Analysis Report

This report is structured as follows.

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Preliminary Reliability Tests

The first step was to execute reliability analysis to check if an acceptable level of reliability is present in order to proceed to the assessment of validity. Reliability is an assessment of the degree of consistency between multiple measurements of a variable. One form of reliability is test–retest, by which consistency is measured between the responses for an individual at two points in time. The objective is to ensure that responses are not too varied across time periods so that a measurement taken at any point in time is reliable. A second and more commonly used measure of reliability is internal consistency, which applies to the consistency among the variables in a summated scale. The rationale for internal consistency is that the individual items or indicators of the scale should all be measuring the same construct and thus be highly intercorrelated (Hair et al., 2014). The analysis in this study was done using Cronbach's Alpha (α). The table below shows the descriptive statistics and Alpha coefficients for the scales under study.

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Learning Climate	LCQ_1	2.501	1.519	0.813	0.961
	LCQ_2	2.483	1.526	0.836	
	LCQ_3	2.372	1.499	0.786	
	LCQ_4	2.471	1.561	0.834	
	LCQ_5	2.309	1.522	0.866	
	LCQ_6	2.655	1.602	0.818	
	LCQ_7	2.359	1.499	0.799	
	LCQ_8	2.424	1.538	0.877	
	LCQ_9	2.241	1.452	0.843	
	LCQ_10	2.490	1.474	0.826	
	LCQ_11	2.510	1.522	0.847	
	LCQ_12	2.805	1.625	0.808	
	LCQ_13_Reversed	2.863	2.060	0.191	
	LCQ_14	2.799	1.528	0.746	
	LCQ_15	2.939	1.643	0.706	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Autonomy Satisfaction	PBNSF_1	1.878	0.950	0.672	0.886
	PBNSF_2	1.969	0.996	0.803	
	PBNSF_3	1.901	0.984	0.787	
	PBNSF_4	1.733	0.994	0.748	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Autonomy Satisfaction	PBNSF_5	3.663	1.247	0.629	0.854
	PBNSF_6	3.733	1.220	0.741	
	PBNSF_7	3.527	1.329	0.678	
	PBNSF_8	3.682	1.280	0.733	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Amotivation	AM_5	1.255	0.674	0.707	0.853
	AM_10	1.346	0.745	0.706	
	AM_13	1.243	0.656	0.705	
	AM_18	1.372	0.756	0.654	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
External Regulation	AM_1	1.593	0.929	0.568	0.801
	AM_8	1.919	0.983	0.683	

	AM_15	1.592	0.914	0.508	
	AM_20	1.539	0.892	0.708	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Introjected Regulation	AM_6	1.760	1.059	0.508	0.694
	AM_11	2.591	1.083	0.316	
	AM_14	1.346	0.741	0.542	
	AM_19	1.272	0.671	0.492	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Identified Regulation	AM_3	3.669	0.631	0.652	0.830
	AM_9	3.524	0.746	0.612	
	AM_12	3.586	0.702	0.695	
	AM_17	3.548	0.715	0.671	

Construct	Item	Mean	Std. Deviation	Item-Total Correlation	α
Intrinsic Regulation	AM_2	3.661	0,634	0.636	0.805
	AM_4	3.534	0,699	0.655	
	AM_7	3.597	0,715	0.638	
	AM_16	3.327	0,857	0.534	

All three coefficients were above 0.700, which means the scales have good reliability. Item 13 was reversed but still showed poor item-total correlation (0.191) which might indicate that this item is not measuring the same aspect as the whole scale. Since the total scale showed good reliability, the item was kept for the validity analysis phase (next Section).

Confirmatory Factor Analysis

The main objective of testing a measurement model is to test construct validity. Construct Validity is defined as “the extent to which a set of measured variables actually represent the theoretical latent construct they are designed to measure” (Hair et al., 2014, p. 543). Confirmatory Factor Analysis (CFA) was used in the analysis, as it is an adequate method to be used as evidence of construct validity of theory-based instruments (Li, 2016). This type of analysis is used when a researcher wishes to confirm a specific pattern of variables that are predicted based on theory or previous analytical studies (DeVellis, 2012). That is, based on knowledge of the theory, he or she assumes the a priori factorial structure and then tests this hypothetical arrangement statistically (Byrne, 2016).

CFA was conducted using SPSS AMOS software, which uses Maximum Likelihood (ML) algorithm to estimate the results. ML is the most common method used to estimate parameters in CFA, because of its attractive statistical properties (i.e., asymptotic unbiasedness, normality, consistency, and maximal efficiency) (Li, 2016). After defining the model in the software and executing the analysis, four main phases were conducted to examine construct validity (1) assessment of model fit; (2) assessment of convergent validity; (3) assessment of discriminant validity and (4) respecification of the model (if necessary). The statistics that were used to assess model fit and their rules of thumb are presented in the table below.

Fit index	Rules of thumb
Root mean square error of approximation (RMSEA)	RMSEA < 0.08
Comparative fit index (CFI)	CFI > 0.90
Normed fit index (NFI)	NFI > 0.85

After the assessment of model fit, convergent and discriminant validity were examined. Convergent validity refers to the "extent to which indicators of a specific construct converge or share a high proportion of variance in common" (Hair et al. 2014, p. 601), while discriminant validity is defined as the "extent to which a construct is truly distinct from other constructs both in terms of how much it correlates with other constructs and how distinctly measured variables represent only this single construct (Hair et al. 2014, p. 601). A second important concept to test is construct's reliability. This was done using the Composite Reliability index (which is based on factor loadings) and Cronbach's Alpha (which is based on correlations). A summary of the indicators used to measure constructs' validity and reliability are detailed below (table below).

Indicator of convergent validity	Definition	Rules of thumb
Factor loadings (λ)	Correlation between the original variables and the factors, and the key to understanding the nature of a particular factor. Squared factor loadings indicate what percentage of the variance in an original variable is explained by a factor.	In the case of high convergent validity, high one-factor loadings would indicate that they converge on a common point, the latent construct. At a minimum, all factor loadings must be statistically significant. Because a significant load can still have quite weak strength, a good rule of thumb is that standardized loading estimates should be 0.5 or higher and ideally 0.7 or higher.
AVE	A summary measure of convergence among a set of items representing a latent construct. It is the average percentage of variation explained (variance extracted) among the items of a construct.	An AVE of 0.5 or higher is a good rule of thumb suggesting adequate convergence. An AVE of less than 0.5 indicates that, on average, more error remains in the items than variance explained by the latent factor structure imposed on the measure.
Indicator of discriminant validity	**Definition**	**Rules of thumb**
AVE and correlations (p)	The squared variance extracted estimates for a construct should be greater than the correlation estimates between this and other constructs.	Squared AVE > p (Fornell & Larcker, 1981).
Indicator of internal consistency	**Definition**	**Rules of thumb**
Construct Reliability (CR)	Measure of reliability and internal consistency of the measured variables representing a latent construct. Must be established before construct validity can be assessed. It is computed from the squared sum of factor loadings for each construct	0.7 or higher suggests good reliability. Reliability between 0.6 and 0.7 may be acceptable, provided that other indicators of a model's construct validity are good.

	and the sum of the error variance terms for a construct.	
Cronbach's Alpha	Cronbach's Alpha is a coefficient that represents the proportion of total variance among items that are due to the construct that they intend to measure	0.7 is the minimum acceptable level (Pallant, 2010).

<u>Convergent Validity and Reliability</u>

The model (with all items) showed acceptable fit (χ^2 (832, N = 1146) = 3544.44; p < .001; χ^2/df = 4.260; RMSEA = 0.053; CFI = 0.919; NFI = 0.897). Convergent validity was not achieved for the construct 'Introjected Regulation' (AVE = 0.395). When examining individual factor loadings, item 'AM_11' showed a poor loading (λ = 0.325) and was therefore deleted before running the analysis a second time. An additional item showed a factor loading lower than 0.500 ('LCQ_13_Rescored') and was also excluded from the 'Learning Climate' scale.

A second model (without both items) showed an even better fit (χ^2 (751, N = 1146) = 3124.18; p < .001; χ^2/df = 4.160; RMSEA = 0.053; CFI = 0.928; NFI = 0.907). The 'introjected regulation' scale still showed a AVE lower than what would be ideal to reflect convergent validity, but barely below the acceptable threshold (AVE = 0.492). Since factor loadings of the three remaining items in the scale were all above 0.500, which is also evidence of convergent validity, the researcher decided to proceed with this solution without excluding any additional item. The final results of convergent validity and reliability are shown below.

Item		**Construct**	**Loadings**	**AVE**	**CR**	**Cronbach's Alpha**
LCQ_1	<---		0.833			
LCQ_2	<---		0.854			
LCQ_3	<---		0.803			
LCQ_4	<---		0.854			
LCQ_5	<---	Learning_Climate	0.883	0.696	0.970	0.969
LCQ_6	<---		0.842			
LCQ_7	<---		0.819			
LCQ_8	<---		0.896			
LCQ_9	<---		0.861			

LCQ_10	<---		0.840			
LCQ_11	<---		0.864			
LCQ_12	<---		0.825			
LCQ_14	<---		0.763			
LCQ_15	<---		0.726			
PBNSF_1	<---	Autonomy_Satisfaction	0.724	0.667	0.889	0.886
PBNSF_2	<---		0.858			
PBNSF_3	<---		0.853			
PBNSF_4	<---		0.825			
PBNSF_5	<---	Autonomy_Frustration	0.706	0.597	0.855	0.854
PBNSF_6	<---		0.822			
PBNSF_7	<---		0.751			
PBNSF_8	<---		0.806			
AM_18	<---	Amotivation	0.736	0.593	0.854	0.853
AM_13	<---		0.785			
AM_10	<---		0.776			
AM_5	<---		0.783			
AM_20	<---	External_Regulation	0.831	0.520	0.810	0.801
AM_15	<---		0.615			
AM_8	<---		0.768			
AM_1	<---		0.648			
AM_19	<---	Introjected_Regulation	0.779	0.492	0.740	0.700
AM_14	<---		0.752			
AM_6	<---		0.551			
AM_17	<---	Identified_Regulation	0.768	0.550	0.830	0.830
AM_12	<---		0.743			
AM_9	<---		0.676			
AM_3	<---		0.776			
AM_16	<---	Intrinsic_Regulation	0.687	0.518	0.866	0.805
AM_7	<---		0.719			
AM_4	<---		0.726			
AM_2	<---		0.730			

<u>Discriminant Validity</u>

After determining convergent validity, the discriminant validity was assessed. The table below shows the squared AVE value (diagonal), along with correlations among constructs, obtained through CFA (non-diagonal values).

All constructs showed good discriminant validity, since the squared AVE (diagonal values are all above the correlations between the constructs. The only exception was between Identified and Intrinsic Regulation, which showed a very high correlation (r =

0.950), above the squared AVE of both constructs. Therefore a researcher should be aware when using both constructs on any predictive algorithm (i.e.. regression models) since they could lead into multicollinearity. If this high correlation is theoretically plausible, then the researcher may proceed with both constructs without problem.

	Learning Climate	Autonomy Satisfaction	Autonomy Frustration	Amotivation	External Regulation	Introjected Regulation	Identified Regulation	Intrinsic Regulation
Learning Climate	**0.834**							
Autonomy Satisfaction	0.588	**0.817**						
Autonomy Frustration	-0.260	-0.444	**0.773**					
Amotivation	0.350	0.428	-0.393	**0.770**				
External Regulation	0.246	0.319	-0.300	0.540	**0.721**			
Introjected Regulation	0.179	0.271	-0.273	0.713	0.718	**0.701**		
Identified Regulation	-0.348	-0.471	0.378	-0.593	-0.176	-0.278	**0.742**	
Intrinsic Regulation	-0.342	-0.413	0.363	-0.557	-0.204	-0.204	0.950	**0.719**

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