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Variable- and Person-centred meta-re-analyses of university students' learning strategies from a cross-cultural perspective

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Abstract

Studies on learning strategies across cultures in higher education inform the internationalisation of teaching and learning. Previous comparisons relied on geographical generalisations (e.g., "Asian", "Western", "Latin-American") or only variable-centred methods, which can overgeneralise the contexts they represent. Eight learning strategy datasets (ILS; Inventory of Learning patterns of Students) from seven countries ($n=4883$) were obtained and (re-)analysed using variable-centred and person-centred (Latent Profile Analysis; LPA) methods. Employing Hofstede's individualism-collectivism and power distance indices as predictors, lower individualism and higher power distance scores corresponded to students' overall combined reporting of meaning-directed, reproduction-directed and application-directed learning strategies. Furthermore, sample LPAs found that less individualistic contexts presented profiles with similar shape (i.e., profiles differed by similar amounts across most learning strategies). More individualistic contexts presented profiles with different shapes (i.e., different profiles preferred different strategies). Multiple "Western" contexts presented profiles that describe the "Asian" and "Latin-American" learner stereotypes. These results question the existence of such stereotypes and point to the usefulness of cultural indicators for making cross-cultural learning strategy comparisons. Theoretical and practical implications are discussed.

Keywords Learning strategies · International · Cross-cultural Analysis · Person-centred Analysis · Learning Patterns

Introduction

The prevailing internationalisation of higher education has strengthened demand for the cross-cultural understanding of student learning strategies (Eaves, 2011; Marambe et al., 2012). Previous literature has investigated the learning experiences of international students in universities and local students in satellite campuses (e.g., Bilsland et al., 2020; Heng, 2018; Wierstra et al., 2003). The recent proliferation of online courses further emphasises the need to

Extended author information available on the last page of the article understand this aspect of students' academic experience (Tapanes et al., 2009; Vermunt & Donche, 2017).

Cross-national studies of students' learning strategies have been limited in the number of nations compared, generalisability to other nations and ability to describe different student profiles of learning strategies within nations. Past analyses have examined learning strategies of samples from different nations to 1) generalise to and compare "Asian" and "Western" contexts, and 2) analyse learning strategies within these geographical labels (e.g., Marambe et al., 2012; Martínez-Fernández & Vermunt, 2015; Purdie et al., 1996). Such broad categorisations are often unclear and fail to adhere to the continuum of cultural characteristics between and within these labels (Eaves, 2011).

A different approach to cultural comparisons is to consider cultural dimensions whose definitions are independent of geographical location, such as individualism-collectivism and power distance. Nation-level indices describing agreement with these dimensions have been developed according to representative samples (Hofstede, 2001; Minkov et al., 2017). Cultural dimensions have been discussed in educational research generally and specifically within learning strategies research (e.g., Aparicio et al., 2016; Tapanes et al., 2009; Watkins, 2000). However, these connections have undergone little empirical testing.

Quantitative cross-national comparisons have predominantly been variable-centred which compares sample-level learning strategy means (Marambe et al., 2012; Vermunt et al., 2014). However, multiple profiles of learning strategies (i.e., subpopulations employing similar learning strategies) may exist within a sample. Person-centred analyses such as Latent Profile Analysis (LPA) employ both quantitative and qualitative perspectives to uncover these profiles. These analyses allow for comparison between different learning strategy combinations.

In learning patterns research, Vermunt and Vermetten (2004) described learning patterns to be influenced by learning experiences, but extending across multiple contexts (e.g., assessments, classes or courses). The Inventory of Learning patterns of Students (ILS; Vermunt, 1996, 1998) measures students' self-reported learning patterns, which includes learning strategies (e.g., Vermunt, 2020; Yu et al., 2021). Learning patterns research differs from the Students' Approaches to Learning (SAL) research tradition, which investigates learning strategies employed in a specific context (Marton & Säljö, 1976; Richardson, 2015). Therefore, responses to the ILS are likely to incur less context-related bias and provide a more appropriate lens to investigate cultural differences in students' ongoing use of learning strategies.

The current study draws upon published and unpublished ILS datasets (one from each of Venezuela, Indonesia, China, Hong Kong, Spain, the Netherlands and two from Belgium) to investigate the cross-cultural use of learning strategies. First, variable-centred conclusions are drawn on the appropriateness of using cultural indicators: individualism-collectivism and power distance for making cross-cultural investigations (Hofstede, 2001; Minkov et al., 2017). Second, LPAs are used to investigate the characteristics of learner profiles for each individual sample. Finally, a qualitative comparison of profiles across samples is undertaken to shed light on profiles that exist across cultures.

Background

Learning strategies

Learning strategy research has focused on the evolving understanding of students' use of surface and deep processing. Surface processing is described by rote memorisation to cope with assessments; while deep processing is characterised by an intention to understand meaning when learning (Marton & Säljö, 1976). SAL research began by identifying which of the two learning approaches students would employ due to specific contextual demands such as assessments or in response to teaching methods (Marton & Säljö, 1976; Richardson, 2015). Biggs et al. (2001) later argued that surface and deep approaches were not dichotomous. Both could be utilised in the same context in varying amounts dependent on learner, timing and purpose (Dinsmore & Alexander, 2012; Kember, 2000). In Alexander's (2003) Model of Domain Learning, students progress through acclimation, competence and proficiency stages in domain learning and mastery. Initially, students predominantly rely on surface-level processing strategies. These eventually decrease as students begin adopting deep-level processing strategies in later stages. Hattie and Donoghue (2016) pointed to the sequential application of surface followed by deep acquiring and consolidating strategies, which lead to transfer towards other learning situations. These learning models map important processes in student learning generally but may fail to address differences in learning strategies between cultures (e.g., Marambe et al., 2012; Marton et al., 2005).

Vermunt (1996, 1998) examined learning strategies including both processing and regulation strategies as part of the Model of Learning Patterns employing the ILS, a self-report questionnaire. Regulation strategies describe methods in which students use to plan, evaluate, steer and monitor their learning. The ILS measures students' external regulation (e.g., willingness to accept regulation from external sources such as class materials and tests), self-regulation (e.g., making study plans, self-testing, monitoring progress, consulting sources outside the syllabus) and lack of regulation (e.g., difficulties with regulating learning processes). Vermunt and Vermetten (2004) conceptualised a learning pattern as a superordinate concept in which the processing and regulation strategies that students usually utilise, their conceptions of learning and their learning orientations are united. Using factor analysis, Vermunt (1996, 1998) found that scales of the ILS loaded onto four factors representing overarching learning patterns: meaning-directed, reproduction-directed, application-directed and undirected. Table 1 presents a description of all of the processing and regulation strategies measured by the ILS, which will be analysed in the current study (Vermunt & Donche, 2017). For a detailed discussion of learning conceptions and orientations, see Vermunt and Donche (2017).

Cross-cultural learning strategies research

Cultural investigation of students' learning strategies alongside academic achievement has led to mixed results. Achievement in Western contexts has been associated with employing a deep approach to learning, however Asian students have been found to succeed academically using a surface approach (e.g., Biggs, 1994). This discrepancy is known as the Asian learner paradox. Marton et al. (2005) and Watkins (2000) resolved this incongruency, stating that such students memorise with an intent to understand and employ a combination of surface and deep learning strategies. The use of learning strategies beyond and within "Western" or "Asian" generalisations remains unclear.

In the SAL research tradition, students adopt learning strategies appropriate for their learning contexts. Cross-cultural studies employing a SAL framework may incur limitations in internal and external validity if compared samples vary on non-cultural factors (e.g., teaching methods, domains, assessments; Leung et al., 2008). However, the ILS measures processing and regulation strategies at the learning pattern level which though shaped by experiences, provide greater consistency over multiple learning contexts

Table 1 Processing and regulation strategies of the ILS

Learning strategies	Traditional learning pattern (Vermunt & Donche, 2017)	Description
Processing Strategies		
Memorising (Stepwise)	Reproduction-directed	Rote memorising, focusing on facts/definitions/characteristics
Analysing (Stepwise)	Reproduction-directed	Studying subject elements separately in a stepwise manner
Relating-Structuring (Deep)	Meaning-directed	Connecting and structuring subject elements into a whole
Critical (Deep)	Meaning-directed	Forming one's own views and conclusions, critical of others' drawn conclusions
Concrete	Application-directed	Applying knowledge practically, connecting with one's own experience
Regulation Strategies		
External Regulation	Reproduction-directed	External sources drive regulation (e.g., teachers, assessments, directions, provided questions)
Self-regulation	Meaning-directed	Regulation driven by self (e.g., planning learning activities, diagnosing problems, adjusting, reflection, consulting self-sought materials)
Lack of Regulation	Undirected	Difficulties in regulating learning

(Vermunt & Donche, 2017). Measurements at this magnification could support meaningful comparisons, within and between cultures.

Cross-cultural learning patterns (ILS) research

Cross-cultural studies employing the ILS have compared contexts using “Western” and “Asian” labels, revealing differences in learning strategy use. Marambe et al. (2012) analysed ILS responses from Sri Lanka, Indonesia and the Netherlands. The Asian learner stereotype (i.e., including a propensity for rote learning) did not extend to Sri Lanka, which presented the lowest memorising scores. Vermunt et al. (2014) further investigated samples from Hong Kong, Spain, Mexico, Colombia, Venezuela, together with the three samples from Marambe et al. (2012) by comparing sample-level factor analyses on mean scale responses. In most contexts, a meaning-directed pattern was identified by the presence of deep processing (both relating-structuring and critical) and self-regulation. However, the pattern also included unconventional yet meaningful loadings for concrete processing, analysing and external regulation. Lack of regulation frequently loaded with a reproduction-directed pattern, which traditionally included only external regulation. Intra-continental differences between samples were often greater than inter-continental differences.

Martínez-Fernández and Vermunt (2015) conducted a path analysis with Latin-American and Spanish samples. External regulation which is a reproduction-directed strategy, predicted meaning-directed strategies (self-regulation directly and deep processing indirectly). These unexpected connections were labelled the Spanish/Latin-American learner paradox. These students more closely resembled Asian students, reporting a mix of strategies from different learning patterns.

The current study shifts away from geographic labels (e.g., Asian, Western, Spanish/Latin-American) and investigates the specificities and generalisabilities of the reviewed findings at within-nation and cross-national levels using widely accepted cultural dimensions (Hofstede, 2001; Triandis et al., 1988).

Individualism-collectivism and power distance

Instead of geographical location, individualism-collectivism and power distance might provide more accurate descriptions of how learning strategies are used across cultures. Individualism-collectivism describes the extent to which individuals in a culture strive for individual or collective goals and has often been discussed alongside student learning (Aparicio et al., 2016; Hofstede, 2001; Marambe et al., 2012; Tapanes et al., 2009; Watkins, 2000). Individualistic cultures may strongly value learning itself whereas collectivistic societies may value skills and formal accreditations (Hofstede, 2001). Students from more individualistic societies have been found to be likely to pursue achievement and mastery goals (e.g., understanding and gaining knowledge) whereas performance goals (e.g., demonstrating one’s ability to others) were more salient in collectivistic cultures (Dekker & Fischer, 2008). These factors may be related to students undertaking different learning strategies in different cultural contexts (Marton et al., 2005; Vermunt et al., 2014).

Power distance describes the degree to which a culture’s less powerful members expect and accept unequal power distribution, which in education clarifies the role of the teacher and nature of the student–teacher relationship (Hofstede, 2001). In high-power distance cultures, teachers are revered for their knowledge. Education is more student-centred in low-power distance societies, with students and teachers being viewed as equals. Wierstra et al. (2003) found higher perceptions of reproduction-oriented learning in southern European countries that have higher power distance compared to students from north-western European and German speaking countries.

Individualism-collectivism and power distance can be represented at the nation level by the IDV (Individualism index) and PDI (Power Distance Index) respectively. These indices were derived from large-scale studies, providing relative values between nations (Hofstede, 2001). Concerns on face validity, theoretical underpinning, and reliability of the IDV led to the development of IDV-COLL, an updated index which presents stronger correlations on known associated variables (e.g., Coefficient of Human Inequality, Rule of Law Index; Minkov et al., 2017). The nation-level values of the IDV, IDV-COLL and PDI will be used to test learning strategy relationships along these cultural dimensions.

Person-centred analysis

Person-centred analyses such as LPA provide advantages over variable-centred methods, namely finding and analysing differences within samples (Hickendorff et al., 2018). LPA quantitatively identifies 1) specific profiles within a sample and 2) individuals' probabilities of membership to each profile. Qualitative level and shape differences between profiles and theory then support the interpretation of the profiles (Morin & Marsh, 2015). Level differences between profiles describe a similar increase or decrease across most or all analysed scales. Shape differences between profiles describe uneven differences between scales and can characterise the use of different or dominant combinations of learning strategies (e.g., meaning-directed vs. reproduction-directed strategies).

In this study, qualitative cultural inferences are made on these profile differences found within and between samples. LPAs are employed for each sample individually to identify within-sample profiles. Second, profiles between samples are qualitatively compared.

Aims

The current study was guided by the following research questions and hypotheses.

RQ1) Variable-centred analysis: How do learning strategies of higher education students as measured by the ILS vary across international contexts on individualism-collectivism and power distance (IDV/IDV-COLL/PDI; Hofstede, 2001; Minkov et al., 2017)?

Hypothesis 1: Consistent with learning patterns research (Vermunt & Donche, 2017), positive correlations within meaning-directed strategies (i.e., relating-structuring and critical processing, and self-regulation) and within reproduction-directed strategies (i.e., memorising and analysing processing, and external regulation) were expected. Lack of regulation (characterised by little use of learning strategies and representing the undirected pattern) was expected to not positively correlate with any other learning strategy.

Hypothesis 2: The Asian and Spanish/Latin-American learner paradoxes suggest that more individualistic and lower power distance contexts would present smaller correlations between inter-learning-pattern strategies, while less individualistic and higher power distance contexts would report larger inter-learning-pattern strategy correlations (Hofstede, 2001; Martínez-Fernández & Vermunt, 2015; Marton et al., 2005; Minkov et al., 2017). The hypothesis would be supported by significant and meaningful multiple regression analyses with each of 1) IDV and PDI, and 2) IDV-COLL and PDI as simultaneous predictors.

Hypothesis 3: Alexander's (2003) and Hattie and Donoghue's (2016) learning models proposed a progressive use of stepwise (surface) towards deep processing strategies. Therefore, ILS processing strategies would be organised across a progressive continuum: memorising, analysing, relating-structuring and critical (Table 1). Higher pairwise correlations between adjacent strategies across samples and overall (i.e., mean across samples) were expected.

RQ2a) Person-centred analysis: How do learning strategy profiles vary according to level and shape within nations?

Hypothesis 4: Collectivistic high-power distance contexts are expected to present profiles that support a blended use of learning strategies (e.g., meaning-directed, application-directed and reproduction-directed) predominantly differing in level (Martínez-Fernández & Vermunt, 2015; Vermunt et al., 2014). Individualistic, low-power distance contexts would present different profile shapes that are consistent with strategies employed in learning patterns research (Table 1; Vermunt & Donche, 2017).

RQ2b) Person-centred analysis: What profiles exist across cultures and how are they represented across different contexts?

Hypothesis 5: Profiles found across sample LPAs would be consistent with original learning patterns research (Vermunt & Donche, 2017). Profiles would present higher levels of learning strategies consistent with the four learning patterns' representative strategies and lower levels of other strategies (Table 1).

Methods

Meta-analytic re-analysis

Rather than amalgamating and analysing the effects reported in individual studies, entire datasets were obtained and (re-)analysed. Researchers who had previously published studies employing the ILS in higher education contexts were contacted to obtain their datasets. A sample size of $n = 250$ served as a guiding minimum to identify profiles. Some researchers provided previously unpublished samples. All received datasets were used in the analysis. Where required, ethics clearances were granted for the original data collection by their corresponding institutional review boards. The resulting cross-national dataset included one sample from each of Venezuela, Indonesia, China, Hong Kong, Spain, the Netherlands and two samples from Belgium, totalling $n = 4883$ students. The samples from Indonesia, the Netherlands and Hong Kong have been analysed previously in cross-cultural research (Marambe et al., 2012; Vermunt et al., 2014; The Hong Kong sample here contains only the tertiary education component from the original sample). Table 2 presents the collection method, year, sample size, previous publishing status, students' faculty composition and nation-level IDV, IDV-COLL and PDI nation values for each sample.

Instruments and indices

The ILS surveys were completed in the sample's national language with items measured from 1 (Seldom/Never) to 5 (Almost Always). Focusing on learning strategies, only the ILS scales described in Table 1 were analysed in the current study. For the samples from Hong Kong and China, these scales totalled 50 items (100-item ILS; Law & Meyer, 2011; Yu et al., 2021). In all other samples, the scales totalled 55 items (120-item ILS; Vermunt, 1996, 1998). Scales varied by at most one item between the two versions. The IDV, PDI and IDV-COLL index values for the samples' origin countries were obtained directly from the large-scale studies of Hofstede (2001) and Minkov et al. (2017). As the current study's samples were collected over several decades, IDV-COLL provides an updated measure of individualism-collectivism (Minkov et al., 2017).

Data analyses

Missing data for all datasets (<1% overall) were imputed in R v.3.5.2 using multiple imputed chain equations (*mice* package). Descriptive statistics, composite reliability (≥0.60 acceptable; Raykov, 1997; Tseng et al., 2006), correlations and multiple regression (*lm*, *lm.beta, vif)* were calculated using R (RQ1, Hypotheses 1–3). Multicollinearity was not considered problematic if $r < 0.90$ (Tabachnick & Fidell, 2007). Cutoffs for small/moderate/large effects were given by $r = 0.10/0.30/0.50$ (Cohen, 1992). LPAs on the imputed datasets were conducted using M*plus* 7.0 (Muthén & Muthén, 1998–2013; RQ2a/2b, Hypotheses 4&5). Code for all analyses is provided in Appendix E.

To address RQ1, pairwise learning strategies correlations means and ranges were calculated for each sample. For Hypothesis 1, sample-level correlations between meaning-directed strategies and sample-level correlations between reproduction-directed strategies were examined. Sample-level correlations between each of application-directed, reproduction-directed and meaning-directed strategies with lack of regulation tested the existence of the undirected pattern.

For Hypothesis 2, inter-learning-pattern strategy correlations were examined alongside corresponding nation-level values of individualism-collectivism (IDV, IDV-COLL) and power distance (PDI) index values (Hofstede, 2001; Minkov et al., 2017). Two multivariate multiple regressions were conducted: 1) IDV and PDI values as independent variables, and 2) IDV-COLL and PDI values as independent variables. The dependent variables for both analyses were sample mean correlations between a) application-directed with meaning-directed strategies, b) application-directed with reproduction-directed strategies, and c) meaning-directed with reproduction-directed strategies.

For Hypothesis 3, mean pairwise correlations across samples for each pair of memorising, analysing, relating-structuring and critical processing were compared to test how closely each processing strategy related to adjacent strategies in the hypothesised progression.

Answering RQ2a and RQ2b (Hypotheses 4&5), LPAs tested fit for one to seven profiles. The final model (i.e., number of profiles) for each sample was chosen based on best agreement between indicators and guiding principles. Indicators included three information criteria: Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC) and sample-size adjusted BIC (SABIC) (Akaike, 1987; Schwartz, 1978). Model choice was supported by a minimum or elbow in BIC, AIC and SABIC (Nylund et al., 2007). An

Table 2 Sample details

	n	Publishing status	Student majors	Collection method/ year	Year of study	IDV	IDV-COLL	PDI
Venezuela	267	Martínez-Fernández (Unpublished)	Social Sciences, Engineering (University)	In-class 2016	1st-year	12	–95	81
Indonesia	888	Ajisuksmo and Vermunt (1999)	Management, Accountancy, Law, Business Administration, Electrical Engineering, Mechanical Engineering Students (University)	In-class 1991	1st-year	14	–171	78
China	318	Yu et al. (2021)	Natural sciences, Engineering and Technology, Humanities, Social science, Medicine (University)	In-class 2015	All	20	–31	80
Hong Kong	444	Law and Meyer (2011)	Business Administration, Hospitality/Tourism, Language Studies (Technical School/University)	In-class 2005	All	25	–5	68
Spain	242	Shum et al. (2021)	Psychology (University)	In-class 2016	2nd-3rd years	51	58	57
Belgium 1	1058	Donche et al. (2013)	Communication sciences, Electromagnetics, Hotel management, Journalism, Office management, Business management, Social work, Teacher education (Technical School/University)	Online 2005	1st-year	75	110	65
Belgium 2	871	Donche (Unpublished)	Communication sciences, Information management systems, Management assistant, Tourism/recreation, Business management (Technical School/University)	In-class 2003	1st-year	75	110	65
The Netherlands	795	Vermunt (1998)	Law, Economy, Econometry, Management information sciences, Sociology, Psychology, Language and literature, and Philosophy (University)	Mail 1988	1st-year	80	182	38

Ranges: IDV (6–91), IDV-COLL (-291(-177 second smallest)–182), PDI (11–104) entropy criterion summarised all posterior probabilities derived by the model, where values closer to one indicate better separation between individuals' probabilistic membership to profiles (Celeux & Soromenho, 1996). Furthermore, Vuong-Lo-Mendell-Rubin and Lo-Mendell-Rubin Likelihood Ratio Tests support a model whose test is significant but is not significant for a model with one more profile (Lo et al., 2001; Vuong, 1989). Lastly, model selection was guided by theoretical meaning of the learning strategy combinations associated with the profiles, profiles satisfying minimum membership ($\geq$ 10% of sample size) and inclusion of similar profiles from a fewer-profiles model.

Results

Composite reliability (Table 3) measures were acceptable except for some marginal values in lack of regulation (Hong Kong : ρ=0.58) and memorising (Indonesia : ρ=0.59; Hong Kong : ρ=0.59). Descriptive statistics are provided in Table 3. Composite reliability is preferred to Cronbach's alpha (see Appendix A) as item loadings are not assumed to be uniform (Raykov, 1997).

Research question 1 (variable-centred analyses)

Both Hypotheses 1 and 2 tested correlations between scale responses within each sample. Full correlation tables are presented in Appendix B.

Addressing Hypothesis 1, all correlations between meaning-directed strategies were large across all samples (r = 0.50–0.75). Except for the Hong Kong sample, meaning-directed strategies did not meaningfully positively correlate with lack of regulation (i.e., undirected pattern; Hong Kong sample: r = 0.09–0.17; all other samples: r = -0.22–0.09). All within reproduction-directed strategies correlations were moderate to large across all samples (r = 0.37–0.61). All but the Indonesian sample presented at least one small/moderate correlation between reproduction-directed and undirected strategies ($r < 0.34$). Only the Hong Kong sample presented a moderate correlation between application-directed strategies and lack of regulation ($r = 0.17$).

Bonferroni-corrected multivariate multiple regression analyses testing Hypothesis 2 are presented in Table 4 (dependent variable inter-learning pattern correlation means) and Table 5. Sample application-directed with reproduction-directed strategy correlations (dependent variable) were meaningful and significant when regressed onto IDV and PDI values (independent variables; $F(2,5) = 15.78$, $p < 0.05$, $R^2 = 0.86$, $R^2_{\text{adjusted}} = 0.81$), and when regressed onto IDV-COLL and PDI values (independent variables; $F(2,5) = 11.62$, $p < 0.05$, $R^2 = 0.82$, $R^2_{\text{adjusted}} = 0.75$). Sample meaning-directed/reproduction-directed strategy correlations (dependent variable) were meaningful and significant when regressed onto IDV and PDI values (independent variables; $F(2,5) = 29.84$, $p < 0.01$, $R^2 = 0.92$, $R^2_{\text{adjusted}} = 0.89$), and when regressed onto IDV-COLL and PDI values (independent variables; $F(2,5) = 20.17$, $p < 0.01$, $R^2 = 0.89$, $R^2_{\text{adjusted}} = 0.85$). Neither IDV and PDI, nor IDV-COLL and PDI were significant predictors for meaning-directed with application-directed strategy correlations.

The significant multiple regressions presented mixed results for significant individual predictors. These might be partly due to small sample size ($n = 8$) and closely related independent variables (IDV/PDI: r = -0.79; IDV-COLL/PDI: r = -0.83). These do not exceed either correlation ($|r| < 0.90$) or Variance Inflation Factor (VIF < 5; Menard, 2001; IDV/PDI: VIF = 2.68; IDV-COLL/PDI: VIF= 3.30) guidelines for multicollinearity.

Table 3 Mean(Standard Deviations)/composite reliability: Rho

	Memorising	Analysing	Relating-structuring	Critical	Concrete	External regulation	Self-regulation	Lack of regulation
Venezuela	2.86(.87)/.77	3.14(.77)/.77	2.98(.77)/.80	2.89(.91)/.75	3.46(.82)/.73	3.26(.64)/.79	2.98(.71)/.81	2.60(.78)/.72
Indonesia	3.32(.80)/.59	2.92(.74)/.63	2.56(.81)/.75	2.18(.84)/.70	2.99(.75)/.65	3.19(.61)/.69	2.76(.73)/.79	2.65(.68)/.62
China	2.90(.69)/.61	2.67(.69)/.65	3.23(.75)/.80	2.94(.81)/.66	3.15(.76)/.73	3.04(.54)/.68	3.04(.68)/.81	2.68(.80)/.71
Hong Kong	2.87(.60)/.58	2.51(.57)/.68	2.42(.63)/.75	2.35(.69)/.70	2.81(.64)/.72	2.92(.52)/.74	2.55(.58)/.80	2.86(.61)/.58
Spain	2.88(.91)/.80	3.11(.65)/.69	3.38(.75)/.83	3.05(.83)/.72	3.74(.63)/.68	3.13(.58)/.64	2.87(.65)/.78	2.60(.70)/.64
Belgium 1	3.21(.84)/.73	2.92(.68)/.67	3.11(.77)/.81	2.58(.79)/.67	3.13(.72)/.68	3.18(.55)/.69	2.53(.64)/.78	2.74(.74)/.72
Belgium 2	3.19(.78)/.67	2.90(.66)/.63	2.89(.76)/.80	2.31(.76)/.66	2.84(.71)/.64	3.15(.52)/.63	2.35(.57)/.73	2.51(.69)/.68
The Netherlands	2.83(.96)/.79	2.72(.69)/.63	3.36(.83)/.83	2.81(.92)/.73	2.81(.80)/.73	3.27(.63)/.64	2.30(.68)/.80	2.41(.76)/.72
Overall	3.08(.84)/.71	2.85(.70)/.65	2.96(.83)/.82	2.54(.87)/.72	3.02(.77)/.70	3.16(.58)/.68	2.58(.69)/.79	2.62(.73)/.68

Overall: discrepancy between 50-item (Hong Kong, China), and 55-item surveys considered missing data

Table 4 Sample inter-learning pattern correlation ranges and means

	Application-directed & Meaning-directed strategies		Application-directed & reproduction-directed strategies		Meaning-directed & reproduction-directed strategies	
	Range	Mean	Range	Mean	Range	Mean
Venezuela	.64/.72	.67	.28/.62	.45	.23/.66	.48
Indonesia	.58/.59	.58	.34/.51	.41	.24/.64	.44
China	.60/.62	.61	.18/.40	.30	.10/.65	.39
Hong Kong	.49/.60	.56	.35/.44	.40	.18/.64	.40
Spain	.47/.60	.53	.01/.34	.21	.07/.62	.31
Belgium 1	.49/.57	.52	.11/.29	.22	.01/.48	.25
Belgium 2	.45/.50	.48	–.05/.17	.07	.01/.42	.19
The Netherlands	.49/.53	.54	–.06/.05	–.01	–.16/.21	.02

Range: low/high

Table 5 Bonferroni-adjusted multivariate multiple regression results

	Application-directed & meaning-directed strategy	Application-directed & reproduction-directed strategies	Meaning-directed & reproduction-directed strategies
IDV and PDI	–	*($p = .02$)	**($p = .008$)
$R^2/R^2_{adjusted}$	.67/.54	.86/.81	.92/.89
$\hat{\beta}$	–.92/–.13	–.69*/.28	–.56*/.46
IDV-COLL and PDI	–	*($p = .04$)	*($p = .014$)
$R^2/R^2_{adjusted}$	.50/.30	.82/.75	.89/.85
$\hat{\beta}$	–.68/.03	–.68/.26	–.52/.46

Independent variables (Table 1): IDV and PDI, IDV-COLL and PDI. Dependent variables: inter-learning pattern correlation means (Table 4)

$^{*}p < .05$, $^{**}p < .01$

Overall, the results support Hypothesis 2 suggesting that samples with lower individualism and higher power distance index values correspond to greater uses of application-directed together with reproduction-directed strategies, and meaning-directed together with reproduction-directed strategies.

For Hypothesis 3, memorising had the greatest overall correlations with analysing ($r_{mean} = 0.47$). Analysing had the greatest overall correlations with memorising and relating-structuring ($r_{mean} = 0.47$). Relating-structuring had the greatest overall correlations with analysing and critical ($r_{mean} = 0.60$). Results are summarised in Table 6 and Fig. 1.

Table 6 Mean correlations(Standard Deviations) between processing strategies across samples

	Memorising	Analysing	Relating-structuring	Critical
Memorising	–			
Analysing	.47(.06)	–		
Relating-Structuring	.24(.20)	.47(.17)	–	
Critical	.01(.14)	.37(.16)	.60(.07)	–

Fig. 1 Sample-level processing strategies correlations. Hypothesised progression: Memorising, Analysing, Relating-Structuring, Critical. Correlations are generally greatest with neighbouring strategies

Research questions 2a and 2b (Person-centred analyses)

Sample LPAs

Supporting criteria for LPA models are summarised in Table 7. Full tests and indicators are provided in Appendix C. Figure 2 presents the profiles and labelling for each sample. Full profile means are presented in Appendix D. The following qualitative descriptions discuss model selection considerations, considered alternative models, level and shape profile differences (Hypothesis 4).

Venezuela (V) The three profiles present obvious level differences (i.e., similar differences in most or all scales). Shape differences (i.e., differences in dominant strategies) were less pronounced. V2 and V3 present middling and high levels of mixed strategies respectively. V1 presents low scores indicative of an undirected learning pattern (i.e., higher lack of regulation with little use of any processing strategies).

Table 7 LPA Model selection criteria

	Chosen model (Profiles)	Supporting criteria			
		Information criteria (AIC,BIC,SABIC)	Log-likelihood ratio tests	Entropy	Minimum profile membership size
Venezuela	3	√(Elbow)	√	√	27%
Indonesia	4	√(Elbow)	√	√	10%
China	2	√(Elbow)	√		46%
Hong Kong	3	√(Elbow)	√	√	20%
Spain	5	√(Minimum)			12%
Belgium 1	4		√		19%
Belgium 2	4	√(Elbow)	√	√	16%
The Netherlands	5	√(Minimum)	√		9%

Indonesia (I) The four profiles present level differences. I1, I2 and I3 present different amounts of dominant reproduction-directed learning strategies. I1's low scores suggest an undirected learning pattern. I4 presents high levels of mixed strategies. Decreases in lack of regulation corresponds to relative increases in all other learning strategies.

China (C) Level differences are pronounced while shape differences are minor. C1 presents low overall values suggesting an undirected pattern. C2 presents high values in all but lack of regulation suggesting a rounded strategy approach.

Hong Kong (H) The three profiles have similar shapes. Low scores in H1 and H2 are indicative of an undirected pattern. H3 presents middling scores in meaning-directed, reproduction-directed and application-directed strategies.

Spain (S) A five-profile solution was chosen over a three-profile solution (supported by a BIC elbow) because of a minimum in BIC and inclusion of similar profiles (S2, S3, S5). There are clear shape differences among profiles. S1 presents higher reproduction-directed strategies while S4 is balanced across strategies. S2, S3 and S5 present progressively higher meaning-directed and application-directed strategies.

Belgium 1 (B1) A four-profile model was chosen over the two-profile model (supported by an elbow) due to support from log-likelihood ratio tests and inclusion of similar profiles (B13, B14). Shape differences are prominent. B11 and B14 present greater meaning-directed strategies, whereas B12 and B13 report greater use of reproduction-directed strategies.

Belgium 2 (B2) There are obvious shape differences between the four profiles. B21, B23 and B24 have similar shape, presenting higher scores for reproduction-directed strategies over meaning-directed strategies. Students in B22 reported greater meaning-directed and application-directed strategies.

The Netherlands (N) The five-profile model includes a profile with marginal membership size (9%, $n=74$). Three prominent shapes are presented: N2 and N3, N1 and N4, and N5.

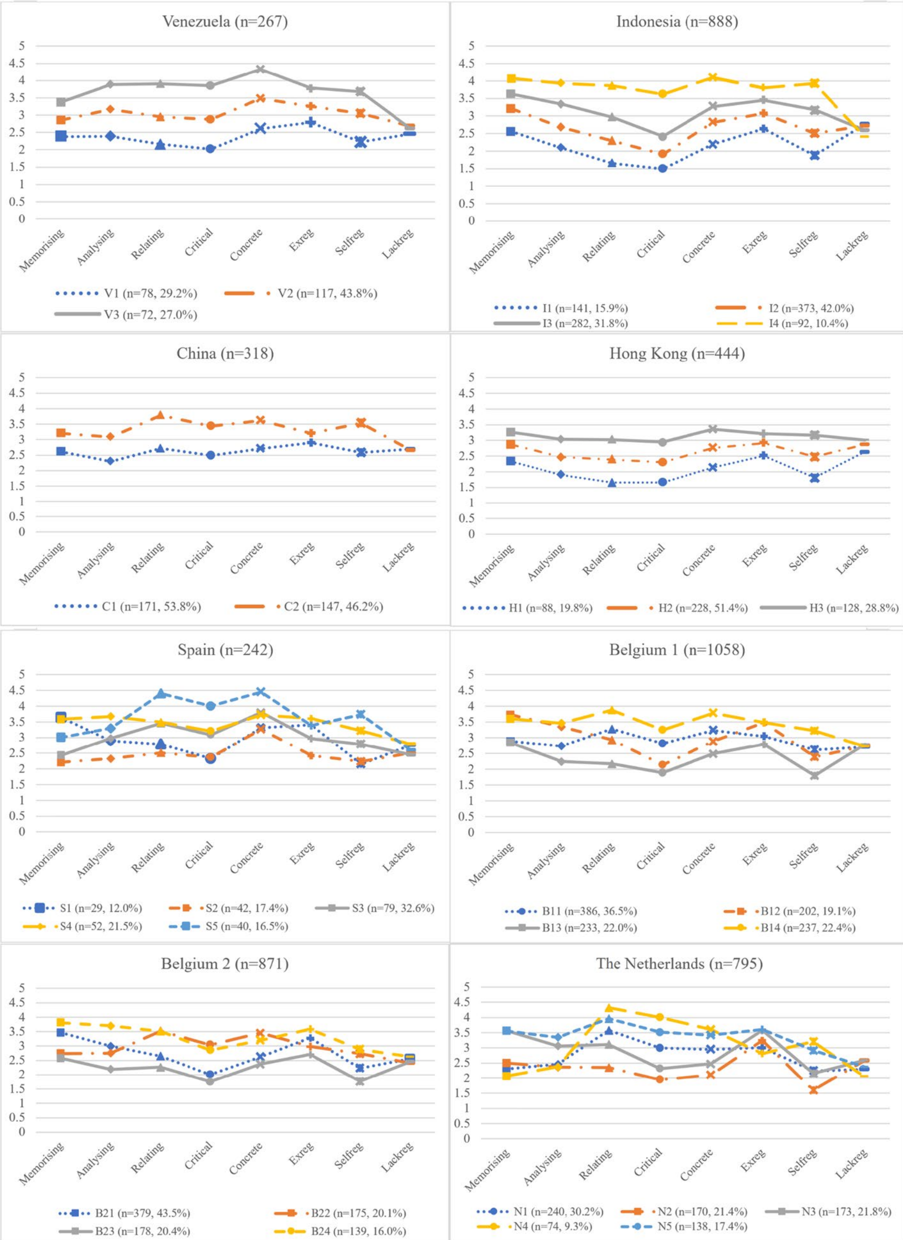

Fig. 2 Sample LPA Profiles and Membership, Relating – Relating-structuring

N2 and N3 have differing levels of reproduction-directed strategies. N1 and N4 present different levels of a meaning-application-directed mixture. N5 represents a high strategic use of learning strategies, reporting high amounts of all processing strategies and external regulation.

Overall results The four samples corresponding to lowest individualism and highest power distance index scores presented profiles with level differences and minimal shape differences. The remaining samples presented clear shape profile differences with some level differences (Hypothesis 4). Addressing Hypothesis 5, profiles across samples presented mixed consistency with learning patterns research. All except for the Spanish and Dutch samples presented a profile with all around low levels of learning strategies (V1, I1, C1, H1, H2, B13, B23), qualitatively reminiscent of the undirected profile. Consistent with Vermunt et al. (2014), many of these profiles presented relatively higher levels of memorising, analysing and external regulation. The Dutch, Venezuelan (N2, V2, application-directed: concrete processing) and Spanish (S2, external regulation) samples each presented profiles with only one dominant learning strategy. Profiles presenting a preference for reproduction-directed strategies (memorising, analysing and external regulation; I2, I3, S1, B12, B21, B24, N3) were common across samples. Profiles demonstrating a qualitative preference for meaning-directed strategies (relating, critical processing and self-regulation) over reproduction-directed strategies (C2, S3, S5, B22, N1, N4) also reported high levels of application-directed strategies (concrete processing). Numerous samples presented a profile with all-around high strategy use (both processing and regulation; V3, I4, H3, S4, B11, B14, N5). This description is consistent with "Asian" and "Latin-American" learner stereotypes described previously (Martínez-Fernández & Vermunt, 2015; Marton et al., 2005). The results above are drawn only from qualitative similarities and differences of the profiles across samples. The classifications above are not definitive and indicate qualitative shape and level trends consistent (or inconsistent) to the existing literature.

Discussion

Two research questions investigated higher education learning strategies across eight international samples.

The first research question examined learning strategies using variable-centred methods at the sample and cross-sample levels. Within meaning-directed learning strategies and within reproduction-directed strategies were strongly correlated in all samples, supporting the ubiquitous existence of meaning-directed and reproduction-directed learning patterns. Lack of regulation did not meaningfully positively correlate with meaning-directed strategies in any sample and correlated moderately with memorising and external regulation strategies in some samples (Hypothesis 1). Increasing collectivism and power distance corresponded to stronger mean correlations between each of meaning-directed strategies with application-directed strategies and meaning-directed strategies with reproduction-directed strategies (multivariate multiple regression analyses; Hypothesis 2). Individualism-collectivism and power distance provide more accuracy in describing cultural differences in learning strategies over broad geography-based Asian and Spanish/Latin-American learner stereotypes. Correlations along the hypothesised memorising, analysing, relating-structuring, critical processing continuum were largest among adjacent strategies and decreased between pairs further apart (Hypothesis 3).

The second research question explored differences within and between samples using person-centred analyses. Profiles from contexts corresponding to lower individualism (Venezuela, Indonesia, China and Hong Kong samples) differed in level whereas profiles from contexts with higher individualism presented obvious shape differences (Hypothesis 4). Profiles consistent with a reproduction-directed learning pattern and profiles consistent with an undirected learning pattern (overall low strategies) appeared consistently across samples. Profiles that reported higher values for meaning-directed strategies over reproduction-directed strategies also reported higher application-directed strategies. Profiles presenting both high meaning-directed and reproduction-directed strategies were present in nearly all samples including individualistic (traditionally Western) contexts (Hypothesis 5).

Theoretical implications

While hypotheses were mostly confirmed, there were several unexpected findings including cultural differences in employed learning strategies.

The greater correlations observed in the neighbouring strategies in the memorising, analysing, relating-structuring, critical continuum suggest that use of one strategy implies a greater likelihood of using an adjacent strategy. Beginning with memorising, and that deep processing yields higher quality outcomes (Vermunt & Donche, 2017), the results support the sequential use of stepwise/surface followed by deep processing strategies described in models involving learning strategies (Alexander, 2003; Hattie & Donoghue, 2016).

Previous cross-cultural studies found an application-directed pattern (whose only learning strategy is concrete processing) only in the Dutch sample (Vermunt, 1996, 1998). In this study, concrete processing is reported alongside both meaning-directed and reproduction-directed strategies supporting some previous findings (Martínez-Fernández & Vermunt, 2015; Vermunt et al., 2014).

Cultural dimensions: individualism-collectivism and power distance

The results indicate that individualism-collectivism and power distance provide robust frameworks to compare learning strategies across cultures. The results encourage a shift away from generalisations based on geography towards comparing national contexts against accepted cultural dimensions. As the samples' original data collection occurred over several decades, evolving cultural dimensions could influence the results. However, the similar results obtained from multiple regression and sample LPAs using both the IDV and the updated IDV-COLL indices support the cultural interpretations made in this study.

The relationships found from regression analyses lend support to students' varied strategy use in more collectivistic and higher power distance cultures. Higher multiple strategy use is consistent with obtaining skills and qualifications through teacher-centred education (in collectivistic, high-power distance contexts) over pursuing interests and valuing the learning process indicative of student-centred education (in individualistic, low-power distance contexts; Hofstede, 2001).

If student learning strategy development occurred between the profiles found within each sample, students in primarily collectivistic cultures may likely increase in level but not change shape. Such students focus on learning skills through teacher-centred instruction in high-power distance cultures. They may view that all processing strategies, self-regulation and external regulation are required. Those in more individualistic low-power distance contexts could also focus on how to learn and more readily adopt different profile shapes (Hofstede, 2001).

The results also address questions regarding "Western" patterns of learning strategy use, namely that Western students might employ combinations of memorisation and understanding (Kember, 2016; Leung et al., 2008). The Asian and Spanish/Latin-American learner paradoxes are described by higher levels of both stepwise and deep processing and both external and self-regulation strategies respectively (Martínez-Fernández & Vermunt, 2015; Marton et al., 2005; Watkins, 2000). Profiles that qualitatively fit these descriptions are consistently found in traditionally "Western" contexts (e.g., S4, B14, and N5). Therefore, the results of this study question the existence and validity of these stereotypes.

Practical implications

Students' learning strategy use is influenced by cultural factors, teaching practices and learning practices. Tightly tied to a student's self-regulation and willingness to be externally regulated are the teaching practices that support them. Process-oriented instruction describes the relationship or "friction" between a student's self-regulation paired with a teacher's external regulation (Vermunt & Verloop, 1999). This friction can be constructive (e.g., when students have low self-regulation and teachers challenge students by expecting a shared role of regulation) or destructive (e.g., when neither students nor teachers provide the necessary regulation to succeed). Power distance may hinder or bolster this guidance through its effects on teacher-student relationships (Hofstede, 2001). Teachers can have strong effects when intervening which if not carefully planned, could impede learning strategy use and development.

The qualitative interpretations of the profiles found across sample-LPAs have implications on teacher regulation practices. Students belonging to profiles that have characteristics qualitatively similar to an undirected pattern present low self-regulation and moderate external regulation. These together would suggest constructive friction led by teacher external regulation (Vermunt & Verloop, 1999). The accompanying low levels of processing strategies suggest that teachers should begin by instructing, facilitating and assessing the use of stepwise processing (memorising then analysing). As students' strategy use and domain knowledge develop, teachers should gradually shift towards supporting deep processing (relating-structuring then critical). These practices are consistent with results found in the proposed processing strategies continuum and learning strategy models (Alexander, 2003; Hattie & Donoghue, 2016).

Profiles demonstrating a preference for memorising, analysing and external regulation are qualitatively reminiscent of a reproduction-directed pattern. In higher-power distance samples, these profiles present moderate self-regulation which could suggest possible destructive friction (Vermunt & Verloop, 1999). These students may benefit from a tapering-off teaching approach, allowing development of processing strategies with less guidance. In lower-power distance samples, these profiles present lower accompanying self-regulation and may require additional external support in employing relating-structuring, critical and concrete processing strategies.

Profiles with higher levels of meaning-directed strategies (relating, critical processing and self-regulation) generally presented comparable levels of external regulation and concrete processing (Vermunt et al., 2014). Employing student-centred teaching practices could support constructive friction in learning strategy development through shared regulation (Vermunt & Verloop, 1999).

In profiles with all-around high strategy use, high levels of both external and self-regulation would traditionally suggest destructive friction (Vermunt & Verloop, 1999). However, accompanying high levels of all processing strategies would signify that these students act opportunistically, using strategies that best suit their achievement goals. Especially in higher-power distance contexts, careful design of higher quality learning outcomes requiring deep processing could improve the quality of learning (Vermunt & Donche, 2017).

Teachers may need to swim against the current of culturally accepted teacher regulation practices to support students' learning strategy development according to the profiles. Supporting student development of processing strategies is an enduring practice that must go beyond introduction of novel techniques (Brown et al., 2017). Process-oriented instruction requires teachers to first diagnose learners and determine the appropriate level of external regulation (i.e., strong, shared, loose) along with corresponding effective instructional strategies (Vermunt & Verloop, 1999). Teachers should model appropriate learning strategies (e.g., self-testing, looking for applications), challenge and activate students to use and practice them, and promote the scaffolding and the instruction of processing techniques (e.g., Dignath & Veenman, 2020).

The current study draws attention to the abundant use of reproduction-directed strategies across student profiles, and their complementary role to meaning-directed strategies. Memorising and analysing may require support as a potential precursor to deep processing strategies. Teachers should focus on facilitating the interplay and transition towards deep processing (Alexander, 2003; Hattie & Donoghue, 2016). Once ready, deep processing strategies required in innovative teaching approaches such as problem-based, project-based and self-directed specialisation learning could be developed using appropriate teacher-regulation strategies (e.g., Vermunt, 2007). While students should be supported to demonstrate deep processing in achieving meaningful outcomes, students may require varying pathways to get there.

Limitations and future directions

The current study's results were based on data from a single self-report instrument. This limitation is balanced by the large-scale and international nature of the study. The ILS and other long multi-construct surveys used in higher education learning research were designed prior to widespread use of latent approach to predictive analysis. As a result, responses to these instruments generally yield marginal fit on construct validity tests (e.g., Confirmatory Factor Analyses; García & Pintrich, 1996; Midgley et al., 2000). However, meta-analyses are limited to the available results and datasets. Shum et al. (2021) presented a systematic method to remove items to improve fit. This practice was not adopted to maintain consistency with previous cross-cultural studies and LPA being a mean-based, rather than a latent construct approach to measurement and analysis (Marambe et al., 2012; Vermunt et al., 2014).

Change in culture over time and within-nation cultural differences may also pose limitations. Despite using an updated index (IDV-COLL in addition to IDV), this limitation can only be redressed by continuing research refining cultural dimensions results.

Noncultural contextual factors may also play a role. For example, first-year students might place a stronger emphasis on rote learning as a survival strategy. Increasing differentiation between meaning-directed and reproduction-directed learning strategies has been observed as students progress through formal education (Vermunt & Vermetten, 2004). A wider range of educational contexts would help clarify the results. Future studies could consider the full model of learning patterns and outcome variables (e.g., achievement, GPA) to capture a more comprehensive picture of students' experience.

Conclusion

Learning strategies were compared across eight samples in seven countries employing Hofstede's individualism-collectivism and power distance cultural indices taking variable-centred and person-centred meta-re-analysis approaches. Variable-centred results revealed the increasing prevalence of all-around strategy use in more collectivistic high-power distance contexts. Latent profile analyses supported variable-centred results, finding that more collectivistic high-power distance contexts presented profiles with primarily level differences, suggesting mixed use of learning strategies. Individualistic low-power distance contexts presented different shapes of learning strategies. Furthermore, traditionally "Western" contexts often presented at least one profile that described students employing learning strategies consistent with "Asian" and "Latin-American" stereotypes. The results point to the limitations of geographical learner stereotypes and support the use of individualism-collectivism and power-distance as cultural dimensions to describe cultural differences in learning strategies. Future cross-cultural studies on learning strategies should be supplemented with person-centred analyses to account for varying practices within and across contexts.

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Data availability The data is not publicly available.

Declarations

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