Profile Analysis via Multidimensional Scaling for the *Revised Two-Factor Learning Process Questionnaire*

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We are grateful to David Kember and John Biggs for allowing us to conduct research with the Revised Learning Process Questionnaire. We are also grateful to them for allowing us to reproduce their copyrighted questionnaire and scales in Appendices A and B.

Paper presented at the Annual Meeting of the National Council on Measurement in Education (New Orleans, LA, April 9-11, 2011).

Abstract

The *Revised Learning Process Questionnaire* has been part of the development of a conceptual understanding of how students learn and what motivates them to engage in particular tasks. We obtained responses from 329 student volunteers at a mid-sized public university in the southeast United States. While looking at the psychometric properties of this questionnaire in a different educational context from which the instrument had been originally validated was one purpose of the study, the main thrust of this research was to use Profile Analysis via Multidimensional Scaling (PAMS) to improve the diagnostic functionality of the instrument as well as further explore the validity of the questionnaire. We found that interpreting the latent structure in terms of the dimensions of Strategy and Motive as opposed to the factors of Deep and Surface approaches to be more appropriate for diagnostic use. We also found that PAMS has the inherent ability to assess an individual's fit within the model, thereby acting as a measure of self-report credibility. Both the Strategy and Motive dimensions were found to have ecological validity through analyzing its relationship to academic performance.

Profile Analysis via Multidimensional Scaling for the *Revised*

Two-Factor Learning Process Questionnaire

Learning and study strategies have been an interest in higher education for decades. From the earliest studies done by Entwistle and Ramsden (1982), looking at the self-perceptions of learning and motivation in the academic environment, researchers have been interested in recording how students study. In recent years, instruments have been developed to record and analyze the phenomenon, to better understand how people study and what factors can be attributed to success or failure in the academic setting. Kember, Biggs, and Leung (2004) and Everson, Weinstein, and Laitusis (2000) are examples of those who have endeavored to evaluate student learning goals, and in addition suggest the realignment of many general education and core curricula across many higher education institutions to help better cater to learning styles and study strategies of college students. Although some research has concentrated on more economic concerns, such as retention of students who struggle academically (Kember & Leung, 2009), other studies have been focused on the development of instruments to delve more into the construct of learning and study strategies (Kaplan, 2008).

The development of learning and studying as a construct has taken various paths. In the early 1970's some of the earlier research was geared toward evaluating how students learn, and within what context does that learning occur. Marton and Säljö (1976a, 1976b), one of the first studies to attempt to describe levels of processing and examine qualitative differences in how students learn, has been the foundation for many studies attempting to develop instruments to measure these constructs. Some of these researchers see learning to be more related to the impetus or motivation of the learner, whether it be intrinsic or extrinsic (Grant & Dweck, 2001), while others recognize the motivational aspects but combine it with cognitive factors (Lufi, Parish-Plass, & Cohen,2003; Scraw, 1994; Tobias & Everson,1997) . Yet even combining these aspects, there are differing opinions of how they are manifested. For example, Weinstein, Palmer, and Schulte (2002) see the learning and study strategies to be a composite of constructs related to skill, will, and self-regulation, while Biggs, Kember, and Leung (2001), conceptualize learning as being composed of motive and strategy, which in either case is ether *surface* or *deep* depending on the complexity of the particular attribute.

For this paper, however, our interest was not to debate the difference between theories, or to champion one specific explanation, but to move forward in the evolution of the instrument itself. That is, as the course of the history of researching learning and study strategies, numerous studies have been conducted in order to determine a more perfect understanding of the representation of these ideas from the data collected. In all cases research designs have been constructed and analysis undertaken to better able to researcher to understand not only how the construct manifests itself, but also how the instrument that assesses the construct operates. For example, Entwistle and Ramsden (1982) looked at the data qualitatively to help first identify the rudimentary questions to be utilized on a survey instrument, in the earliest development of the Learning Process Questionnaire. Later, Kember et al. (2004) ran a variety of exploratory factor analyses to determine the latent structure of the constructs, and later, confirmatory factor analyses to see how well the instrument represents that construct.

More specifically, these instruments have been evaluated and validated. Utilizing factor analytic procedures helped refine the constructs that emerged from the data collected. For example, for the Learning Process Questionnaire (LPQ) the conceptualization of Deep Approach and Surface Approach were realized. Biggs et al. (2001) went further to demonstrate that motives and strategies are found within these learning approaches by the representation of the factor structure. In the analysis of the LPQ and its subsequent revisions, Kember et al. (2004) were able to clearly show the factors found in the instrument, and how those factors related to one another.

It is now imperative that we take yet another step forward, and that is to show how to apply the instrument when describing samples of people. In short, the construct has been confirmed, the instrument's ability to detect that construct has been confirmed, and it is now time to apply the instrument to help students. Factor analysis determines how the construct is manifested within the instrument (exploratory) and whether the instrument consistently demonstrates the existence of the factors for that construct (confirmatory), while PAMS looks at the instrument in terms of what it tells us about people.

The current study was conducted with two major purposes. The first is to evaluate the psychometric properties of the *Revised Two-Factor Learning Process Questionnaire*, a later version of the LPQ (R-LPQ-2F; Kember et al., 2004). It is important to note that the sample used to confirm the two-factor version of the questionnaire was comprised of secondary students in Hong Kong, which required that the survey be translated into Chinese. As there may be some subtle issues in translation from English to Chinese, as well as cross-cultural differences in academic experiences, it is essential to determine if the Deep Approach and Surface Approach structure can be replicated with a more rural, American population. In addition, in order to use this survey for a sample of post-secondary students, it is important to replicate the findings with that age group. This included evaluating the ecological validity of the instrument by looking at relationships between the instrument factors and academic performance indicators such as GPA and student retention. In addition, this study engaged in the next level of progression in the analysis, by using Profile Analysis via Multidimensional Scaling (PAMS) in order to explore the characteristics of respondents of the R-LPQ-2F.

As PAMS can be used to develop profiles for individual test takers, it can be used as a means for improving the diagnostic functionality of the instrument. The two-factor structure, identified by Kember et al. (2004), is indeed useful for describing the construct of the learning process and identifying how the instrument operates in terms of Deep Approach and Surface Approach. However, being able to use the instrument to interpret the data affords a richer utilization of the instrument, both diagnostically and prescriptively. For example, which students are more likely to be retained, maintain high GPA's, or finish within 4 years? Describing student in terms of the dimensions of strategy and motive will allow us to identify "those with him motive low strategy" or "high strategy use, high motivation" and be better prepared to associate that with their academic successes or failures.

PAMS is a method that can be used to explore individual profiles of test takers for assessments with multiple subtests. Profiles such as these can be instrumental in looking at strengths and weaknesses of test takers within the subtests as well as affording the ability to make an evaluation that can be used to remediate problem behaviors (Kim, Davison, & Frisby, 2007). Also, PAMS allows a researcher to identify students who develop in an idiographic manner or are not explained by the model for whatever reason, whereas this capability is not inherent in factor analysis.

Method

Participants

We distributed a web-based version of the R-LPQ-2F to students at a mid-sized public university in the southeast United States. A total of 329 volunteers (227 women and 102 men) responded. Ages ranged from 17 years old to 64 years old (*M* = 27). Approximately 89.4% were white and 31.3% were graduate students. Since the R-LPQ-2F and its psychometric properties were originally produced by a large sample of secondary school students in Hong Kong, our sample is important in determining whether those psychometric properties are consistent in a university setting and across cultures.

Materials

The R-LPQ-2F consists of 22 items which can be summarized into two broad factors of Deep Approach and Surface Approach. Within Deep Approach, there are subscales for Deep Motive and Deep Strategy, and, within Surface Approach, there are subscales for Surface Motive and Surface Strategy. Further, these subscales contain two subcomponents each. Items were answered on a 5-point Likert-type scale ranging from 1 (*this item is never or only rarely true of me*) to 5 (*this item is always or almost always true of me*). Standard R-LPQ-2F instructions were presented to participants. Appendices A and B contain the questionnaire and scales, respectively (Kember et al., 2004).

Results

Construct Validity

First, we conducted a confirmatory factor analysis using EQS (Version 6.1) to determine if the full hierarchical model (see Figure 1) found by Kember et al. (2004) has good construct validity with our sample. The model was fitted from the covariance matrix. The variances for the Deep Approach and Surface Approach constructs were fixed to one, which is less restrictive than constraining factor pattern coefficients (MacCallum, 1995). This presumes that the variables are independently estimated for different groups and that the same model fits different groups (Thompson, 2004). Hu and Bentler (1999) recommended that a Comparative Fit Index (CFI) value greater than or equal to .96 in combination with a Standardized Root Mean Squared Residual (SRMR) value less than .09 would minimize the errors of rejecting a model when it is true and accepting a model when it is false. As a result, the CFI and SRMR were used to analyze model fit.

The CFI fell below the cut-off (CFI = 0.810), but the SRMR was right at the cut-off (SRMR = 0.092). These values were not as good as those found by Kember et al. (2004), where the CFI was 0.967 and the SRMR was 0.036, but are still good. It is possible that our lower fit indices are due to a smaller sample size (N = 329 compared to N = 801). It is important to note that all of the paths were statistically significant at the α = .05 level, indicating that all items and lower-order factors have a significant and useful contribution to the model. Also, we found a modest negative correlation between Deep Approach and Surface Approach whereas Kember et al. (2004) found a modest positive correlation. Intuitively, it makes more sense for this correlation to be negative because a positive correlation implies that a student who utilizes more surface strategies and motives would be more likely to also be utilizing more deep strategies and motives. The standardized solution for the hierarchical model is shown in Figure 1.

Next, multidimensional scaling (MDS), conducted in SAS (Version 9.1.3), was used to further explore the latent variable model of the R-LPQ-2F. Dimensions in MDS are similar to factors in factor analysis. In fact, if the data satisfy a simple structure factor model then those factors can be seen within the MDS solution even though the MDS dimensions and factors do not need to neatly map onto each other (Davison & Skay, 1991). The variable space in factor analysis is representative of the underlying relationships of a set of attributes with respect to a sample of individuals. MDS is different from factor analysis in that dimensions are interpreted as characteristics of the objects to which the individual pays attention when he/she makes judgments. In other words, MDS focuses on item differences more than individual differences.

MDS uses proximities, or measures of how similar or dissimilar different objects are, to derive a geometric configuration of points representing the “hidden structure” of the data with each point representing an object (Kruskal & Wish, 1978). These proximities were calculated using the city-block, or Minkowski-1, metric from observed student responses of the R-LPQ-2F. This metric is suitable for describing certain types of psychological data because it emphasizes psychological judgmental processes (Weinberg, 1991).

These proximities are used to derive dimensions, or coordinate axes, representing underlying characteristics of the objects under study. The goal is to obtain the lowest dimensionality that best explains the underlying structure of the data (MacCallum, 1974). Choosing the dimensionality is usually done through the use of goodness-of-fit statistics, Krustal’s stress formula 1 (STRESS 1) being a common statistic. This stress value is the square root of a normalized “residual sum of squares,” and indicates the level of fit for a specific dimensionality (Kruskal & Wish, 1978). STRESS 1 values closer to 0 represent better configurations. Stress values partially depend on the number of objects and the dimensionality, so for the most accurate interpretation of stress the number of objects should be large compared to the number of dimensions. One rule of thumb is that the number of objects should be more than four times the number of dimensions (Kruskal & Wish, 1978). Since the R-LPQ-2F contains 22 items, the number of dimensions should be no more than five.

Figure 1. Hierarchical Model for Motive and Strategy Scales in R-LPQ-2F

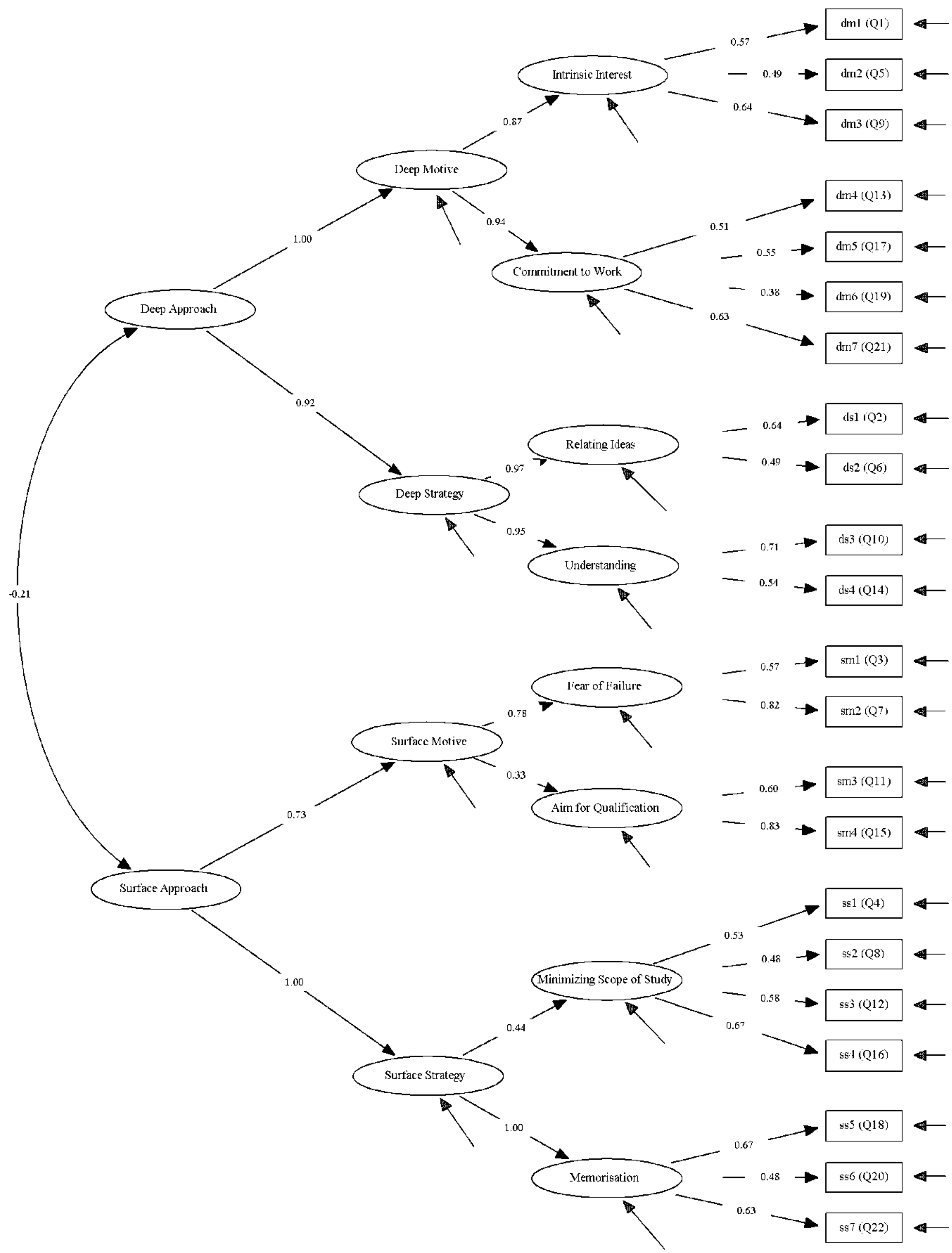

Figure 1. Hierarchical Model for Motive and Strategy Scales in R-LPQ-2F (N = 329).

A plot of STRESS 1 versus dimensionality is useful in determining how many dimensions to retain and can be interpreted in a similar manner to the scree plot in an exploratory factor analysis. An “elbow” in the plot suggests that additional dimensions offer negligible improvement of fit, thereby giving an indication about the lowest dimensionality that best explains the underlying structure of the data (Weinberg, 1991). A solution should not be accepted if the STRESS 1 is above 0.10 (Kruskal & Wish, 1978; Manly, 2004). Also, increasing the number of dimensions is questionable once STRESS 1 is already less than 0.05 (Manly, 2004). The plot of STRESS 1 versus dimensionality for our data shows an elbow at two dimensions (see Figure 2). This two dimension solution has a STRESS 1 value of 0.08.

Figure 2. STRESS 1 Values Plotted as a Function of Dimensionality

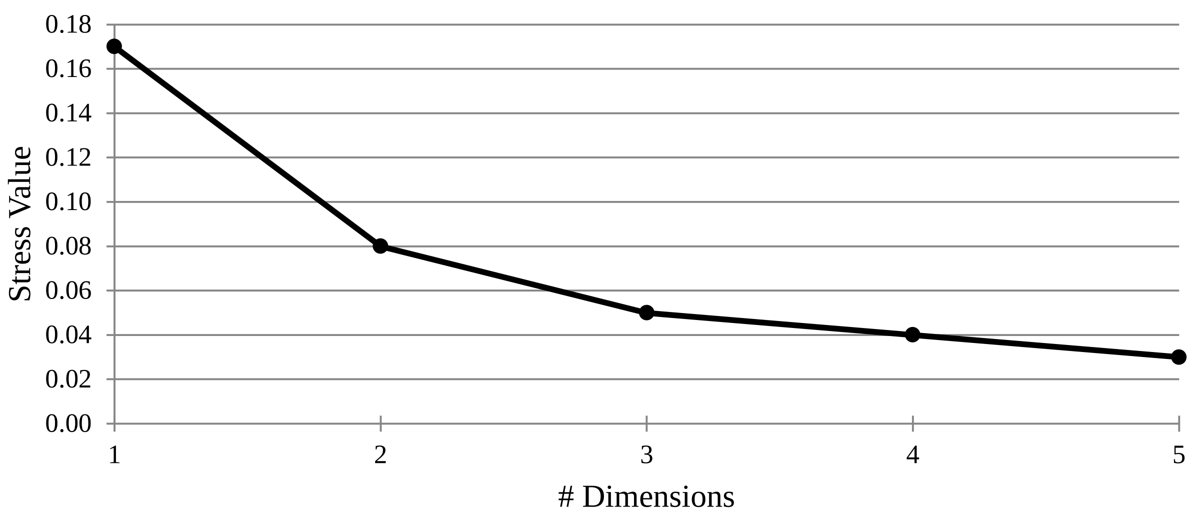

Figure 2. STRESS 1 values plotted for MDS solutions of different dimensionalities. An “elbow” is an indication about the true number of dimensions (Weinberg, 1991). This elbow should not be accepted if the STRESS 1 value is above 0.10 (Kruskal & Wish, 1978). This graph signifies that the two-dimension solution has the most accurate representation of the proximity measures with the lowest dimensionality.

We scaled the two dimensions (i.e., normalized) to a root-mean-square value of 1 and adjusted the dimension coefficients to compensate (see Table 1). These dimension coefficients describe the relationships between the variables which represent characteristics of the individuals in our study (see Figure 3). The high points and low points are typically mirror images of each other and can be used to label the dimensions (Ding, 2001). The low end of Dimension 1 on this graph is represented by items 4, 8, 12, 16, and 22. The items are all Surface Strategy items in the hierarchical factor model. The high end of the dimension is represented by items 2, 10, 11, 14 and 15. Items 2, 10, and 14 are all Deep Strategy items in the hierarchical factor model and items 11 and 15 are Surface Motive items in the factor model. Based on the MDS solution, Dimension 1 appears to represent Strategy, with negative values representing Surface Strategy and positive values representing Deep Strategy. The low end of Dimension 2 is represented by items 3, 7, 11 and 15, which are all Surface Motive items. The high end of Dimension 2 is represented by items 5, 13, and 17, which are Deep Motive items, and item 6, which is a Deep Strategy item. Based on the MDS solution, Dimension 1 appears to represent Motive, with negative values representing Surface Motive and positive values representing Deep Motive.

Table 1

Two-Dimensional MDS Solution

Item #	Dimension 1	Dimension 2
1	0.088	0.736
2	1.281	0.266
3	0.733	-2.071
4	-1.230	-0.029
5	0.548	1.017
6	0.161	1.849
7	0.031	-2.154
8	-1.656	0.538
9	0.686	0.187
10	1.291	0.145
11	1.547	-1.300
12	-1.296	0.283
13	-0.685	1.075
14	1.015	0.085
15	1.217	-1.270
16	-1.572	0.306
17	0.027	1.279
18	-0.879	-0.759
19	0.207	-0.145
20	-0.611	-0.530
21	0.543	0.685
22	-1.444	-0.194

Figure 3. Configuration Obtained by Applying Multidimensional Scaling to the R-LPQ-2F

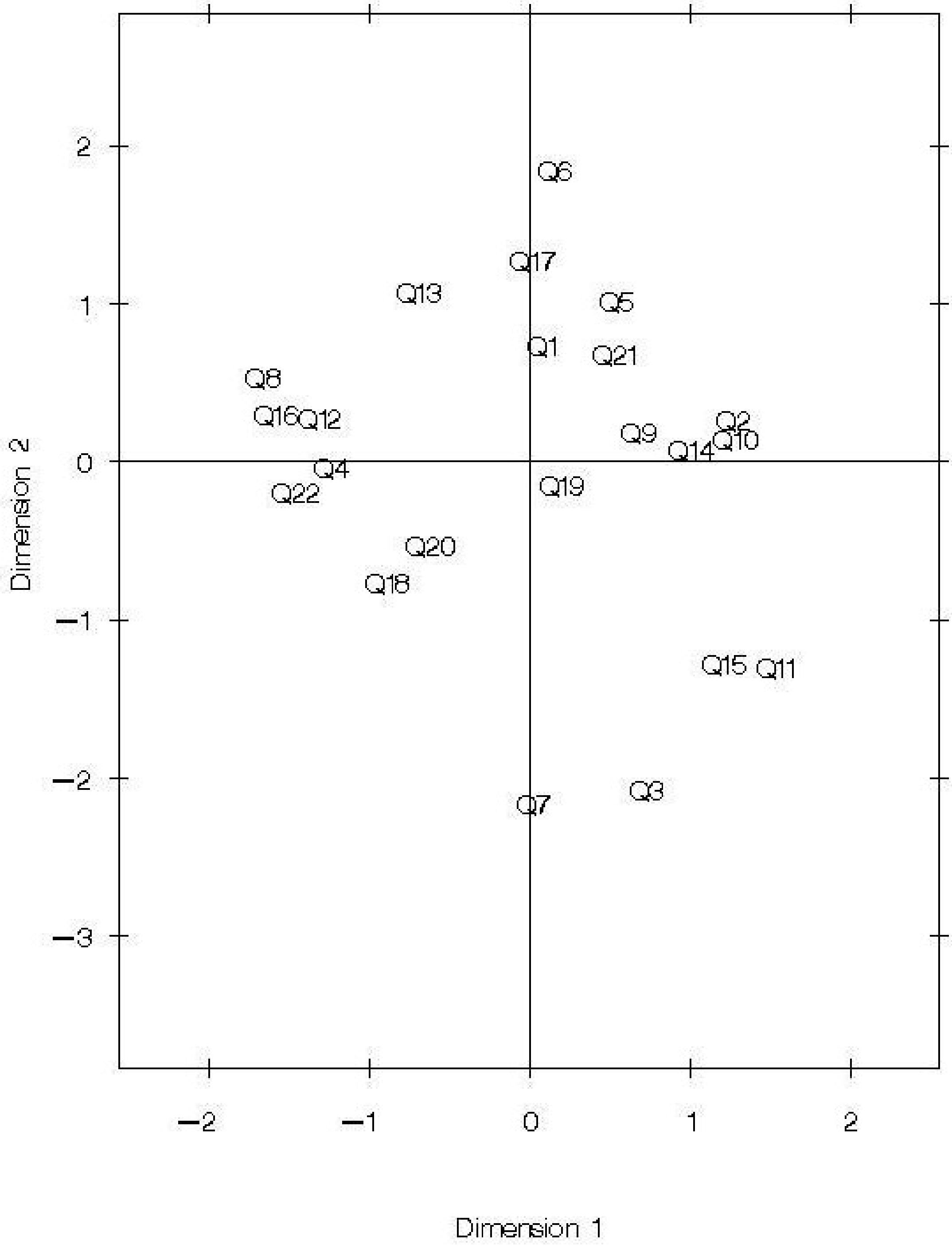

Figure 3. Configuration obtained by applying multidimensional scaling to the R-LPQ-2F. The dimensions were scaled (i.e., normalized) to a root-mean-square value of 1, and the dimension coefficients were adjusted to compensate. Dimension 1 appears to reflect “Strategy” and Dimension 2 appears to reflect “Motive.”

Although items do not need to neatly map onto the factors in the hierarchical factor model (Davison & Skay, 1991), most of the R-LPQ-2F items in our study did. This is further evidence of the construct validity of the latent model. Those that did not were items 6, 11, and 15. Item 6 is “I like constructing theories to fit odd things together.” The content of this question can be interpreted as either a Strategy or a Motive, explaining a possible reason why it fell on the Motive dimension instead of Strategy. Items 11 and 15 do fall under Surface Motive, but seem to also fall in the MDS solution under Deep Strategy. These items have to do with doing well in school in order to get a better job, so we do not know why they fall on both dimensions. Although it is not the purpose of the current study to improve the R-LPQ-2F, it is possible that removing items 6, 11, and 15 or changing the latent model to compensate for these items might improve the model fit obtained from our factor analysis.

Profile Analysis

MDS cannot describe individual differences until the profile analysis is applied. PAMS can be used to build profiles (i.e., interpret the MDS dimensions as latent profiles) through re-parameterizing the linear latent variable model. These profiles can be used diagnostically because PAMS can be used to determine group membership of people where the membership is not known in advance of the analysis. A PAMS model calculates person parameters which are essentially profile match indices that signify the direction and magnitude of the match between the actual profile of the person and the dimension profile. Factor analysis emphasizes how tasks vary in their sensitivity to person variates whereas MDS emphasizes how people vary in their sensitivity to the task dimensions. A PAMS model therefore studies the latent “person,” that is “types” among people as opposed to “factors” among variables (Ding, 2001), so that the latent variables can be interpreted as profile patterns (Ding, 2006). This is essentially a variation of the traditional factor model. PAMS studies clusters of people and each cluster is a hypothetical "prototypical person." Person parameters (i.e., dimension weights) are derived by linearly regressing each person's observed scores onto the dimension scale values obtained from the MDS analysis (Davison, Kim, & Ding, 2001).

A fit statistic is derived in this analysis (i.e., the R^2 from the regression) indicating the proportion of variance in an individual's observed data that can be accounted for by the profiles (Davison et al., 2001; Ding, 2006). This fit statistic is important to identify individuals who develop in an idiographic manner or answered the instrument randomly and therefore do not fit within the overall model. It can also represent the credibility of an individual's response as some may over- or under-exaggerate responses or not take the assessment seriously. It can be used to calculate the F-statistic and probability value used in regression to determine whether any of the explanatory variables are statistically related to the dependent variable. This probability value represents whether an individual fits within the overall model. PAMS goes beyond factor analysis and allows a researcher to look at whether an individual can be accurately described in the context of the latent model, such as is the case with unreliable respondents.

We computed person parameters and fit statistics for everyone in our sample. Table 2 contains the person parameters (i.e., dimension weights), level parameter (i.e., intercept from the regression), fit and significance, cumulative GPA, and semester GPA at the university for eight students from our sample (see Figure 4 for a plot of the person parameters). These eight students are good illustrations of how PAMS can be used to assign profiles for diagnostic use. Student 198 is an example of one who has poor fit and poor probability of being accurately placed in a profile. Since the R-LPQ-2F has been shown to have good reliability and construct validity, and since the MDS solution maps fairly close to the hierarchical factor model, this student most likely responded unreliably. It might be worthwhile to re-administer the R-LPQ-2F or collect data from other sources for this student.

The other students significantly fit within the overall model and can be assigned to a profile. Students 5 and 275 have positive weights for both dimensions and therefore have both Deep Strategy and Deep Motive. Interestingly enough, these students also have the highest cumulative GPA of those in the table. Student 275 also has the highest semester GPA (student 5 took only S/U courses so a GPA could not be calculated). Student 175 is the opposite, having both negative weights for both dimensions and therefore have both Surface Strategy and Surface Motive. This student has the lowest cumulative GPA of those in the table and one of the lowest semester GPAs. Students 23, 81, and 99 have Deep Strategy and Surface Motive and student 58 has Surface Strategy and Deep Motive.

Table 2

PAMS Person Parameters for Eight Students: R-LPQ-2F Profiles

Student	Dimension 1 Wt. (Strategy)	Dimension 2 Wt. (Motive)	Level Par.	Fit (R^2)	p-value	Cumulative GPA	Semester GPA
5	1.036	0.267	3.136	.536	.004	4.000	S
23	0.358	-0.729	2.818	.503	.006	3.289	2.750
58	-0.854	0.145	1.864	.432	.015	2.726	2.879
81	0.543	-0.444	2.000	.358	.033	3.271	2.685
99	0.734	-0.534	3.227	.414	.018	3.750	4.000
175	-0.116	-0.748	3.000	.456	.011	1.629	2.018
198	0.090	-0.031	3.136	.004	.840	2.119	1.686
275	1.358	0.432	2.909	.905	<.001	4.000	4.000

Figure 4. Profile Plot for Eight Students

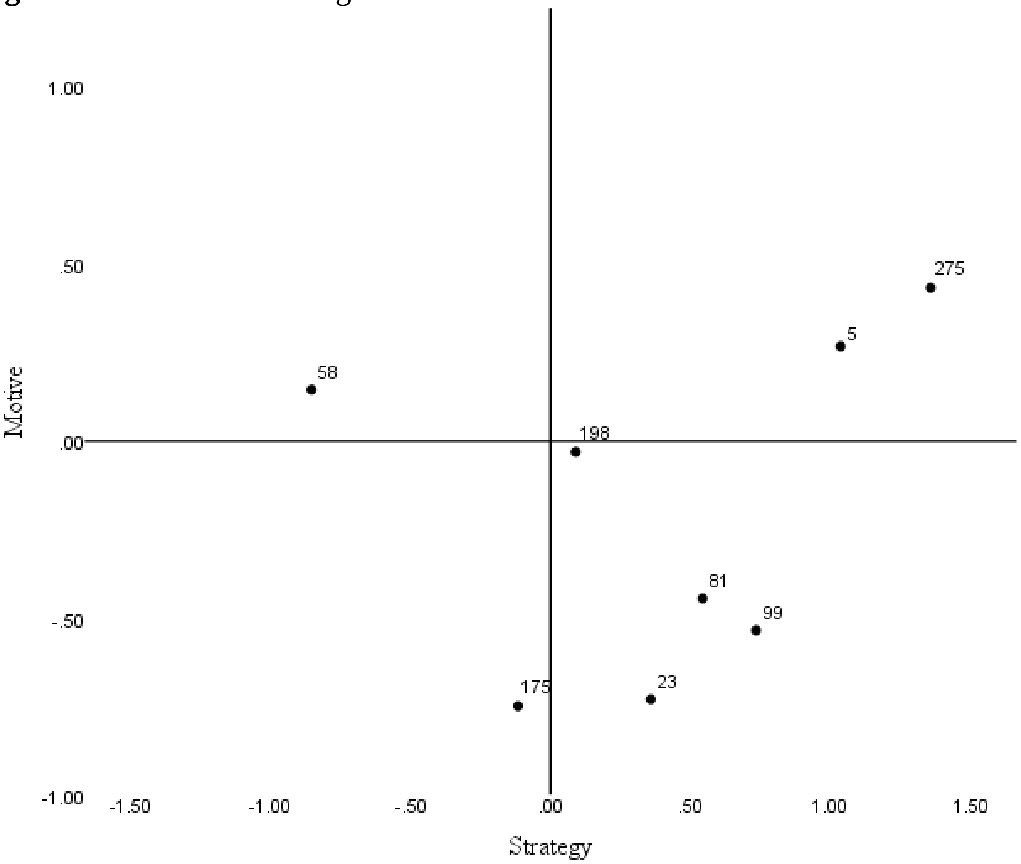

Figure 4. Configuration obtained by plotting the dimension weights for each respondent.

PAMS describes people in terms of continuous person profile indices that specify to what extent people are mixtures of the various types whereas factor analysis describes people in terms of discrete groupings. PAMS profile information can be utilized clinically to make differential diagnoses and to design appropriate interventions based on an individual's profile pattern. To illustrate this we have also computed the factor scores for the same eight students (see Table 3). Since factor analysis describes people in terms of discrete groupings, the dimensions of Motive and Strategy are represented as the factors Surface Motive, Deep Motive, Surface Strategy, and Deep Strategy. Students 81, 99, 175, and 198 have almost identical factor scores for Surface Motive and Deep Motive and students 81 and 99 also have almost identical factor scores for

Surface Strategy and Deep Strategy. These students cannot be profiled accurately using factor scores. The PAMS model can classify each one though, as seen above in Table 2.

Table 3

Factor Scores for Eight Students

Student	Surface Motive	Deep Motive	Surface Strategy	Deep Strategy
5	13	26	12	18
23	18	13	17	14
58	4	8	22	7
81	13	13	9	9
99	20	19	16	16
175	17	17	22	10
198	14	13	23	19
275	13	25	8	18

Ecological Validity

We have discussed how PAMS can be used to assign individuals to profiles based on a latent model. The next step is to determine whether these profiles have a relationship with behavioral measures such as semester GPA and whether or not the student is retained the following semester. To do this we conducted a multiple regression, regressing each student's semester GPA onto their level and dimension parameters. For retention we conducted a logistic regression. We included gender (i.e., male or female), race (i.e., white or non-white), credit type (i.e., resident credit or distance education), and class level (i.e., graduate or undergraduate) as controls in the models. Of the 329 student volunteers, 29 had missing values for one or more of the variables, leaving us with 300 for the regressions. The results for the semester GPA model show that Strategy has a significant positive relationship with academic performance (see Table 4). This intuitively makes sense since surface strategies revolve around learning for examinations, memorization, and devoting as little time to learning as possible and deep strategies revolve around learning to understand the material and relating ideas. Motive was also significant, but had a negative relationship with academic performance. This makes sense since Deep Motive involves having an intrinsic interest and commitment whereas Surface Motive has to do more with doing well in school and not wanting to get poor marks. These results indicate that Strategy and Motive are significantly related to academic performance.

Since PAMS allows a researcher to identify students who develop in an idiographic manner and are not explained by the model through the calculation of a fit statistic, we decided to run the regression again, only this time removing students with a low fit. This capability is not inherent in factor scores and is an important component of a PAMS analysis. Students were removed based on the probability of their fit (using $\alpha = .05$), such as student 198. Doing this allows us to look more closely at the relationship of each profile to semester GPA, which is important because only those who fit within the model can be profiled and helped with the use of an intervention. After removing those with poor fit we were left with 244 for the regression analysis. Overall the results are exactly the same as when all students were left in (see Table 4). This second regression is noteworthy, though, because it shows that the PAMS method can be applied from a diagnostician viewpoint in order to make more accurate decisions and determine which students we may need additional data for.

Table 4

Regression Parameters for Regressing Semester GPA onto PAMS Dimensions

	All Observations		Excluding Observations	
Variable	Parameter Estimate	Standardized Estimate	Parameter Estimate	Standardized Estimate
Intercept	3.1594***	0	2.9755***	0
Gender (1 = Female, 0 = Male)	-0.0609	-0.0310	-0.1903	-0.0983
Race (1 = White, 0 = Non-white)	0.3263*	0.1097	0.2797	0.0970
Credit Type (1 = Resident Credit, 0 = Distance Education)	-0.1197	-0.0443	-0.1320	-0.0526
Class Level (1 = Graduate, 0 = Undergraduate)	0.4092***	0.1987	0.3873***	0.1992
Dimension 1 Wt. (Strategy)	0.4963***	0.2102	0.6677***	0.2538
Dimension 2 Wt. (Motive)	-0.3242**	-0.1485	-0.3774**	-0.1866
PAMS Level	-0.2144	-0.0849	-0.1578	-0.0644

Note. The model using all observations has an adjusted R^2=.0749 and the model excluding observations has an adjusted R^2=.0825.

* $p < .10$. ** $p < .05$. *** $p < .01$.

As with most diagnostic tests and self-reports, some students are going to give invalid results. The ability to eliminate unreliable respondents is not a new idea, as it is common in such instruments as the MMPI. Hahn (2005) notes that when "using a client's self-report, it is crucial to determine the credibility of the individual's performance—for example, whether he or she has cooperated fully with the evaluation" (p. 65). The advantage with PAMS is that this can be done without the need for an extra validity scale, as the fit statistic in PAMS is a measure of how well an individual's item responses fit within the model. This ability allows a clinician to apply the appropriate assessment and offer more relevant assistance to students.

We also ran a multiple regression, regressing each student's semester GPA on the factor scores, in order to show a comparison between PAMS and factor analysis. In this model none of the subscales were significant, showing no evidence of ecological validity (see Table 5). Also, whereas the PAMS model has only two dimensions as independent variables, the factor analysis model has four subscales, thus increasing the complexity of drawing inference. It is possible that the complexity of interpreting each side of each dimension as a discrete factor instead of continuous dimensions is why this model has no significance. It makes sense that Deep Strategy is related to Surface Strategy and Deep Motive is related to Surface Motive, and that looking at each separately without including that relationship could affect the significance of each in the model.

Table 5

Regression Parameters for Regressing Semester GPA onto Factor Scores

Variable	Parameter Estimate	Standardized Estimate
Intercept	3.0935***	0
Gender (1 = Female, 0 = Male)	0.0025	0.0013
Race (1 = White, 0 = Non-white)	0.3137*	0.1055
Credit Type (1 = Resident Credit, 0 = Distance Education)	-0.1216	-0.0450
Class Level (1 = Graduate, 0 = Undergraduate)	0.4267***	0.2072
Deep Motive Subscale	-0.0168	-0.0825
Deep Strategy Subscale	0.0139	0.0454
Surface Motive Subscale	0.0162	0.0584
Surface Strategy Subscale	-0.0211	-0.0951

Note. This model has an adjusted R^2=.0518.
* p < .10. ** p < .05. *** p < .01.

Next we conducted logistic regressions, regressing retention on the PAMS dimensions and regressing retention on the factor scores. Retention was coded as 1 for students who enrolled in the next semester and 0 for those who did not. Those students who graduated prior to the next semester were removed prior to the analysis. Like before, we ran this regression including all observations and again excluding those with low fit (see Table 6). The model with all observations did not yield a significant relationship for Strategy and Motive. Strategy did have a mildly significant negative relationship with retention in the model that removed those with poor fit though. This indicates that those who use more surface strategies are for some reason more likely to enroll again the next semester. This makes sense since Deep Strategy deals with trying to understand the material and relate it with other subjects and Surface Strategy deals with studying for examinations and to get by in school. Those utilizing deep strategies might be transferring out or may be leaving because they are not concerned with learning solely to do well in school. Finally, we conducted this logistic regression using the factor subscales instead of the PAMS dimensions (see Table 7). We obtained similar results in that Surface Strategy has a significant positive relationship with the probability of whether a student will return next semester.

Table 6

Logistic Regression Parameters for Regressing Retention onto PAMS Dimensions

	All Observations (N = 277)		Removing Observations (N = 227)	
Variable	Estimate	Odds Ratio	Estimate	Odds Ratio
Intercept	-0.5222	0.593	0.5496	1.733
Gender (1 = Female, 0 = Male)	-0.1019	0.903	-0.0820	0.921
Race (1 = White, 0 = Non-white)	0.4686*	1.598	0.5104*	1.666
Credit Type (1 = Resident Credit, 0 = Distance Education)	0.5516***	1.736	0.4581**	1.581
Class Level (1 = Graduate, 0 = Undergraduate)	-0.1018	0.903	-0.1391	0.870
Dimension 1 Wt. (Strategy)	-0.9985	0.368	-1.5736*	0.207
Dimension 2 Wt. (Motive)	0.4705	1.601	0.6218	1.862
PAMS Level	0.8354	2.306	0.6734	1.961

* $p < .10$. ** $p < .05$. *** $p < .01$.

Table 7

Logistic Regression Parameters for Regressing Retention onto Factor Scores (N = 277)

Variable	Estimate	Odds Ratio
Intercept	-0.7426	0.476
Gender (1 = Female, 0 = Male)	-0.0871	0.917
Race (1 = White, 0 = Non-white)	0.4768**	1.611
Credit Type (1 = Resident Credit, 0 = Distance Education)	0.5414***	1.718
Class Level (1 = Graduate, 0 = Undergraduate)	-0.1148	0.892
Deep Motive Subscale	0.0357	1.036
Deep Strategy Subscale	0.0305	1.031
Surface Motive Subscale	-0.0705	0.932
Surface Strategy Subscale	0.1232**	1.131

* $p < .10$. ** $p < .05$. *** $p < .01$.

Discussion

The LPQ and its subsequent revisions have been part of the development of a conceptual understanding of how students learn, their motivation to engage in particular tasks, and the strategies they utilize to reach their academic goals. It has been generally accepted throughout the literature that these approaches to learning can be reduced to Deep Approach and Surface Approach, which encompass the motives and strategies which follow suit. Even with a smaller sample, the factor analysis accomplished in this study clearly confirmed the findings seen in previous studies as the subscales of Deep Motive, Surface Motive, Deep Strategy, and Surface Strategy emerged in the R-LPQ-2F.

Both factor analysis and PAMS techniques have advantages and disadvantages, and depending on the instrument and the latent construct, one may be more appropriate than the other for determining how to best use the instrument practically. In the case of the R-LPQ-2F, PAMS definitely seems to provide a better understanding of the application of the constructs of “motive” and “strategy” to students in higher education.

Diagnostically, these factors might be utilized to represent personality characteristics, but they can be cumbersome and difficult to interpret. That is, in order to use this instrument as a means for remediation, student support, or simply reflection, information concerning the student needs to be easily attainable and useable. For example, if a student completes the assessment and indicates utilization of both deep and surface learning approaches, whether he is more surface than deep or more deep than surface will have bearing how that student might alter his learning approach. The PAMS model does indeed help look at the individual test taker and a profile that represents characteristics of that individual. That is, the PAMS model allows for a "person-level" interpretation of the analysis.

PAMS basically allows for a conversion of the data into profiles so that overarching behaviors can be more easily categorized. The analysis forms a representation of how these behaviors play out in relationship to one another. A profile is basically a person's performance on a set of scores (Ding, 2001). PAMS extends MDS by interpreting the MDS dimensions as latent profiles (i.e., each dimension represents a group of individuals with similar characteristics; Ding, 2001, 2006; Kim et al., 2007). PAMS represents what profiles of variables exist in the population and how individuals differ in those profiles (Ding, 2006). In this particular case, the dimensions Motive and Strategy and level of processing (deep and surface) allow for a learner personality "type" to be developed. More specifically, the dimensions show how a person functions in the academic environment which can then be tied to other variables.

In this study, the dimension of Strategy can clearly be seen as a continuum from surface to deep. In addition, student profiles which fall along that dimension have been shown to relate significantly to GPA. In short, the capacity to utilize this instrument diagnostically has become readily apparent. A student profile is directly linked to the desired or undesired behaviors which now can be addressed, altered, and remediated. Although it seems intuitively obvious for students to use deep strategies because they are more efficacious, some students are unable to assess their own strategy use, and they continue to use methods that do not work. These students may be unable to see that their techniques are unsuccessful, or they may simply have a limited repertoire of study skills from which to pull. Helping students become more aware of the strategies they use, helping them monitor and regulate these strategies, and helping them choose between more successful and less successful strategies is essential. Counselors and advisors would be able to use these student profiles to determine whether it is indeed the strategies employed by the student that are affecting the academic outcomes. Also inherent in PAMS is the ability to identify individuals who do not fit within the model or who respond unreliably which allows one to identify those individuals with which further data, possibly from other outside sources, are needed. This might indicate the need for more diagnostic information or further testing in other areas and allows for the maximization of resources for helping individual students.

The dimension of Motive can also clearly be seen as a continuum from surface to deep. Student profiles which fall along that dimension have been shown to relate negatively to GPA. This makes sense since Deep Motive involves having an intrinsic interest and commitment whereas Surface Motive has to do more with doing well in school and not wanting to get poor marks. Unfortunately, this is less than ideal. Our mission is to develop students into lifelong learners and yet get good grades. We may not want to intervene with students based on Motive, but instead intervene with our curriculums to change the nature of Motive's relationship with academic performance.

As the current research offers a new perspective on the learning approach dimensions, allows the development of profiles, and affords an opportunity to diagnostically assess students concerning their strategies and motives, there is still the question of what other academic and personal factors are related to both dimensions. We have clearly identified the continuums of

Strategy and Motive, surface to deep, and have demonstrated those characteristics to be strongly related to semester GPA and mildly related to retention. For future research it might be beneficial to collect drop/withdraw/failure statistics, learning outcomes, variables related to what the students do after they graduate, and how possible interventions and curriculums improve students’ strategies and motives.

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Appendix A

Revised Learning Process Questionnaire (R-LPQ-2F)

This questionnaire has a number of questions about your attitudes towards your studies and your usual way of studying.

There is no *right* way of studying. It depends on what suits your own style and the course you are studying. It is accordingly important that you answer each question as honestly as you can. If you think your answer to a question would depend on the subject being studied, give the answer that would apply to the subject(s) most important to you.

Please fill in the appropriate circle alongside the question number on the ‘‘General Purpose Survey/Answer Sheet’’. The letters alongside each number stand for the following response.

A — this item is *never* or *only rarely* true of me
B — this item is *sometimes* true of me
C — this item is true of me about *half the time*
D — this item is *frequently* true of me
E — this item is *always* or *almost always* true of me

Please choose the *one* most appropriate response to each question. Fill the oval on the Answer Sheet that best fits your immediate reaction. Do not spend a long time on each item: your first reaction is probably the best one. Please answer each item.

Do not worry about projecting a good image. Your answers are CONFIDENTIAL.

Thank you for your cooperation.

(1) I find that at times studying makes me feel really happy and satisfied.
(2) I try to relate what I have learned in one subject to what I learn in other subjects.
(3) I am discouraged by a poor mark on a test and worry about how I will do on the next test.
(4) I see no point in learning material which is not likely to be in the examination.
(5) I feel that nearly any topic can be highly interesting once I get into it.
(6) I like constructing theories to fit odd things together.
(7) Even when I have studied hard for a test, I worry that I may not be able to do well in it.
(8) As long as I feel I am doing enough to pass, I devote as little time to studying as I can. There are many more interesting things to do.
(9) I work hard at my studies because I find the material interesting.
(10) I try to relate new material, as I am reading it, to what I already know on that topic.
(11) Whether I like it or not, I can see that doing well in school is a good way to get a well-paid job.
(12) I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra.

(13) I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes.
(14) When I read a textbook, I try to understand what the author means.
(15) I intend to get my A Levels [or equivalent qualification] because I feel that I will then be able to get a better job.
(16) I find it is not helpful to study topics in depth. You don’t really need to know much in order to get by in most topics.
(17) I come to most classes with questions in mind that I want answering.
(18) I learn some things by rote, going over and over them until I know them by heart even if I do not understand them.
(19) I find I am continually going over my school work in my mind at times like when I am on the bus, walking, or lying in bed, and so on.
(20) I find the best way to pass examinations is to try to remember answers to likely questions.
(21) I like to do enough work on a topic so that I can form my own conclusions before I am satisfied.
(22) I find I can get by in most assessment by memorising key sections rather than trying to understand them.

Appendix B

Scales in the Revised Learning Process Questionnaire (R-LPQ-2F)

The number in parentheses is the item number in the questionnaire.

Deep approach

Deep motive

Intrinsic interest
I find that at times studying makes me feel really happy and satisfied. (1)
I feel that nearly any topic can be highly interesting once I get into it. (5)
I work hard at my studies because I find the material interesting. (9)

Commitment to work
I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes. (13)
I come to most classes with questions in mind that I want answering. (17)
I find I am continually going over my school work in my mind at times like when I am on the bus, walking, or lying in bed, and so on. (19)
I like to do enough work on a topic so that I can form my own conclusions before I am satisfied. (21)

Deep strategy

Relating ideas
I try to relate what I have learned in one subject to what I learn in other subjects. (2)
I like constructing theories to fit odd things together. (6)

Understanding
I try to relate new material, as I am reading it, to what I already know on that topic. (10)
When I read a textbook, I try to understand what the author means. (14)

Surface approach

Surface motive

Fear of failure
I am discouraged by a poor mark on a test and worry about how I will do on the next test. (3)
Even when I have studied hard for a test, I worry that I may not be able to do well in it. (7)

Aim for qualification
Whether I like it or not, I can see that doing well in school is a good way to get a well-paid job. (11)
I intend to get my A Levels because I feel that I will then be able to get a better job. (15)

Surface strategy

Minimizing scope of study
I see no point in learning material which is not likely to be in the examination. (4)
As long as I feel I am doing enough to pass, I devote as little time to studying as I can. There are many more interesting things to do. (8)
I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra. (12)
I find it is not helpful to study topics in depth. You don't really need to know much in order to get by in most topics. (16)

Memorisation
I learn some things by rote, going over and over them until I know them by heart. (18)
I find the best way to pass examinations is to try to remember answers to likely questions. (20)
I find I can get by in most assessment by memorising key sections rather than trying to understand them. (22)

To calculate scores on the scales use the following response scores.

A = 1, B = 2, C = 3, D = 4, E = 5

Scores for the two main scales, deep approach (DA) and surface approach (SA), can then be calculated by adding the following item scores:

DA = 1 + 2 + 5 + 6 + 9 + 10 + 13 + 14 + 17 + 19 + 21
SA = 3 + 4 + 7 + 8 + 11 + 12 + 15 + 16 +18 + 20 + 22

Each contains identifiable strategy (DS and SS) and motive (DM and SM) subscales. The subscale and scale scores can be calculated by adding item scores as follows:

DM = 1 + 5 + 9 + 13 + 17 + 19 + 21
DS = 2 + 6 + 10 + 14
SM = 3 + 7 + 11 + 15
SS = 4 + 8 + 12 + 16 +18 + 20 + 22