Using multidimensional scaling to improve functionality of the Revised Learning Process Questionnaire

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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 USA. We first investigated whether the psychometric properties and latent factor structure of this questionnaire are replicable in a different educational context and with students from a different country than that originally used to create and validate the questionnaire. We found this to be true. Second, we used Profile Analysis via Multidimensional Scaling (PAMS) to improve the diagnostic functionality of the instrument as well as further explore the latent structure of the questionnaire. The factor structure was evident in this solution, but 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. The Strategy dimension was found to have ecological validity through analysing its relationship to academic performance.

Keywords: R-LPQ-2F; learning process; confirmatory factor analysis; multidimensional scaling; profile analysis

Understanding how students learn, process information and gain new knowledge has been of interest to many researchers (Melancon 2002; Murphy and Alexander 2002). More recently, with the evaluation of student learning goals and the realignment of many general education and core curricula across many higher education institutions, learning styles and study strategies of college students have resurfaced as an area of interest (Everson, Weinstein, and Laitusis 2000; Kember, Biggs, and Leung 2004). For some, this research is motivated by a concern for improving retention of students who struggle with academics and eventually drop out (Kember and Leung 2009). For others, it is more for development of constructs to promote understanding of these processes and facilitate communication across disciplines (Kaplan 2008).

As many researchers began to specifically address issues of learning and attempt to define components for successful learning outcomes, a variety of theories and perspectives have emerged. Tobias and Everson (1997) as well as Lufi, Parish-Plass, and Cohen (2003) recognised that successful learning is a product of many factors
such as adequate prior knowledge and attention. Some saw this learning as primarily
task-based, as Scraw (1994) described a student’s ability to utilise a variety of cogni-
tive strategies and apply these skills in the appropriate academic environment to
contribute to successful learning. Others (Grant and Dweck 2003) saw the character-
isation of learning to be more related to the impetus of the learner and whether or not
they are motivated by performance factors and gaining the acknowledgement of
others or whether they are driven to learn by the intrinsic reinforcement that gaining
new knowledge holds. Some researchers (Tobias, Howard, and Laitusis 1999; Wein-
stein 1996) utilised the notion of cognitive strategies to regulate learning, but
combined it with other factors such as motivation and teacher perceptions.

Starting in the early 1970s, many researchers engaged in a series of studies evalu-
ating how students learn, the context of that learning and how instruments may be
used to assess that construct. In two seminal pieces, Marton and Säljö (1976a, 1976b)
describe an initial attempt to differentiate levels of processing and examine qualitative
differences in how students learn. Through qualitative interviews they categorised the
processes students used to evaluate and learn reading material. Entwistle and Rams-
den (1982) later compiled the work of many researchers before them, including that
of Marton and Säljö, and described in detail the process and the product of qualitative
interviews with college students in a variety of scenarios which inquired about their
understanding of how they learn. They evaluated much more than just knowledge and
skills, such as the capacity of students to utilise these abilities in the context of learn-
ing. Within this work, they described the process of developing an instrument to evalu-
ate the approaches to studying and why they chose the medium of self-report of
students’ perceptions. It was noted that originally the development of this instrument
was not necessarily to directly improve academic success, but to evaluate the
approaches students used when engaging in a learning task. Their efforts were the
impetus for the development of the Approaches to Studying Inventory and its subse-
quent later versions that have been utilised to this day. These instruments include the
Approaches and Study Skills Inventory (Entwistle, Tait, and McCune 2000), the Study
Process Questionnaire (Biggs, Kember, and Leung 2001) and the Learning Process
Questionnaire (LPQ; Kember, Biggs, and Leung 2004).

As these instruments were evaluated and validated, factor analytic procedures
helped refine the constructs that emerged from the data collected. Although there were
some differences among the instruments, a few common factors emerged. First, the
learning approaches of the Deep Approach and Surface Approach were identified.
Although not always defined exactly the same, it seemed evident that these overarch-
ing factors pertain to a specific type of activities students engage in during the learning
process. Biggs, Kember, and Leung (2001) went further to demonstrate that motives
and strategies are found within these learning approaches by the representation of the
factor structure. Motives indicate why students choose to behave the way they do, and
strategies are what activities they choose to engage in. For example, a student who
identifies a personal interest in the material learned may be demonstrating Deep
Motive, whereas a student who is just trying to make a grade is demonstrating Surface
Motive. Concerning strategies, a student who attempts to relate new material with
previously learned material would be considered to have Deep Strategy, whereas a
student who utilises rote memorisation would be exhibiting Surface Strategy. In the
analysis of the LPQ and its subsequent revisions, Kember, Biggs, and Leung (2004)
demonstrated clearly how the instrument operates and described the relationships of
these factors to one another.
Entwistle (2000) stated that the goal of the instruments was to identify how students behaved in everyday situations. Based on this, it seems more likely that students see their motives and strategies clearly, but whether these are deep or surface is an artefact of how their behaviour is classified. The ideas presented in the previous research do not take into account the possibility that students are not consciously engaging in these approaches as the factor analysis bears out. That is, students behave in particular ways for particular reasons but rarely do they engage in the activity of classifying those actions. A student may say, ‘I just want an A in that class’, and is clearly depicting a motive at this point but the actions taken by the student in light of that motive are not readily identified. It is unlikely that a student would indicate that they have deep or surface motives.

The purpose of this study is twofold. First, the psychometric properties and latent factor structure of the Revised Two-Factor Learning Process Questionnaire, a later version of the LPQ (R-LPQ-2F; Kember, Biggs, and Leung 2004), were evaluated. Although the R-LPQ-2F has been assessed in a number of ways, there are still many questions to be answered concerning replicability of results in different contexts and with different samples. 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.

Second, Profile Analysis via Multidimensional Scaling (PAMS) analysis was conducted to explore the characteristics of respondents of the R-LPQ-2F and to develop profiles for individual test-takers. This will serve to improve the diagnostic functionality of the instrument as well as confirm the latent structure. The two-factor structure, identified by Kember, Biggs, and Leung (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. It is, however, more difficult to interpret the data in this format in terms of utilising the instrument both diagnostically and prescriptively. 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 ‘understanding relative strengths and weaknesses of test-takers in their subtest scores, and this profile information [can be used] clinically to make differential diagnosis and to design appropriate interventions based on an individual’s profile pattern’ (Kim, Davison, and Frisby 2007, 2). 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 USA. 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 summarised 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 five-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 1 and 2 contain the questionnaire and scales, respectively (Kember, Biggs, and Leung 2004).

**Results**

**Reliability**

Our first aim was to investigate the reliability of the R-LPQ-2F. We computed Cronbach $\alpha$ values using SPSS (Version 17.0.0; SPSS Inc., Chicago, IL) to determine if the two approaches, four subscales and eight subcomponents have good reliability with our sample. All of these $\alpha$ values, with the exception of that for the Relating Ideas subcomponent ($\alpha = 0.468$), are above 0.50 (see Table 1). The Cronbach $\alpha$ values are very consistent with those found by Kember, Biggs, and Leung (2004) and show good reliability.

**Latent factor structure**

Second, we conducted a confirmatory factor analysis using EQS (Version 6.1) (Multivariate Software, Encino, CA; http://www.mvsoft.com/index.htm) to determine if the

Table 1. Cronbach $\alpha$ values for the approaches, subscales and subcomponents of the R-LPQ-2F.

<table>
<thead>
<tr>
<th>Item no.</th>
<th>Cronbach $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep Approach</td>
<td>0.795</td>
</tr>
<tr>
<td>Deep motive</td>
<td>0.706</td>
</tr>
<tr>
<td>Intrinsic interest</td>
<td>0.570</td>
</tr>
<tr>
<td>Commitment to work</td>
<td>0.590</td>
</tr>
<tr>
<td>Deep strategy</td>
<td>0.651</td>
</tr>
<tr>
<td>Relating ideas</td>
<td>0.468</td>
</tr>
<tr>
<td>Understanding</td>
<td>0.545</td>
</tr>
<tr>
<td>Surface Approach</td>
<td>0.658</td>
</tr>
<tr>
<td>Surface motive</td>
<td>0.560</td>
</tr>
<tr>
<td>Fear of failure</td>
<td>0.631</td>
</tr>
<tr>
<td>Aim for qualification</td>
<td>0.661</td>
</tr>
<tr>
<td>Surface strategy</td>
<td>0.662</td>
</tr>
<tr>
<td>Minimising scope of study</td>
<td>0.647</td>
</tr>
<tr>
<td>Memorisation</td>
<td>0.617</td>
</tr>
</tbody>
</table>
full hierarchical model (see Figure 1) found by Kember, Biggs, and Leung (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

Figure 1. Hierarchical model for motive and strategy scales in R-LPQ-2F ($N = 329$).
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and Bentler (1999) recommended that a Comparative Fit Index (CFI) value greater than or equal to 0.96 in combination with a Standardised Root Mean Square Residual (SRMR) value less than 0.09 would minimise 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 analyse 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, Biggs, and Leung (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 \(\alpha = 0.05\) 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, Biggs, and Leung (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 utilises more surface strategies and motives would be more likely to also be utilising more deep strategies and motives. The standardised solution for the hierarchical model is shown in Figure 1.

Profile analysis via multidimensional scaling

Next, multidimensional scaling (MDS), conducted in SAS (Version 9.1.3) (SAS Institute Inc., Cary, NC), 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 and Skay 1991).

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 and 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 emphasises psychological judgemental 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, Kruskal’s stress formula 1 (STRESS 1) being a common statistic. This stress value is the square root of a normalised ‘residual sum of squares’, and indicates the level of fit for a specific dimensionality (Kruskal and 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 and Wish 1978). Since the R-LPQ-2F contains 22 items, the number of dimensions should be five or less.

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 value is above 0.10 (Kruskal and 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.

We scaled the two dimensions (i.e., normalised) to a root mean square value of 1 and adjusted the dimension coefficients to compensate (see Table 2). 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.

Although items do not need to neatly map onto the factors in the hierarchical factor model (Davison and 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.

PAMS can be used to build profiles (i.e., interpret the MDS dimensions as latent profiles). 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. A PAMS model 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). 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, and 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

### Table 2. Two-dimensional MDS solution.

<table>
<thead>
<tr>
<th>Item nos.</th>
<th>Dimension 1</th>
<th>Dimension 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.088</td>
<td>0.736</td>
</tr>
<tr>
<td>2</td>
<td>1.281</td>
<td>0.266</td>
</tr>
<tr>
<td>3</td>
<td>0.733</td>
<td>-2.071</td>
</tr>
<tr>
<td>4</td>
<td>-1.230</td>
<td>-0.029</td>
</tr>
<tr>
<td>5</td>
<td>0.548</td>
<td>1.017</td>
</tr>
<tr>
<td>6</td>
<td>0.161</td>
<td>1.849</td>
</tr>
<tr>
<td>7</td>
<td>0.031</td>
<td>-2.154</td>
</tr>
<tr>
<td>8</td>
<td>-1.656</td>
<td>0.538</td>
</tr>
<tr>
<td>9</td>
<td>0.686</td>
<td>0.187</td>
</tr>
<tr>
<td>10</td>
<td>1.291</td>
<td>0.145</td>
</tr>
<tr>
<td>11</td>
<td>1.547</td>
<td>-1.300</td>
</tr>
<tr>
<td>12</td>
<td>-1.296</td>
<td>0.283</td>
</tr>
<tr>
<td>13</td>
<td>-0.685</td>
<td>1.075</td>
</tr>
<tr>
<td>14</td>
<td>1.015</td>
<td>0.085</td>
</tr>
<tr>
<td>15</td>
<td>1.217</td>
<td>-1.270</td>
</tr>
<tr>
<td>16</td>
<td>-1.572</td>
<td>0.306</td>
</tr>
<tr>
<td>17</td>
<td>0.027</td>
<td>1.279</td>
</tr>
<tr>
<td>18</td>
<td>-0.879</td>
<td>-0.759</td>
</tr>
<tr>
<td>19</td>
<td>0.207</td>
<td>-0.145</td>
</tr>
<tr>
<td>20</td>
<td>-0.611</td>
<td>-0.530</td>
</tr>
<tr>
<td>21</td>
<td>0.543</td>
<td>0.685</td>
</tr>
<tr>
<td>22</td>
<td>-1.444</td>
<td>-0.194</td>
</tr>
</tbody>
</table>
by the profiles (Davison, Kim, and Ding 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. This is important because factor analysis does not allow 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. Also, simplifying the factors of Deep Motive, Deep Strategy, Surface Motive and Surface Strategy into the two dimensions of Motive and Strategy allows a researcher to categorise students more easily. For example, with factor analysis, it is possible to have a student with high scores for both Deep Strategy and Surface Strategy. In that case, it would be hard to classify that student, if indeed that student reliably filled out the instrument and fits within the overall model.

We computed person parameters and fit statistics for everyone in our sample. Table 3 contains the person parameters (i.e., dimension weights), level parameter (i.e., intercept from the regression), fit and significance, and cumulative GPA at the university for six students from our sample. These six 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 five 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 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. Student 23 has Deep Strategy and Surface Motive and student 58 has Surface Strategy and Deep Motive.

**Ecological validity**

We have discussed how PAMS can be used to assign individuals to profiles based on a latent model. Anecdotally, there seems to be a relationship between the profiles and cumulative GPA. The next step is to determine whether this relationship is significant. To do this we conducted a multiple regression, regressing each student’s cumulative GPA.

### Table 3. Person parameters for six students: R-LPQ-2F profiles.

<table>
<thead>
<tr>
<th>Student</th>
<th>Dimension 1 weights (Strategy)</th>
<th>Dimension 2 weights (Motive)</th>
<th>Level parameters</th>
<th>Fit ($R^2$)</th>
<th>p-value</th>
<th>GPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>1.036</td>
<td>0.267</td>
<td>3.136</td>
<td>0.536</td>
<td>0.004</td>
<td>4.000</td>
</tr>
<tr>
<td>23</td>
<td>0.358</td>
<td>−0.729</td>
<td>2.818</td>
<td>0.503</td>
<td>0.006</td>
<td>3.289</td>
</tr>
<tr>
<td>58</td>
<td>−0.854</td>
<td>0.145</td>
<td>1.864</td>
<td>0.432</td>
<td>0.015</td>
<td>2.726</td>
</tr>
<tr>
<td>175</td>
<td>−0.116</td>
<td>−0.748</td>
<td>3.000</td>
<td>0.456</td>
<td>0.011</td>
<td>1.629</td>
</tr>
<tr>
<td>198</td>
<td>0.090</td>
<td>−0.031</td>
<td>3.136</td>
<td>0.004</td>
<td>0.840</td>
<td>2.119</td>
</tr>
<tr>
<td>275</td>
<td>1.358</td>
<td>0.432</td>
<td>2.909</td>
<td>0.905</td>
<td>&lt;0.001</td>
<td>4.000</td>
</tr>
</tbody>
</table>
GPA onto their level and dimension parameters. Of the 329 student volunteers, 29 did not have a cumulative GPA, leaving us with 310 for the regression. The results indicate that Strategy has a significant positive relationship with cumulative GPA (see Table 4). Motive is not significantly related to cumulative GPA. These results indicate that learning strategy is significantly related to academic performance and is evidence of ecological validity.

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 $\alpha = 0.05$), such as student 198. Doing this allows us to look more closely at the relationship of each profile to cumulative GPA, which is important because only those who fit within the model can be profiled and helped with the use of an intervention. Of the 310 student volunteers with cumulative GPAs 44 were removed, leaving us with 266 for the regression analysis. Overall, the results are exactly the same as when all students were left in (see Table 5). This second regression is noteworthy, though, because it shows how the PAMS method can be applied from a diagnostician viewpoint for individual students.

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’ (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.

Table 4. Regression parameters for cumulative GPA.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimate</th>
<th>Standardised estimate</th>
<th>SE</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.995</td>
<td>0</td>
<td>0.399</td>
<td>7.51</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dimension 1 weights (Strategy)</td>
<td>0.597</td>
<td>0.271</td>
<td>0.149</td>
<td>4.02</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dimension 2 weights (Motive)</td>
<td>-0.179</td>
<td>-0.087</td>
<td>0.133</td>
<td>-1.35</td>
<td>0.179</td>
</tr>
<tr>
<td>Level</td>
<td>-0.037</td>
<td>-0.016</td>
<td>0.138</td>
<td>-0.27</td>
<td>0.789</td>
</tr>
</tbody>
</table>

Table 5. Regression parameters for cumulative GPA – removing observations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimate</th>
<th>Standardised estimate</th>
<th>SE</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.145</td>
<td>0</td>
<td>0.456</td>
<td>6.90</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dimension 1 weights (Strategy)</td>
<td>0.737</td>
<td>0.289</td>
<td>0.202</td>
<td>3.65</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dimension 2 weights (Motive)</td>
<td>-0.235</td>
<td>-0.120</td>
<td>0.151</td>
<td>-1.56</td>
<td>0.121</td>
</tr>
<tr>
<td>Level</td>
<td>-0.131</td>
<td>-0.055</td>
<td>0.157</td>
<td>-0.840</td>
<td>0.403</td>
</tr>
</tbody>
</table>
Discussion

The LPQ and its subsequent revisions have been part of the development of a conceptual understanding of how students learn, what motivates them to engage in particular tasks and what strategies they engage in 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. Although important in the validation of the instrument, factor analysis alone adds little information concerning the application of such an instrument in academic situations and less information in terms of the individuals taking the assessment.

Diagnostically, these factors might be utilised 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 utilisation 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, although exploratory in itself, 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. In other words, while factor analysis is often used to help interpret the constructs represented by the instrument, PAMS speaks more to the individual taking the test. It addresses who is taking the assessment, not just what the assessment is about.

PAMS basically allows for a conversion of the data into profiles so that overarching behaviours can be more easily categorised. The analysis forms a representation of how these behaviours 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, Davison, and Frisby 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 utilise this instrument diagnostically has become readily apparent. A student profile is directly linked to the desired or undesired behaviours 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. Counsellors 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 maximisation of resources for helping individual students.

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 strategy use, there is still the question of what academic or personal factors are related to Motive. Although there is not a specific interaction demonstrated by PAMS, there does appear to be quadrants that represent the behavioural characteristics of the test-takers. We have clearly identified the continuum of Strategy, surface to deep, and have demonstrated those characteristics to be significantly related to cumulative GPA; however, even though a continuum has also been demonstrated for Motive, from surface to deep, the relationship to another variable has not been accomplished with this study. That is, with the information collected for each participant, we did not have external variables with which to investigate the relationship to Motive. For future research, it might be beneficial to collect data such as retention rates, graduation rates, or drop/withdraw/failure statistics, to determine if Motive is indeed significantly related to those factors.

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References


Appendix 1. Revised Learning Process Questionnaire (R-LPQ-2F)

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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 2. 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