, 2004). Person-centred results indicated that students did not readily differentiate between Construction and Intake of Knowledge, suggesting combinations and different processing approaches may be used. A process-oriented approach targeting all aspects of the meaning-directed LP is recommended. This study takes a step towards using higher-quality analytical techniques that account for measurement error and construct validity, a step we hope is replicated by future studies in this area.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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