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A latent profile analysis of college students' achievement goal orientation

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Abstract

Achievement goal research has grown increasingly complex with the number of proposed goal orientations that motivate students. As the number of proposed goal constructs proliferates, a variety of data analytic challenges have emerged, such as profiling students on different types of goal pursuit as well as evaluating the relationships of multiple goal pursuit with different educational outcomes. The purpose of the current article is to showcase the advantages of using latent profile analysis (LPA) over other traditional techniques (such as multiple regression and cluster analysis) when analyzing multidimensional data like achievement goals. Specifically, we review the advantages of LPA over traditional person- and variable-centered analyses and then provide a critical look at three different conceptualizations of goal orientation (2-, 3-, and 4-factor) using LPA.

Keywords: Goal orientation; Goal pursuit; Latent profile analysis

1. Introduction

In recent years, many researchers have proposed increasingly complex models to describe the construct of achievement goal orientation (Elliot, 1999; Elliot & McGregor, 2001; Pintrich, 2000). There is much debate as to whether more complex definitions are

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needed to fully capture the breadth of the construct, or whether more parsimonious conceptualizations can suffice (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Midgley, Kaplan, & Middleton, 2001). In addition to the idea of more complex conceptualizations, a recently purported notion by several goal orientation theorists is that a person may be benefited by endorsing multiple goals (i.e., the multiple goal perspective). When a researcher uses more complex models of goal orientation along with a multiple goal perspective, another level of complexity is added to the already difficult tasks of: (1) describing the typical goal orientation profiles of students in a sample and (2) analyzing the relationships of goal orientation with other variables.

Our article has two purposes. The first is to discuss the disadvantages of using traditional data analytic techniques (e.g., multiple regression, cluster analysis) when more complex conceptualizations of goal orientation are being utilized and to demonstrate latent profile analysis (LPA), a technique which offers many advantages over traditional methods. The second aim of our article is to provide evidence as to whether more complex models of goal orientation are needed to justify their use over more simplistic models. As noted by Elliot (1999), one way in which such evidence can be collected is by showing that the more complex models are better able to predict achievement-related outcomes. To accomplish this, we use LPA with 2-, 3-, and 4-factor conceptualizations of goal orientation to better understand if more complex conceptualizations are needed to better differentiate among individuals' goal orientations and to more accurately predict achievement-related outcomes. Before discussing the data analytic techniques that are traditionally used in goal orientation research and speculating as to the utility of more complex models, we first describe the development of achievement goal orientation theory.

1.1. Development of achievement goal orientation theory

For the past two decades, achievement goal orientation has been one of the primary constructs used in the study of achievement motivation (see Elliot, 2005 for a review). An individual's achievement goal orientation represents one's purpose for engaging in achievement-related behavior, as well as one's orientation towards evaluating his or her competence in the achievement activity. For instance, individuals who pursue achievement-related behavior for the purpose of *developing* their skills and who evaluate their competence by the extent to which they have mastered the task or shown self-improvement would be labeled as having a *mastery goal orientation*. Alternatively, individuals who pursue achievement-related behavior for the purpose of *demonstrating* their skills and who evaluate their competence in relation to others would be labeled as having a *performance goal orientation*.

In addition to distinguishing goal orientations based on a mastery or performance focus, goal orientations also can be differentiated by whether an individual is guided by the notion of attaining positive outcomes (an approach focus) or by the notion of avoiding negative outcomes (an avoidance focus). Elliot and McGregor (2001) argued that such distinctions in achievement goals can be nicely represented along two dimensions: how competence is defined (mastery vs. performance) and how competence is valenced (approach vs. avoid). Fully crossing these two dimensions leads to four potential goal orientations: *mastery-approach*, *mastery-avoidance*, *performance-approach*, and *performance-avoidance*. Students with a mastery-approach or a mastery-avoidance goal orientation are alike in that they both are focused on mastering the material and developing their skills. The mastery-approach student, however, seeks to gain as much knowledge and skills as possible, whereas the mastery-avoidance student is focused on not losing the knowledge and skills they already have or misunderstanding the material. Similarly, students with a performance-approach or a performance-avoidance goal orientation are alike in that both are concerned about their performance in relation to their peers. The performance-approach student, however, is focused on performing better than other students, whereas the performance-avoidance student is focused on not performing worse than other students.

Early goal orientation theorists focused predominantly on distinguishing goal orientations by how competence is defined (e.g., Dweck, 1986; Nicholls, 1984). When using some form of a competency-defined framework, some would conceptualize mastery and performance goals as being a mix of both approach and avoidance strivings, whereas others would conceptualize the goals as being reflective of only approach strivings (see Elliot, 2005; for a review). However, interest in the particular conceptualization being used in a study increased when it was speculated that differences in how the goals were defined and valenced resulted in differences in the relationships found between goals and other variables. For example, researchers (Elliot & Church, 1997; Elliot & Harackiewicz, 1996) noted that the inconsistent patterns of positive, negative, and null relationships between performance goal orientations and other variables across different studies could be explained by reclassifying past research studies along valence of performance goals, with approach strivings in a performance goal orientation being most associated with positive processes and outcomes[1] (e.g., intrinsic motivation, high self-esteem, effort, persistence, and performance) and avoidance strivings being most associated with negative processes and outcomes (e.g., reduced intrinsic motivation, low self-esteem, anxiety, procrastination, and poor performance).

Theoretical and historical arguments were also provided in support for the separation of performance goals into approach and avoidance components. As noted by Elliot (1999, 2005), the approach-avoidance distinction not only had a rich tradition in early theories of motivation, but has had a prevalent role across all major fields of psychology. These arguments, along with empirical evidence showing more explanatory power when performance goals were distinguished by valence, led many theorists to utilize a 3-factor conceptualization of goal orientation that left the mastery factor intact but separated the performance factor into the factors of performance-approach and performance-avoidance (Elliot & Church, 1997; Elliot & Harackiewicz, 1996; Middleton & Midgley, 1997; Midgley et al., 1998).

Unlike performance goals, the findings for mastery goals (typically defined as being approach-valenced) have been consistent across studies and associated with a range of positive outcomes. Thus, it was not empirical evidence that drove the division of the mastery orientation into approach and avoidance valences, but the same theoretical and historical arguments made above for the split of the performance factor. A call was made for a 4-factor conceptualization (Elliot, 1999; Pintrich, 2000) and Elliot and McGregor (2001) were among the first to offer empirical evidence supporting the utility of adding a mastery-avoidance goal orientation.

For the remainder of the article, we will use the following terminology to refer to the different conceptualizations of goal orientation. We term the conceptualization involving only mastery-approach and performance-approach orientations as the 2-factor model; the conceptualization involving mastery-approach, performance-approach, and

[1] Research does not support the notion that all processes and outcomes associated with a performance-approach orientation are positive; a performance-approach orientation has been linked to test anxiety, shallow processing of material and decreased help-seeking behavior (Midgley et al., 2001).

performance-avoidance as the 3-factor model; and the same conceptualization with the addition of the mastery-avoidance orientation as the 4-factor model[2].

1.2. Methodological and data-analytic issues when studying goal orientation

Several researchers have chosen to demonstrate support for the more complex 3- and 4-factor goal orientation models by showing how the separation of goal orientations by valence yields a larger number of distinct factors that predict (and are predicted by) different variables (e.g., Conroy, Elliot, & Hofer, 2003; Elliot & Church, 1997; Elliot & McGregor, 2001; Middleton & Midgley, 1997; Skaalvik, 1997). Although these studies are important in the investigation of the utility of more complex models, they oftentimes utilize variable-centered as opposed to person-centered analyses. In a variable-centered analysis (such as regression), process and outcome variables are typically related to each goal orientation separately. In a person-centered analysis (such as cluster analysis), the differences in process and outcome variables are examined for various subgroups of students, with subgroups consisting of students who have similar profiles across the various dimensions of goal orientation.

The use of person-centered analytic techniques is particularly important for goal orientation researchers interested in an increasingly popular notion in goal orientation theory known as the multiple goal perspective. The multiple goal perspective states that an individual is optimally motivated by endorsing more than one goal orientation. The idea of adopting multiple goals simultaneously is not new to the field of goal orientation research (Barron & Harackiewicz, 2000; Harackiewicz et al., 2002; Midgley et al., 2001; Wentzel, 1992). However, there is still debate regarding which combination of goals leads to the most adaptive outcomes, and how the effects of multiple goals are best revealed. For researchers who favor the multiple-goal perspective, a person-centered approach to investigating the utility of more complex goal orientation theories is warranted particularly since, as noted by Bråten and Olaussen (2005), "...persons move through instructional environments, not variables..." (p. 360). In the following section, we describe the traditional analyses that have been used by researchers to capture the typical levels of goal orientation in their sample and to relate the different levels to processes and outcomes. The section begins with a review of variable-centered methods, including descriptive statistics, correlations, and multiple regression, and ends with a review of person-centered methods, including median split techniques and cluster analysis. When describing different techniques that have been used, we have highlighted a number of example studies that have adopted a particular approach. Our goal is to provide the readers with examples, however it is not our intent to identify or single out a particular researcher or article. In fact, many of the researchers noted for adopting a less optimal approach (including past achievement goal work of the second author of the current article) now adopt and use more sophisticated approaches.

[2] There are other conceptualizations of goal-orientation using the same number of factors as those we have specified here but with qualitatively different factors. For instance, some may prefer a 2-factor model with the performance factor including both avoidance and approach strivings. However, using a reduced factor model that combines approach and avoidance strivings is problematic based on theory and past research (Elliot, 2005). Moreover, a number of multiple goal researchers have begun investigating the relative merits of simply pursuing approach goals (e.g., being high in mastery-approach and performance-approach), which have been argued to both be associated with positive effects (Barron & Harackiewicz, 2001; Linnenbrink, 2005).

1.3. Traditional variable-centered methods used in past goal orientation research

1.3.1. Descriptive statistics and correlations

There are a variety of different methods researchers could employ to describe the levels of goal adoption in a sample. Descriptive statistics would indicate the typical level and variability of *each* goal, but fail to capture the relationships *among* goals. To obtain this information, early goal investigators calculated bivariate correlations between different goal measures. Bivariate correlations revealed that measures of mastery and performance goals generally shared null (or slightly positive) relationships (see Harackiewicz, Barron, & Elliot, 1998 for a review). Thus, rather than being motivated by one goal or the other, any combination of mastery and performance goals appears possible for any given person. If any combination is possible, it is of interest to ask whether there are certain combinations of goals that are more common than others.

1.3.2. Multiple regression

In addition to describing the goal orientation profiles in a sample, researchers must decide whether to examine goals separately or together when examining the relationships of goals with other variables. For example, a number of early investigations were limited to simple, correlational approaches (Miller, Behrens, & Greene, 1993; Nolen, 1988) that just evaluated the bivariate correlations of each goal with different types of educational outcomes. However, it may be more informative to study how certain combinations of mastery and performance goals relate to other variables rather than how each goal relates separately. One popular method researchers have adopted to examine the relationship of multiple goals with other variables is multiple regression. Investigations by numerous researchers have used multiple regression (e.g., Elliot & Church, 1997; Harackiewicz, Barron, Carter, Lehto, & Elliot, 1997; Kaplan & Midgley, 1997; Middleton & Midgley, 1997; Skaalvik, 1997).

The use of regression models to study the relationship of goals with other variables becomes increasingly complicated as the conceptualization of the construct becomes more complex. For instance, if studying interactive relationships of the goals with other variables, use of the 4-factor conceptualization in a regression model would entail including the four-way interaction, all three- and two-way interactions, and all main effects (e.g., see Elliot & McGregor, 2001). Accurate estimation of all parameters would require a large sample size and interpretation of the results might be difficult and possibly complicated by multicollinearity. Even if a researcher were able to overcome such problems, multiple regression techniques are limited in that they only allow the researcher to describe the relationships of goals with other variables, not to characterize the common goal orientation profiles in their sample.

1.4. Traditional person-centered methods used in past goal orientation research

1.4.1. Median split techniques

Median split techniques are a seductively easy way to: first, identify the most common goal patterns in the sample and then second, examine the relationships of such patterns or "profiles" with other variables. Using median split procedures, participants are first categorized as "high" if their score falls above the median on a goal factor or "low" if their score falls below the median. When using a 2-factor conceptualization of goals, median split procedures have the possibility of capturing four distinct profiles[3]. Once participants are classified into one of these four groups, differences among profiles in outcome variables can be examined using analysis of variance (ANOVA) techniques.

Although easy to implement, there are a number of known problems with median split procedures (Maxwell & Delaney, 1993). In fact, many of the goal orientation studies that have utilized the technique often recognize its limitations and supplement their median-splits with additional analyses (e.g., Kaplan & Midgley, 1997; Meece & Holt, 1993). Perhaps most problematic is the dependency of the procedure on the sample median being used. Because the median may vary in value, comparison of the results across studies is complicated.

As noted by MacCallum, Zhang, Preacher, and Rucker (2002) in their review of the troubles associated with dichotomizing continuous variables, a problem with median split procedures has to do with the questionable homogeneity of the cases classified in each profile as well as the problematic use of labels such as "low" and "high" to characterize cases falling below and above the median. A solution to the above problem may be to split each goal factor into more than two categories. This would help create more homogeneous groups, but with an increase in the number of categories, the number of possible profiles increases exponentially (# possible profiles = # of categories$^{\#\text{ factors}}$). The number of possible profiles becomes larger, and therefore less parsimonious, when using more complex conceptualizations of goal orientation.

1.4.2. Cluster analysis

When the purpose is to divide persons into homogeneous subgroups, cluster analysis can be used as an alternative to median split techniques. Cluster analysis is a statistical technique for finding "clusters" of observations that have similar values on a set of variables. In this exploratory technique, clusters are created such that the differences within clusters on a set of measures are minimized and the differences between clusters are maximized. Readers interested in cluster analytic techniques should consult: Aldenderfer and Blashfield (1984), Everitt, Landau, and Leese (2001), Hair, Anderson, Tatham, and Black (1998) and Kaufman and Rousseeuw (2005).

There are a variety of different cluster analysis methods to choose from. Some goal orientation researchers, such as Bråten and Olaussen (2005), have employed agglomerative hierarchical techniques which start with each observation in its own cluster and proceed by combining clusters with similar values on the cluster indicators, which are the variables used as input into the cluster analysis. A common method for combining clusters in a hierarchical analysis is Ward's method, which creates clusters so that the within cluster variance across all variables is as small as possible. It is largely the decision of the researcher as to which of the solutions, between N clusters and one cluster, to interpret. Although there are statistics that can be used for such an endeavor (e.g., pseudo F-statistic; Calinksi & Harabasz, 1974), many of these statistics are of questionable utility or may only be appropriate for use with particular kinds of data (Milligan & Cooper, 1985). Instead of relying upon statistics, researchers typically examine a variety of different cluster solutions and use

[3] When using median split procedures, the correlation between the variables dictates the number and nature of the profiles that can be captured. For instance, with either strong negative or positive correlations, it is likely that only two of the four profiles might be captured, whereas with null correlations, it is likely that all profiles will be represented. This is not necessarily problematic, but an interesting relationship to note.

theory and oftentimes, their own judgment to decide upon a solution. The lack of rigorous guidelines to aid in the selection of a solution is an often cited weakness of hierarchical cluster analysis.

The subjectivity associated with this method can be overcome somewhat by showing that one's solution replicates well when employing a different method of clustering on a separate sample. To this end, some researchers choose to supplement their hierarchical analysis by executing a non-hierarchical cluster analysis (a.k.a. optimization clustering) with a separate sample. In non-hierarchical cluster analysis the number of clusters is specified in advance and some initial partition, often based on the results of a hierarchical analysis, is used to assign observations to clusters. Observations are then reassigned to different clusters until a criterion is met. As with hierarchical clustering, a commonly used criterion is to create clusters so that the within-group variance across all cluster indicators is a minimum.

A number of studies using either hierarchical, non-hierarchical, or some combination of the two cluster analytic methods in the motivation and achievement goal orientation literature do exist (e.g., Ainley, 1993; Bembenutty, 1999; Bråten & Olaussen, 2005; Etnier, Sidman, Hancock, & Lee, 2004; Hodge & Petlichkoff, 2000; Kaplan & Bos, 1995; Meece & Holt, 1993; Ntoumanis, 2002; Salisbury-Glennon, Gorrell, Sanders, Boyd, & Kamen, 1999; Turner, Thorpe, & Meyer, 1998; Urdan & Midgley, 1994). Trying to summarize the results of these cluster analytic studies is quite difficult for a variety of reasons. First, synthesis of the results is complicated by the fact that a variety of different populations are the focus of the studies employing cluster analytic techniques. Another complication is the variety of different variables that are used as cluster indicators. This is quite problematic because it is well known that the results of a cluster analysis are quite dependent on the variables that are used as cluster indicators. Most importantly, trying to synthesize the results of different cluster analytic studies is difficult because of the subjective nature of cluster analysis. Because of the subjectivity associated with traditional cluster analytic techniques, researchers are turning more towards model-based cluster analytic techniques, such as LPA, which offer more rigorous criteria for determining the number of clusters to retain in addition to several other advantages.

1.5. Latent profile analysis

LPA is a latent variable modeling technique that is known in the literature by a variety of names, including latent class cluster analysis (Vermunt & Magidson, 2002) and finite mixture modeling (McLachlan & Peel, 2000). A good introduction to this technique and to latent variable modeling in general can be found in Magidson and Vermunt (2002, 2004), Muthén (2001, 2004), Muthén and Muthén (2000), and Vermunt and Magidson (2002). A more technical but very thorough treatment is given in McLachlan and Peel (2000). The goal of LPA is the same as that of cluster analysis: to identify clusters of observations that have similar values on cluster indicators. The main difference between LPA and traditional cluster analytic techniques is that LPA is model-based, whereas hierarchical and most non-hierarchical applications of cluster analysis are not.

LPA is a type of latent variable mixture model. The term *latent variable* in this situation is referring to the latent categorical variable of cluster membership. This latent categorical variable has K number of categories or clusters. A person's value on this variable is thought to cause his or her levels on the observed cluster indicators, which in our situation would be the different measures of goal orientation. The term *mixture* is referring to the notion that the data are not being sampled from a population that can be described by a single probability distribution. Instead, the data are conceived as being sampled from a population composed of a mix of distributions, one for each cluster, with each cluster distribution characterized by its own unique set of parameters.

When latent variable mixture modeling is used with only continuous cluster indicators, it is often called LPA. When only categorical variables are used, the technique is often called latent class analysis (LCA). This distinction is not necessary because it is the same model, a latent variable mixture model, which is being used in both situations. In fact, the distinction made between LPA and LCA seems even more unnecessary when one considers the fact that both categorical and continuous cluster indicators can be used simultaneously in latent variable mixture models.

Although standard clustering techniques can also be used with both categorical and continuous cluster indicators, the use of latent variable mixture modeling for such a purpose is relatively less difficult. Mixture modeling is also advantageous because indicators on different scales do not need to be transformed prior to their input into the analysis. With traditional clustering techniques, it is recommended that variables on different scales or with widely divergent variances be standardized prior to the analysis. With latent variable mixture modeling, no such transformation is necessary.

To further illustrate the notion of LPA, consider an example where a continuous variable y_i is used as a single indicator of cluster membership for person i in our sample of size N ($i = 1,\ldots,N$). To make the example more concrete, one could consider the use of just a single goal orientation factor (e.g., mastery-approach) as the continuous variable. Although the number of clusters, K, is not typically known a priori, suppose there are two different clusters of persons ($K = 2$) in our population. In mixture modeling this would translate into the presence of two different distributions, typically assumed to be normal, from which our data were sampled. Note that although the population distribution is assumed to be a mixture of two normal distributions in this example, the population distribution itself need not be normal.

In LPA, it is possible for a unique set of parameters to be estimated for each cluster. For instance, parameters μ_1 and σ_1^2 could be estimated for Cluster 1 and parameters μ_2 and σ_2^2 could be estimated for Cluster 2. This is the most complex model that could be estimated for this example and more parsimonious models could be specified by constraining some of the parameters to be equal across clusters. For example, one could allow the means for each distribution to remain unique but constrain the variances to be equal across clusters; or one could allow the variances to remain unique across clusters and constrain the means to be equal.

In addition to the parameters of each cluster's distribution, LPA also provides estimates for the mixing proportion or the weight given to each cluster in the population. The model for this example can be represented using the following equation:

$$f(y_i|\boldsymbol{\theta}) = \pi_1 f_1(y_i|\mu_1, \sigma_1^2) + \pi_2 f_2(y_i|\mu_2, \sigma_2^2), \tag{1}$$

which shows that the distribution of our cluster indicator, y_i, given the model parameters ($\boldsymbol{\theta} = \pi_1, \mu_1, \sigma_1^2, \pi_2, \mu_2, \sigma_2^2$) is a weighted mixture of two separate distributions, each characterized by a unique set of parameters. The weights in a mixture model are non-negative and must sum to one. If the weights in our example were estimated to be $\pi_1 = .60$ and

$\pi_2 = .40$, it would imply that 60% of our population can be described by the parameters of Cluster 1 and 40% of our population by the parameters of Cluster 2.

When more than one continuous cluster indicator is used in LPA, the multivariate distribution of the r cluster indicators, contained in vector $\mathbf{y}_i$ for person i, is conceived of as a weighted mixture of K different distributions, typically assumed to be multivariate normal. For instance, if the subscales associated with either the 2-, 3-, or 4-factor conceptualization of goal orientation were used as cluster indicators, a multivariate LPA model would need to be utilized. The multivariate representation of Eq. (1) with r indicators and K clusters is,

$$f(\mathbf{y}_i|\boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k f_k(\mathbf{y}_i|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k). \tag{2}$$

As with the univariate model, the weights in Eq. (2) are constrained to be non-negative and must sum to one. In the univariate example shown in Eq. (1), the distribution for each cluster was defined by only two parameters, a mean and a variance. In the multivariate case, the distribution for each cluster k is now defined by a mean vector $\boldsymbol{\mu}_k$ and covariance matrix $\boldsymbol{\Sigma}_k$.

In the univariate example using a single cluster indicator, we discussed how a variety of different models could be fit to the data by allowing the means and/or the variances of the single cluster indicator to freely vary or be constrained across clusters. When dealing with multiple cluster indicators, the number of possible models that can be specified increases substantially. Consider a multivariate example using two clusters ($K = 2$) and four cluster indicators ($r = 4$). Numerous models are possible when just considering the mean vectors. For instance, the most complex model for the mean vectors would allow the means of all four indicators to vary across the two clusters, resulting in eight means to be estimated. A more simplistic model would constrain the mean vector to be equal across clusters, resulting in only four means to be estimated. These are just two of a variety of different models that could be specified for the mean vectors with other examples including those that allow the means of only certain indicators to remain constant across clusters.

Of course, above we only consider the mean vectors for each cluster, which typically are specified to freely vary across both indicators and clusters. When considering the covariance matrix for a given cluster ($\boldsymbol{\Sigma}_k$), the focus is no longer on the average levels of the indicators in each cluster, but on the extent to which each indicator varies and how the indicators relate to one another. A variety of different specifications for $\boldsymbol{\Sigma}_k$ are shown in Table 1. We will describe each of the specifications below, using the multivariate example that includes two clusters ($K = 2$) and four cluster indicators ($r = 4$).

A parsimonious form of $\boldsymbol{\Sigma}_k$ is shown for Model A, where the variances are allowed to differ across indicators within a cluster (thus the different subscripts for the variances), but are constrained to be equal across clusters. Additionally, the indicators are constrained to be unrelated to one another both within and across clusters (e.g., all covariances are zero). In our example, Model A would result in the estimation of four variances and no covariances. A more complex version of this model is shown with Model C, where the variances are now allowed to differ across clusters (thus the additional k subscript for each variance). In our example, Model C would result in the estimation of eight variances and no covariances.

Model A can also be made more complex by allowing the covariances among the indicators to be freely estimated within a cluster, but with both the variances and covariances

Table 1
Five different parameterizations of covariance matrix $\mathbf{\Sigma}_k$ for r cluster indicators

Model	$\mathbf{\Sigma}_k$
A	$\begin{bmatrix} \sigma_1^2 & & & \\ 0 & \sigma_2^2 & & \\ \vdots & \vdots & \ddots & \\ 0 & 0 & \cdots & \sigma_r^2 \end{bmatrix}$
B	$\begin{bmatrix} \sigma_1^2 & & & \\ \sigma_{21} & \sigma_2^2 & & \\ \vdots & \vdots & \ddots & \\ \sigma_{r1} & \sigma_{r2} & \cdots & \sigma_r^2 \end{bmatrix}$
C	$\begin{bmatrix} \sigma_{1k}^2 & & & \\ 0 & \sigma_{2k}^2 & & \\ \vdots & \vdots & \ddots & \\ 0 & 0 & \cdots & \sigma_{rk}^2 \end{bmatrix}$
D	$\begin{bmatrix} \sigma_{1k}^2 & & & \\ \sigma_{21} & \sigma_{2k}^2 & & \\ \vdots & \vdots & \ddots & \\ \sigma_{r1} & \sigma_{r2} & \cdots & \sigma_{rk}^2 \end{bmatrix}$
E	$\begin{bmatrix} \sigma_{1k}^2 & & & \\ \sigma_{21k} & \sigma_{2k}^2 & & \\ \vdots & \vdots & \ddots & \\ \sigma_{r1k} & \sigma_{r2k} & \cdots & \sigma_{rk}^2 \end{bmatrix}$

constrained to be the same across clusters. The resulting model is Model B and four variances and six covariances would be estimated for our example. Model B can be made more complex by allowing the variances to differ across indicators, but constraining the covariances to remain the same across clusters. This specification results in Model D and in our example eight variances and six covariances would be estimated. The most complex model is Model E which allows both the variances and covariances to vary across clusters. In our example, we would be estimating eight variances and 12 covariances using Model E. Note that the models in Table 1 are nested; for instance, Model A is obtained from Model B by setting all covariances in Model B to zero.

None of the specifications shown in Table 1 can be used in LPA to obtain the results from traditional cluster analysis because the former is a model-based procedure while the latter is not[4]. However, one of the forms of $\mathbf{\Sigma}_k$ can be altered to convey the data for which traditional cluster analytic procedures are most appropriate. Traditional cluster analytic results are most appropriate to use when $\mathbf{\Sigma}_k$ follows the Model C specification,

[4] If a model-based clustering method known as the classification maximum likelihood technique (Banfield & Raftery, 1993) is used with Model C and the variances of cluster indicators within a cluster are constrained to be equal, then the results are equivalent to non-hierarchical methods that utilize the criterion of minimizing the within-group variance. The classification maximum likelihood technique differs from LPA in that the technique conceives the observations as being sampled from single as opposed to a mixture of probability distributions (for further information, see Everitt et al., 2001).

with the additional restriction of constraining the variances of cluster indicators to be equal within a cluster. Thus, an additional advantage of LPA over traditional methods is that it can accommodate data having a variety of different forms of $\mathbf{\Sigma}_k$.

Another advantage of LPA is the availability of more rigorous criteria to use in deciding upon one's final model. In order to understand some of the criteria, it is first important to understand the estimation methods used in LPA. Although there are several different estimation methods to choose from in LPA, model parameters are commonly estimated using maximum likelihood (ML) estimation via the EM algorithm. Readers interested in ML estimation should consult the primer by Enders (2005) or McLachlan and Peel (2000) if interested in how ML estimation using the EM algorithm is employed in mixture modeling. Conceptually in ML, several different sets of model parameter estimates are "tried out" with the data. Each set is associated with a likelihood value, which is the probability of observing the sample data assuming that set of parameter estimates. Because it is the intent of ML estimation to find the parameter estimates most likely to have given rise to the sample data, the final parameter estimates chosen are those associated with the highest likelihood value.

The logarithmic value of the likelihood (the log-likelihood or LL) is often used because it is more mathematically tractable. The LL of the final parameter estimates is used as a measure of model fit with higher values (e.g., closer to 0) indicating better fit than lower values. For models specifying the same number of clusters, more complex models (e.g., Model B) will always fit the data better than more simplistic models (e.g., Model A) and thus will always have LL values that are higher. A χ^2 difference test can be used to determine if the more complex model fits significantly better than the more simplistic model. This test entails taking two times the difference of the log-likelihoods of nested models and comparing the value against a χ^2 distribution with degrees of freedom equal to the difference in the number of parameters being estimated. The χ^2 difference test only can be used to decide among the models in Table 1 when the models specify the same number of clusters.

Another significance test, the Lo–Mendell–Rubin likelihood ratio test (LMR; Lo, Mendell, & Rubin, 2001) offered in the output of Mplus version 3.01 (Muthén & Muthén, 2004), can be used to compare the fit of models that specify different number of clusters, but that utilize the same parameterization. When estimating a model with K clusters, the null hypothesis of this test is that the data have been generated by a model with $K-1$ clusters, with the researcher typically specifying the omitted cluster in the $K-1$ solution as being the smallest cluster in the K solution. A small p-value associated with the LMR test supports the retention of a more complex solution with at least K clusters.

Other fit statistics are employed in LPA that can aid the researcher in deciding upon the number of clusters to retain. The Bayesian information criterion (BIC; Schwartz, 1978) can be used to compare models with different numbers of clusters and/or specifying different parameterizations. The BIC is simply a form of the log-likelihood, specifically

$$\mathrm{BIC} = -2LL + p\ln N, \tag{3}$$

where p is the number of parameters being estimated and N is the sample size. A sample-size adjusted BIC can also be consulted, which uses N^* (where $N^* = (N+2)/24$) as opposed to N in Eq. (3). Lower values of both the BIC and the sample-size adjusted BIC are indicative of better model fit.

The BIC may seem to be a more favorable index over the χ^2 difference test or LMR because it can be used to compare the fit of any model, regardless of the parameterization being used or the number of clusters specified. However, the BIC does not provide a significance test to assess the fit of competing models. It is for this reason that both the χ^2 difference test and the LMR should be employed since both can be used to examine whether the fit of a model is significantly better than the fit of another model. While the χ^2 difference test is used with models having different parameterizations but specifying the same number of clusters, the LMR is used with models having the same parameterization but specifying different numbers of clusters.

In addition, tests of multivariate skewness and kurtosis (SK) described in Muthén (2004) can be used to assess the fit of the model to the data. For a given model, multiple data sets are generated according to the estimated model parameters. Values of multivariate skewness and kurtosis are then calculated for each data set and used to create a distribution. The values of multivariate skewness and kurtosis in the observed sample are then compared to these distributions with the resulting two-sided probability value (i.e., p-value) indicating how likely the observed values are given the values estimated by the model-generated data. High p-values associated with the SK tests are indicative of model fit; low p-values indicate that the model does not fit the data. Muthén (2004) illustrated the use of the SK tests, but also noted that these tests need further investigation.

A researcher decides upon the final model by consulting the BICs, LMRs, χ^2 difference tests, and SK tests. As with traditional methods, it is also recommended that the cluster profiles be inspected with consideration of theory, sample size, and the uniqueness of the profiles. After the decision regarding the final model has been made persons are classified into clusters. In order to classify a given person, the probabilities of belonging in each cluster are first calculated. These K posterior probabilities are calculated for each person using the following equation:

$$\boldsymbol{\pi}_{k|\mathbf{y}_i} = \frac{\boldsymbol{\pi}_k f_k(\mathbf{y}_i|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{k=1}^{K} \boldsymbol{\pi}_k f_k(\mathbf{y}_i|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}. \tag{4}$$

Eq. (4) utilizes the final model parameters as well as the individual's values on the cluster indicators. A commonly used method of assigning persons to clusters after the posterior probabilities are calculated is modal assignment, where assignment is made to the cluster associated with the largest of the posterior probabilities.

At this point, the sample statistics for each cluster are examined to ensure that the values conform to the population parameters estimated by the model. For example, confidence in the fit of Model A to the data is increased when the sample covariances or correlations among indicators are null in all clusters. There are two different means by which the sample statistics for a given cluster can be computed. The first uses only those observations assigned to Cluster k to compute the sample statistics for Cluster k. The second uses all observations to compute the sample statistics for Cluster k with observations weighted by the posterior probabilities associated with Cluster k.

Posterior probabilities are also used to calculate the classification table and entropy statistics, both of which are used in assessing the classification utility of the model. There are as many rows and columns in the classification table as there are clusters. The kth row of the classification table contains K posterior probabilities, averaged across only those per-

Table 2
Example of a classification table for a four cluster solution

Cluster	n	Average posterior probability associated with Cluster			
		1	2	3	4
1	308	**0.835**	0.000	0.000	0.165
2	285	0.003	**0.890**	0.018	0.090
3	248	0.009	0.008	**0.709**	0.274
4	1027	0.130	0.004	0.062	**0.805**

Note. Values in bold represent the average posterior probability associated with the clusters to which persons were assigned.

sons assigned to the kth cluster. In the kth row, the largest average posterior probability will be associated with Cluster k with all other averages in that row being lower.

To illustrate, a hypothetical classification table for a four cluster solution is shown in Table 2. The first row contains the averages based on only the 308 persons that were assigned to the first cluster. Because these persons were assigned to the first cluster using modal assignment, as anticipated the average posterior probability for these persons is highest for Cluster 1. Similarly, the highest average for those 285 persons assigned to the second cluster is associated with Cluster 2. Note that these averages, the averages associated with the clusters to which persons were assigned, are captured in the main diagonal of the classification table. For this reason, higher averages on the main diagonal of the classification table reflect greater accuracy in the assignment of persons to clusters.

The remaining averages can be examined to determine which particular clusters may not be distinct from one another. For instance, the third row of the table contains the average posterior probabilities for persons assigned to the third cluster. As expected, the highest average (.709) is associated with the cluster to which these persons were assigned, Cluster 3. The second highest average for persons assigned to the third cluster is associated with Cluster 4 (.274). Because the value of this average is sizeable, it indicates some overlap between Clusters 3 and 4.

Although the classification table is more informative, its information can be captured using a single statistic. This statistic is known as the entropy statistic and it ranges from 0 to 1 with higher values indicative of higher classification utility. As of yet, there is no cutoff value for the entropy statistic; that is, there is no set value that needs to be exceeded in order for researchers to deem their model as having adequate model classification utility. The statistic is best used to compare the classification utility of different models fit to the same sample or of the same model fit to different samples. The entropy statistic E is calculated using the posterior probabilities from Eq. (4), the overall sample size N and number of clusters K.

$$E = 1 - \frac{\sum_{i=1}^{N}\sum_{k=1}^{K}(-\pi_{k|\mathbf{y_i}} \ln \pi_{k|\mathbf{y_i}})}{N \ln K} \tag{5}$$

In traditional clustering techniques persons are assigned to clusters on an all-or-none basis. In contrast, LPA allows membership of a person to each cluster to a certain degree, allowing for fractional cluster membership as captured in the posterior probabilities.

Although the modal assignment of persons to clusters results in a person being classified in only one cluster in LPA, the entropy statistic and classification table in LPA can be used to examine the degree to which this classification is accurate.

When creating the classification table and computing the entropy statistic, the posterior probabilities are calculated using the same sample used to estimate the model parameters. An advantage of LPA over traditional clustering methods is the ease with which the model parameter estimates of one sample can be used to compute the posterior probabilities and assign cluster membership to persons in a second sample. For instance, if the same cluster indicators have been collected from a second sample in the same population, Eq. (4) can easily be used to classify persons into clusters. For cross-validation purposes, the entropy statistic and classification table for this second sample can then be examined to assess the utility of the model to classify persons in another sample.

After a researcher decides upon the final model, the typical next step is to examine the relation between cluster membership and external variables, variables that were not used to determine cluster membership. This is often executed to offer validity evidence for the cluster solution. There are two ways in which the relationship between clusters resulting from LPA and external variables can be examined. The first is to use ANOVA with each external variable serving as the dependent variable and cluster membership as the independent variable. Similarly, multiple regression can be used with each external variable serving again as the dependent variable, but with the posterior probabilities of cluster membership serving as the independent variables. The advantage of using the posterior probabilities to represent cluster membership is that the accuracy of classifying persons into clusters can be incorporated into the analysis.

A second approach to exploring the relationships between external variables and cluster membership is to include the external variables directly in the LPA model. In this approach, external variables can be specified to have relationships with the latent categorical variable of cluster membership and/or the cluster indicators in a variety of different ways. For instance, some variables may be specified as background variables (a.k.a., covariates) that can be used to predict cluster membership, while other variables may be specified as outcomes of cluster membership. Use of this approach requires a solid understanding of one's variables as well as the relationships that would be anticipated based on theory. Consult Muthén (2004) for further information and examples using this integrated strategy.

1.6. Applying latent profile analysis in the present study

To date, there are only a small number of studies that have used person-centered analytic methods to examine the goal orientation profiles of college students. Furthermore, our review of the literature revealed that the use of small samples and cluster analysis procedures further complicated our ability to generalize the results of these studies. Thus, the purpose of the present study was to add to the existing literature by using both a large sample ($N = 1868$) and a more advanced statistical technique, LPA, to identify the typical goal orientation profiles of college students. In addition, we compared the three latent profile analysis solutions obtained when using as cluster indicators the factors in the different conceptualizations of goal orientation. Specifically, we examined the LPA solutions obtained using a 2-, 3-, and 4-factor model of goal orientation to better understand if more complex conceptualizations were needed to: (1) better differentiate among individuals' goal orientations and (2) to more accurately predict achievement-related outcomes.

We used three steps to accomplish the purposes of our study. In Step 1, LPA was used with data from 1868 college students (Sample 1) to classify students into clusters with separate sets of analyses being conducted, one for each conceptualization of goal orientation. Step 2 was used to examine the classification accuracy of our three final solutions obtained in Step 1. In this step, the classification accuracy of the model in Sample 1 was examined by using the resulting model parameters to classify college students from a second sample ($N = 2290$) into goal orientation clusters.

In Step 3 of our study, we used multiple regression procedures to examine the extent to which the cluster membership related to measures of motivational disposition and academic achievement. By using the estimated posterior probabilities of cluster membership as predictors in our regression models, we were able to incorporate the classification accuracy of our LPA models when examining the differences among the clusters in measures of motivational disposition and academic achievement. Examination of the relation of cluster membership to motivational disposition was undertaken to offer validity evidence for the cluster solutions found in Step 1. The extent to which the cluster membership related to academic achievement was pursued to determine if the cluster solutions based on the more complex conceptualizations of goal orientation could more accurately predict an achievement-related outcome.

2. Method

2.1. Samples

We utilized two samples of college sophomores from a mid-sized, Southeastern university who completed achievement goal measures during a semi-annual institution-wide Assessment Day. Data for the first sample (Sample 1) were collected in February 2003, and data for the second sample (Sample 2) were collected in February 2004. Multivariate outliers were detected by calculating Mahalanobis distance; 11 outliers in Sample 1 and 28 outliers in Sample 2 were deleted, yielding a final sample size of 1868 and 2290 students in Samples 1 and 2, respectively. It is generally recommended that multivariate outliers be deleted prior to using cluster analytic techniques (Hair et al., 1998) and particularly when employing the SK tests (Muthén, 2004). Gender and ethnicity breakdowns were similar in each sample. Specifically, 61% of students in Sample 1 and 62% in Sample 2 were female. In Samples 1 and 2 respectively, 83% and 85% of the students reported their ethnicity as Anglo-American with the remaining ethnicities each represented with percentages less than 5%.

2.2. Measures

2.2.1. Achievement goal orientation questionnaire

Achievement goals were measured using a modified version of Elliot and McGregor's (2001) achievement goal questionnaire that assesses a 4-factor conceptualization of achievement goals, which includes mastery-approach, performance-approach, performance-avoidance, and mastery-avoidance. The original questionnaire was modified in the current study to measure college students' goals for their semester rather than for a

Table 3
Descriptive statistics, coefficient alphas, and correlations among goal orientation subscales for Samples 1 and 2

		Mastery-approach	Performance-approach	Performance-avoidance	Mastery-avoidance
	Mastery-approach	.81/.80	.27	.05	.18
	Performance-approach	.35	.87/.87	.41	.08
	Performance-avoidance	.08	.38	.66/.69	.31
	Mastery-avoidance	.20	.12	.32	.75/.75
Sample 1	M	16.29	15.34	12.70	11.78
	SD	3.20	4.10	4.02	3.88
	Skewness	−.64	−.72	−.19	.08
	Kurtosis	.22	.18	−.48	−.39
Sample 2	M	16.59	15.34	12.59	11.66
	SD	3.07	4.17	4.12	3.82
	Skewness	−.53	−.71	.05	−.22
	Kurtosis	−.12	.17	−.33	−.47

Note. Correlations below the main diagonal are for Sample 1, correlations above the main diagonal are for Sample 2. Values on the main diagonal represent the coefficient alphas for Sample 1 and Sample 2 (Sample 1/Sample 2). The maximum possible score on each of the goal orientation measures is 21.

specific course. Students responded to 12 statements using a 7-point scale (1 = *not at all true of me*, 7 = *very true of me*). To represent each of the four goal orientation factors, the three items associated with each factor were used to form a simple-sum subscale total. Support for the creation of subscales using this modified instrument has been offered by several factor analytic studies showing acceptable fit for the 4-factor model (Finney & Davis, 2003; Finney, Pieper, & Barron, 2004). Thus, the subscale scores, each on a scale of 3–21, were used as input into the latent profile analyses. Descriptive statistics, coefficient alphas, and correlations among the subscales for both samples are shown in Table 3.

2.2.2. *Work and family orientation questionnaire*

To compare students' achievement goal profiles to a more general personality measure of motivational disposition, responses to Spence and Helmreich's (1983) work and family orientation questionnaire were collected. The work and family orientation questionnaire is based on Murray's (1938) definition for need for achievement and assesses three separate subscales that capture an individual's general disposition toward approach motivation. A six-item work subscale measures one's general desire to work hard and do a good job, an eight-item mastery subscale measures a general preference for challenging tasks and reaching personal goals for achievement, and a five-item competitiveness subscale measures a general enjoyment of interpersonal competition and the desire to be better than others. Students were asked to indicate the extent to which they agreed with each of the items using a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*). Because previous research has found the work and mastery orientation subscales of this measure to be highly correlated (Harackiewicz et al., 1997; Spence & Helmreich, 1983), these two subscales are often collapsed into a single workmastery subscale. We believed that validity evidence for our cluster solutions would be provided if the ordering of cluster means on the mastery-approach subscale corresponded to their ordering on the workmastery measure and if the cluster ordering on the performance-approach subscale were similar to their ordering on the competitiveness subscale.

2.2.3. Motive to avoid failure

To compare students' achievement goal profiles to a more general personality measure that assesses avoidance motivation, responses to Hagtvet and Benson's (1997) motive to avoid failure scale were collected. The six items on the motive to avoid failure scale are intended to measure Atkinson's definition (1964, 1974) of motive to avoid failure, which is conceptualized as a unidimensional disposition for avoiding achievement situations. Students were asked to determine the extent to which they experienced the behavior described by each of the items using a 4-point scale (1 = *almost never*, 4 = *almost always*). We believed that validity evidence for our cluster solutions would be indicated by larger differences among clusters in motive to avoid failure when avoidance factors of goal orientation were included in the model, with clusters higher in their avoidance goal levels endorsing higher levels of motive to avoid failure.

2.2.4. Academic ability & performance

The final clusters were examined for differences in the academic performance measure of semester grade point average (GPA). This semester grade point average (GPA) was obtained directly from university records and reflects the GPA for the semester in which the student completed the achievement goal measure. Because we were assessing students' goal orientations for a particular semester, we were interested in the relationship between goal orientation profiles and GPA for the semester in question. To better understand differences among the profiles in academic achievement we controlled for ability differences by obtaining the students' SAT total scores from university records and using SAT as a covariate when examining differences among clusters in semester GPA. It is quite common in goal research with college students to use SAT as a covariate when examining the relationships between goal orientation and academic performance (e.g., Elliot & McGregor, 2001; Finney et al., 2004). Descriptive statistics for measures of motivational disposition, SAT, and semester GPA are shown in Table 4 for Sample 1. This table also contains the

Table 4
Descriptive statistics, coefficient alphas, and correlations for the measures of motivational disposition and academic ability and performance for Sample 1

	Workmastery	Competitiveness	Motive to avoid failure	Semester GPA	SAT
Mastery-approach	.50	.12	−.16	.15	−.11
Performance-approach	.26	.52	.02	.21	.02
Performance-avoidance	−.02	.27	.29	−.12	−.22
Mastery-avoidance	.08	.10	.27	−.11	−.15
N	1489	1610	1815	1211	1211
Maximum possible	35	25	24	4	1600
M	26.02	17.66	13.22	3.02	1150.30
SD	3.43	4.12	3.42	.66	111.44
Alpha	.79	.79	.83		

Note. Correlations are based on pairwise deletion of missing data.

correlations of each of these measures with the achievement goal subscales as well as values of coefficient alpha for the measures of motivational disposition.

2.3. Analysis

2.3.1. Step 1: Identifying the cluster solutions for the 2-, 3-, and 4-factor conceptualizations of goal orientation in Sample 1

Our first research question entailed identifying the common goal orientation profiles for each conceptualization of goal orientation. To this end, we fit a variety of different models, each differing in the number of clusters specified and in the particular parameterization of the covariance matrix $\mathbf{\Sigma}_k$. Specifically, three separate sets of analyses were conducted, one for each conceptualization of goal orientation. In the first set of analyses, only mastery-approach and performance-approach were used as cluster indicators. In the second set of analyses, mastery-approach, performance-approach, and performance-avoidance were used as cluster indicators. In the third set of analyses, mastery-approach, performance-approach, performance-avoidance, and mastery-avoidance were used as cluster indicators.

We decided to examine solutions containing no more than 5, 6, and 7 clusters respectively for the 2-, 3-, and 4-factor representations of goal orientation because our previous cluster analysis study (Pastor, Barron, Davis, & Miller, 2004) indicated these solutions as the final cluster solutions. Also, because LPA allows for more flexible parameterizations (e.g., variances can differ across clusters) than traditional techniques, oftentimes fewer clusters can be used to represent the data when using these models (Vermunt & Magidson, 2002). For this reason, we anticipated finding fewer clusters using LPA than in our previous study and felt comfortable setting the maximum at these values.

In every LPA model, means were allowed to vary across both cluster indicators and clusters. We examined the five different parameterizations of $\mathbf{\Sigma}_k$ shown in Table 1 for each model specifying a given number of clusters. For instance, in the 2-factor conceptualization, we examined the fit of Models A, B, C, D, and E for solutions specifying 1, 2, 3, 4, and 5 clusters. For the remainder of the article we will refer to these models by first using the number of clusters specified followed by the letter associated with the particular parameterization in Table 1. For example, Model 3A refers to the model with three clusters and the Model A parameterization. The BIC, LMR, χ^2 difference tests, sample size, and uniqueness of the cluster profiles for each solution were considered in deciding upon our final model. To compute the sample statistics for each cluster, all observations were used and weighted by the posterior probabilities associated with the cluster. To obtain an idea of model fit, we examined the results of the SK tests (although cautiously given the call for further research with these tests).

2.3.2. Step 2: Examining the classification accuracy of the models using both Sample 1 and Sample 2

The classification accuracy of each solution in Sample 1 was examined using both the entropy statistics and the average posterior probabilities in the classification tables. Then for each conceptualization of goal orientation, the models estimated using Sample 1 were cross-validated using Sample 2. To cross-validate, Eq. (4) was used along with the estimated model parameters of the final solutions in Step 1 to compute the posterior probabilities of cluster membership for students in Sample 2 with modal assignment used to assign students to clusters. The accuracy of the model in classifying students in Sample 2 was assessed by examining the entropy statistics and the average posterior probabilities in the classification tables.

2.3.3. Step 3: Use of regression to examine the relationship between cluster membership and measures of motivational disposition and academic performance

For each conceptualization of goal orientation, relationship between membership in the resulting clusters and measures of motivational disposition (workmastery, competitiveness, and motive to avoid failure) and academic performance (semester GPA) were examined. A straightforward approach to examining differences among clusters in these variables would be to use ANOVA. Another approach that would yield equivalent results is the use of multiple regression, with cluster membership represented in the model using dummy-coded predictor variables. When using dummy-coded variables, an individual would be considered as either belonging to a cluster (1) or not belonging to a cluster (0). However, in order to incorporate the accuracy with which an individual can be classified into a cluster, the posterior probabilities as opposed to dummy-coded variables were used as predictors in the multiple regression model below:

$$Y_i = \left[\sum_{k=1}^{K} \beta_k (\pi_k)_i\right] + e_i. \tag{6}$$

The estimated posterior probabilities of cluster membership (π_k for $k = 1$–K) were used as the independent variables and either workmastery, competitiveness, motive to avoid failure, or semester GPA as the dependent variable (Y_i). The intercept of the model was forced to zero so that the resulting coefficients ($\beta_1, \beta_2, \ldots, \beta_k$) would represent the average of the dependent variable for each cluster, weighted by the accuracy with which persons could be classified. To determine whether the averages varied across clusters, we tested the null hypothesis that $\beta_1 = \beta_2 = \cdots = \beta_k$ using an F-statistic calculated with the error sums of squares of two models: the model in Eq. (6) and a model specifying only an intercept term. Significant results were followed by all pairwise comparisons which also used an F-statistic, testing the fit of the model in Eq. (6) to the fit of a restricted model that specified the corresponding coefficients for the two clusters to be equal. We used a conservative alpha level ($\alpha = .01$) for all tests to control our Type I error rate. Effect sizes were reported on an R^2 metric, with rules of thumb considering values of .01, .09, and .25 to be of small, medium and large practical significance (Cohen, 1988).

When examining the relation of cluster membership to semester GPA, we used the model in Eq. (6) and also included SAT score as a predictor variable. This allowed us to examine cluster differences in semester GPA once controlling for cluster differences in academic ability.

2.4. Software

Mplus version 3.01 (Muthén & Muthén, 2004) was used for the analyses in Steps 1 and 2. In Step 1, model parameters were estimated using maximum likelihood estimation via the EM algorithm. Because convergence on a local maximum is a common problem in latent variable mixture modeling, an Mplus feature was utilized in an attempt to circumvent this problem. To use this feature, the user supplies a number which dictates how many random sets of starting values will be used. For each set of starting values, maximum likelihood optimization is performed resulting in a log-likelihood for each set. Starting values in the final optimizations are based on the sets associated with the highest log-likelihood values. We asked for 100 different sets of starting values and from this 100, the ten that yielded the highest log-likelihood to be used in the final optimizations. For models where convergence was problematic, we provided our own starting values to be used in addition to the random sets of starting values. For cross-validation of the models in Step 2, the Mplus syntax files for our final solutions in Step 1 were modified to: (1) read in the Sample 2 data and (2) fix the parameters at the values obtained in the final Step 1 solutions. Data files with cluster membership information from the Step 1 analyses were output from Mplus and used as input into SAS (version 9.1) to execute the Step 3 analyses with PROC REG. Examples of the Mplus syntax used for Steps 1 and 2 are shown in Appendix A.

3. Results

3.1. Step 1: Identifying the cluster solutions for the 2-, 3-, and 4-factor conceptualizations of goal orientation in Sample 1

The BICs and sample-size adjusted BICs for a selection of the Step 1 models are shown in Table 5. Values bolded in the table indicate models where the performance-approach mean for a single cluster had to be fixed at a particular value in order to achieve convergence[5]. To help organize our results for Step 1 below, we discuss the findings separately for each conceptualization of goal orientation (specifically, whether analyses are based on a 2-, 3-, or 4-factor framework). Recall that the models are named such that the number represents the number of clusters specified and the letter represents the particular parameterization of the covariance matrix $\mathbf{\Sigma}_k$ used in Table 1.

3.1.1. 2-Factors

The lowest BIC for the 2-factor model was associated with Model 4D whereas the lowest sample-size adjusted BICs were associated with Models 5D and 5E. For Models 4D, 5D, and 5E, we inspected the cluster profiles, sample size, and sample statistics for each cluster. We rejected Models 4D and 5D because the sample statistics for these models did not correspond well with the estimated model parameters. Specifically, the sample statistics indicated large differences among clusters in the covariance between mastery-approach and performance-approach, which was constrained to be equal across clusters in Models 4D and 5D. Model 5E allowed the covariance to vary across clusters, and had sample statistics that corresponded well with the model parameters. Also supporting the retention of Model 5E was the significance of the χ^2 difference test, which indicated that Model 5E fit the data significantly better than Model 5D ($\chi^2(4) = 17.11$, $p = .002$). Although the profiles yielded by Model 5E were distinct, the fifth cluster only represented about 6% of students. We decided that this cluster should be retained after consulting the

[5] For a particular cluster the performance-approach mean was incredibly close to the upper limit of the scale, therefore for these models we chose to fix the mean for this cluster to 20.5. When parameter values are at the boundaries of the parameter space, it is not uncommon to have convergence problems when using ML estimation. Remedies to this problem are numerous and include fixing the estimate at a particular value or using an alternative estimation procedure (e.g., Bayesian). We chose to fix the value at 20.5 as opposed to the maximum of the scale so that the performance-approach variance estimate for this cluster would not be constrained to zero.

Table 5
BICs and sample-size adjusted BICs for a selection of the 2-, 3-, and 4-factor models in Step 1

	Model parameterization	BIC				Sample-size adjusted BIC			
		Number of clusters				Number of clusters			
		4	5	6	7	4	5	6	7
2-Factor	C	**19480**	**19493**			**19422**	**19420**		
	D	**19469**	**19478**			**19409**	**19402**		
	E	**19484**	**19491**			**19414**	**19402**		
3-Factor	C	29712	29719	**29599**		29626	29611	**29472**	
	D	29660	**29601**	**29597**		29565	**29487**	**29460**	
	E	29648	**29568**	**29613**		29524	**29416**	**29428**	
4-Factor	C	39913	39891	**39779**	**39753**	39802	39751	**39614**	**39560**
	D	39736	39727	**39695**	**39716**	39606	39569	**39511**	**39504**
	E	**39725**	**39719**	**39760**	**39853**	**39541**	**39487**	**39480**	**39526**

Note. Values are bolded for models in which the performance-approach mean of a single cluster was fixed to 20.5 in order to achieve convergence.

Lo–Mendell–Rubin likelihood ratio test that had a significant p-value for Model 5E ($p = .003$), indicating that the four-cluster solution should be rejected in favor of the five-cluster solution. To be certain that Model 5E should be retained over a more complex model specifying six clusters, we fit an additional model, Model 6E, to the data. The BIC and sample-size adjusted BIC for this model were larger (19512 and 19404, respectively) than those for 5E and the Lo–Mendell–Rubin likelihood ratio test was not significant ($p = .08$), supporting retention of the five-cluster solution. The solution for Model 6E also included a sixth cluster that was not distinct from the other clusters, therefore supporting retention of Model 5E. The SK tests supported the fit of the model to the data with multivariate skewness and kurtosis p-values of .84 and .16, respectively.

3.1.2. 3-Factors

Both the BIC and the sample-size adjusted BIC favored Model 5E for the 3-factor conceptualization of goal orientation. This model yielded distinct profiles each representing a sizeable number of students with retention of this model also being supported by the close correspondence between the estimated model parameters for Model 5E and the sample statistics in each cluster. The significant χ^2 difference test ($\chi^2(12) = 123.56$, $p < .001$), comparing the fit of Model 5E with that of Model 5D, implied that significantly better fit was obtained with Model 5E, which allowed the covariances among mastery-approach, performance-approach and performance-avoidance to vary across clusters. Also supporting our retention of Model 5E were the results of the Lo–Mendell–Rubin likelihood ratio test, which showed that Model 5E fit significantly better than Model 4E ($p = .002$) and not significantly worse than Model 6E ($p = .237$). Model 6E was also rejected because the sixth cluster that emerged represented only 5% of students who had a similar pattern of means as the fifth cluster in Model 5E. The SK tests supported the fit of the model to the data with multivariate skewness and kurtosis p-values of .38 and .13, respectively.

3.1.3. 4-Factors

The BIC and sample-size adjusted BIC for the 4-factor conceptualization were lowest for Models 6D and 6E, respectively. Because the covariances among the four factors varied widely across clusters in the sample statistics for Model 6D, we focused on Model 6E, which allowed the covariances to vary across clusters. Supporting the retention of Model 6E was the significant χ^2 difference test ($\chi^2(30) = 161.64$, $p < .001$), which tested whether Model 6E fit significantly better than Model 6D. Although there was a close correspondence between the clusters' estimated model parameters and sample statistics for Model 6E, the Lo–Mendell–Rubin likelihood ratio test indicated that Model 6E did not fit significantly better than Model 5E ($p = .57$). This was not surprising given that Model 6E only differed from Model 5E in having a sixth cluster representing only 2% of students. Upon inspection of the cluster profiles for Models 5E and 6E, we decided to retain the solution for Model 6E since the sixth cluster in this solution had an incredibly unique profile. If we had retained Model 5E, the 2% of students who were classified in this sixth cluster would have been merged into the third cluster. We feel that the goal orientation profile of these students would not have been well captured had they been classified into this cluster and thus chose to retain Model 6E. The SK tests supported the fit of the model to the data with multivariate skewness and kurtosis p-values of .12 and .21, respectively.

In summary, our favored models were Models 5E, 5E, and 6E for the 2-, 3-, and 4-factor solutions, respectively. The estimated model means and proportions for each solution by cluster are shown in Table 6 and the profiles for each cluster displayed graphically in Figs. 1–3. The standard deviations and correlations among factors for each solution by cluster are shown in Table 7. With the exception of the sixth cluster in the 4-factor solution, clusters with similar profiles were found across the different conceptualizations of goal orientation. For this reason, we describe below how each cluster is represented in the 2-, 3-, and 4-factor solutions.

3.1.4. Cluster 1

Across all solutions, Cluster 1 consistently represents about 12–15% of students. In the 2-, 3-, and 4-factor solutions, Cluster 1 is characterized by a high mastery-approach mean (~18.65) and an even higher performance-approach mean (20.5; recall that the performance-approach mean was fixed to 20.5 in all solutions in order to achieve convergence). In both the 3- and 4-factor solutions, this cluster has a moderate mean on performance-avoidance (~13.4) and in the 4-factor solution, has a moderately low mean on mastery-avoidance (11.65). The standard deviations for each goal orientation measure indicate that students vary little from one another in this cluster on the approach factors, but vary quite substantially on the avoidance factors. Across solutions, there seems to be a small positive correlation (~.30) between the approach factors for Cluster 1, with all other factors having either minor or null relationships with one another (see Table 7).

3.1.5. Cluster 2

Cluster 2 represents about 9-12% of students in the various solutions. Cluster 2 has equally high approach means (~18.4) across all solutions and in both the 3- and 4-factor solutions, has a moderately low mean on performance-avoidance (~12). In the 4-factor solution, this cluster also has a moderately low mean on mastery-avoidance (12.46). The standard deviations for each factor indicate that students vary little from one another in this cluster on the approach measures, but vary quite substantially on the avoidance factors. Across solutions, there is little to no relationship among the different measures of goal orientation for Cluster 2 (see Table 7).

Table 6
Estimated model proportions and goal orientation means for the 2-, 3-, and 4-factor cluster solutions

	Cluster	Estimated model proportions	Mastery-approach	Performance-approach	Performance-avoidance	Mastery-avoidance
2-Factor	1	0.15	18.60	20.50		
	2	0.12	18.71	18.21		
	3	0.32	16.81	16.20		
	4	0.35	14.52	13.00		
	5	0.06	13.23	6.69		
3-Factor	1	0.12	18.76	20.50	13.38	
	2	0.09	18.42	18.13	11.46	
	3	0.25	16.92	16.64	15.84	
	4	0.44	15.26	14.14	11.75	
	5	0.10	13.83	7.90	9.06	
4-Factor	1	0.13	18.62	20.50	13.47	11.65
	2	0.11	18.59	18.16	12.70	12.46
	3	0.30	16.45	16.05	14.75	12.98
	4	0.24	15.05	14.31	10.80	9.63
	5	0.20	14.29	10.27	10.75	11.63
	6	0.02	20.75	19.16	19.15	18.87

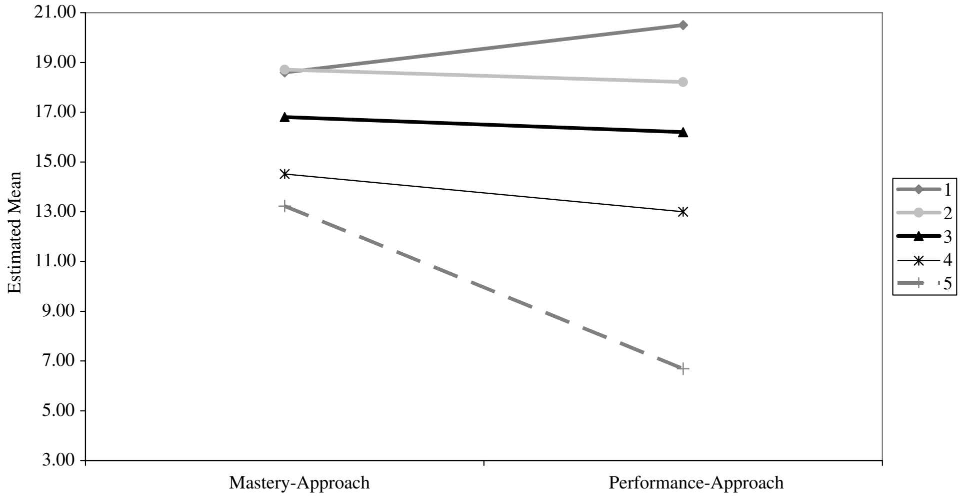

Fig. 1. LPA solution for the 2-factor conceptualization of goals.

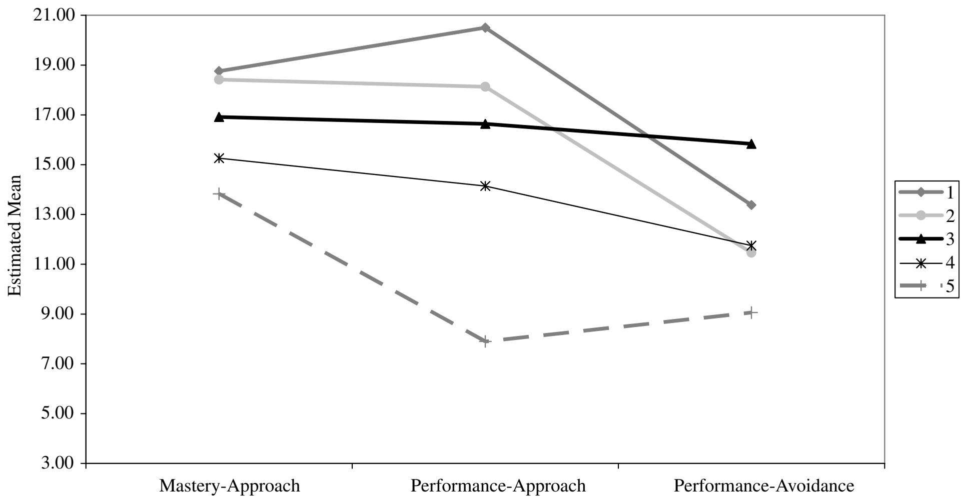

Fig. 2. LPA solution for the 3-factor conceptualization of goals.

3.1.6. Cluster 3

Whereas Cluster 3 is the largest cluster in the 4-factor solution, representing 30% of students, it is only the second largest cluster in both the 2- and 3-factor solutions, representing 32% and 25% of students in these solutions, respectively. Across all solutions, Cluster 3 has moderately high means on both approach factors (∼16.5). In the 3- and 4-factor solutions, this cluster has a moderate mean on performance-avoidance (∼15.5) and in the 4-factor solution, has a moderate mean on mastery-avoidance (12.98). The standard deviations indicate modest variability for this cluster and are the same across goal orientation measures and solutions. This cluster is characterized by a high positive relationship between the performance factors in the 3- and 4-factor solution. All other rela-

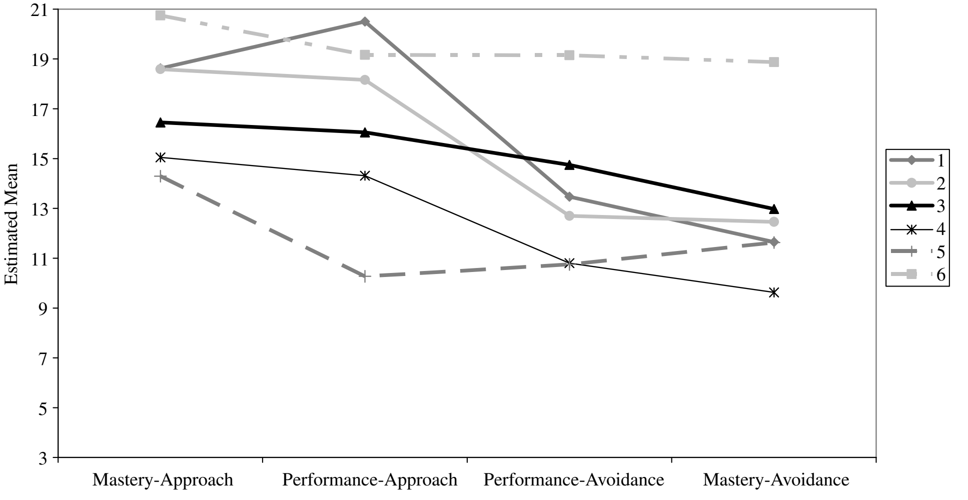

Fig. 3. LPA solution for the 4-factor conceptualization of goals.

tionships among the different measures of goal orientation for this cluster are either small in magnitude or null (see Table 7).

3.1.7. Cluster 4

Cluster 4 is the largest cluster in the 2- and 3-factor solutions, representing 35% and 44% of students in these solutions, respectively. In the 4-factor solution, it is the second largest cluster and represents 24% of students. Across all solutions, Cluster 4 has moderately high mastery-approach means (~15) and moderate performance-approach means (~14). In the 3- and 4-factor solutions, Cluster 4 has a moderately low performance-avoidance mean (~10.5) and in the 4-factor solution, a low mastery-avoidance mean (9.63). The standard deviations are of modest variability and the same across goal orientation measures and solutions. This cluster is characterized by a moderate negative relationship between mastery-approach and performance-avoidance that is larger in the 4-factor solution (−.31) than in the 3-factor solution (−.23). All other relationships among the factors for Cluster 4 are either very small in magnitude or null (see Table 7).

3.1.8. Cluster 5

Cluster 5 represents 10% or fewer students in the 2- and 3-factor solutions and 20% of students in the 4-factor solution. The mastery-approach mean for Cluster 5 is similar across solutions and is moderate in size (~13.8). The performance-approach mean is consistently low in the 2- and 3-factor solutions (~7.5), but is estimated as only somewhat low for this cluster in the 4-factor solution (10.27). The performance-avoidance mean for Cluster 5 is moderately low in the 3- and 4-factor solutions (~10) and the mastery-avoidance mean is also moderately low in the 4-factor solution (11.63). Across solutions, the standard deviations indicate that for all factors, variation of students from the mean is quite substantial. This cluster is characterized by negative relationships between mastery-approach and the performance factors. These relationships vary in size across the different solutions. In both the 3- and 4-factor solutions, there is a strong positive rela-

Table 7
Standard deviations and correlations among goal orientation factors by cluster for the 2-, 3-, and 4-factor solutions

Cluster		2-factor		Cluster		3-factor			Cluster		4-factor			
		MAP	PAP			MAP	PAP	PAV			MAP	PAP	PAV	MAV
1	MAP	**1.90**		1	MAP	**1.79**			1	MAP	**1.80**			
	PAP	0.33	**0.53**		PAP	0.36	**0.53**			PAP	0.30	**0.53**		
					PAV	0.23	0.04	**5.16**		PAV	0.10	0.02	**5.03**	
										MAV	−0.08	−0.06	0.10	**4.60**
2	MAP	**1.45**		2	MAP	**1.54**			2	MAP	**1.39**			
	PAP	0.15	**0.76**		PAP	0.13	**0.73**			PAP	0.18	**0.78**		
					PAV	−0.10	−0.16	**3.98**		PAV	−0.05	−0.09	**4.29**	
										MAV	−0.21	−0.18	0.21	**4.31**
3	MAP	**2.30**		3	MAP	**2.33**			3	MAP	**2.30**			
	PAP	−0.29	**1.93**		PAP	0.17	**2.22**			PAP	−0.13	**2.19**		
					PAV	0.25	0.65	**2.36**		PAV	−0.11	0.45	**2.48**	
										MAV	0.21	−0.01	0.09	**2.96**
4	MAP	**2.96**		4	MAP	**3.07**			4	MAP	**3.05**			
	PAP	−0.29	**2.87**		PAP	−0.08	**2.99**			PAP	−0.06	**2.89**		
					PAV	−0.23	0.13	**3.28**		PAV	−0.31	−0.11	**3.30**	
										MAV	−0.19	−0.04	0.20	**3.10**
5	MAP	**4.47**		5	MAP	**4.18**			5	MAP	**3.75**			
	PAP	−0.38	**2.67**		PAP	−0.22	**3.04**			PAP	−0.10	**3.79**		
					PAV	−0.24	0.67	**3.15**		PAV	−0.15	0.69	**3.62**	
										MAV	0.43	0.16	0.28	**3.73**
									6	MAP	**0.44**			
										PAP	−0.07	**1.96**		
										PAV	0.07	0.67	**1.51**	
										MAV	0.08	0.03	0.17	**1.74**

Note. Bolded values are standard deviations, non-bolded values are correlations. MAP, mastery-approach; PAP, performance-approach; PAV, performance-avoidance; MAV, mastery-avoidance.

tionship between the performance factors (∼.68). In the 4-factor solution, the correlations in Table 7 show a fairly strong positive relationship between the mastery factors (.43) and modest positive relationship between the avoidance factors (.28).

3.1.9. Cluster 6

Cluster 6, which represents only 2% of students in the 4-factor solution, is similar to Clusters 1 and 2 in that it is characterized by high means on the approach factors. Cluster 6 has a very high mean on mastery-approach (20.75) and a somewhat lower mean on performance-approach (19.16). Unlike any of the clusters in the 3-factor solution, Cluster 6 is characterized by a high performance-avoidance mean (19.15). It also has the highest mean on the mastery-avoidance scale (18.87) in the 4-factor solution. Perhaps because the means for this cluster are near the maximum of the scale, there is little variation among students in the four factors as evidenced by the small standard deviations for the factors in the 4-factor solution. When considering relationships among the factors in the 4-factor solution, Cluster 6 has a strong positive relationship between the performance factors, with all other relationships being null. The null relationships may partly be attributable to the low variance of the scores in this cluster.

3.2. Step 2: Examining the classification accuracy of the models using both Sample 1 and Sample 2

For all conceptualizations of goal orientation, the values of the entropy statistics were moderate in value and similar in both samples. The entropy statistics for the 2-, 3-, and 4-factors solutions were .71, .67, and .67 in Sample 1 and .68 for all solutions in Sample 2. Selected average posterior probabilities from the classification tables are shown in Table 8. Recall that in a classification table each row contains the K average posterior probabilities for persons assigned to a given cluster, with the highest average typically associated with the cluster to which the persons were assigned. For each solution and sample, the left portion of Table 8 contains the highest average posterior probabilities for persons assigned to a given cluster. As anticipated, the highest averages are associated with the clusters to which the persons were assigned. The right portion of the table contains the second highest averages for persons assigned to a given cluster. These values are of interest because they help identify clusters that are not well distinguished from one another. For instance, in the 2-factor solution persons assigned to Cluster 2 have a sizeable average posterior probability associated with Cluster 3 in both samples (.22), indicating overlap between the two clusters.

For all conceptualizations of goal orientation, the values in Table 8 are similar across samples, indicating that the final models in Step 1 have consistent classification accuracy when applied to a different sample. Accurate classification is most difficult for persons assigned to Clusters 2 and 3 in the 2-factor solution, with persons classified in these clusters having about a .20 average posterior probability associated with assignment in Clusters 3 and 4, respectively. Classification is also the most problematic for these clusters in the 3-factor solution, with persons classified in Clusters 2 and 3 each having about a .20 average posterior probability associated with assignment in Cluster 4. In the 4-factor solution, classification is the least accurate for Clusters 2, 3, and 4, with persons classified in these clusters having about .11 to .18 average posterior probability associated with assignment in Clusters 3, 4, and 5, respectively.

Table 8
Highest and second highest average posterior probabilities for persons assigned to a given cluster by cluster solution and sample

	Cluster	Highest average			Second highest average		
		Associated with cluster	Sample 1	Sample 2	Associated with cluster	Sample 1	Sample 2
2-Factor	1	1	0.93	0.93	3	0.05	0.05
	2	2	0.76	0.74	3	0.22	0.22
	3	3	0.72	0.70	4	0.20	0.21
	4	4	0.82	0.81	3	0.13	0.15
	5	5	0.84	0.80	4	0.16	0.20
3-Factor	1	1	0.85	0.87	3	0.11	0.10
	2	2	0.73	0.72	4	0.19	0.19
	3	3	0.71	0.72	4	0.19	0.20
	4	4	0.78	0.78	3	0.13	0.12
	5	5	0.84	0.84	4	0.16	0.16
4-Factor	1	1	0.89	0.90	3	0.06	0.06
	2	2	0.73	0.70	3	0.18	0.18
	3	3	0.73	0.74	4	0.12	0.11
	4	4	0.70	0.71	5	0.15	0.14
	5	5	0.77	0.80	4	0.18	0.16
	6	6	0.82	0.83	1	0.10	0.09

3.3. Step 3: Use of regression to examine the relationship between cluster membership and measures of motivational disposition and academic performance

The multiple regression results are reported as effect sizes for each conceptualization in Table 9. In addition, the Z-score averages (weighted by the degree of cluster membership) were plotted for each variable by cluster for the 2-, 3-, and 4-factor solutions in Figs. 4, 5 and Fig. 6, respectively. This illustration was used to characterize the magnitude of the differences between clusters since the distance between the Z-score means is similar to Cohen's d in interpretation and value. The ellipses within the figures convey the results of the pairwise statistical significance tests. Means in different ellipses are significantly different from one another; means within the same ellipse are not. It should be noted that the means in the figures for semester GPA are the adjusted means, or the means for each cluster once controlling for SAT scores.

Table 9
Measures of practical significance (R^2) when examining relations of cluster membership to motivational disposition and academic performance

	Workmastery	Competitiveness	Motive to avoid failure	Semester GPA[a]
2-Factor	.15	.22	<.01	.05
3-Factor	.13	.23	.05	.04
4-Factor	.14	.23	.06	.06

Note. R^2 values of .01, .09, and .25 considered to be small, medium, and large effects, respectively.
[a] Effect sizes for semester GPA once controlling for SAT scores.

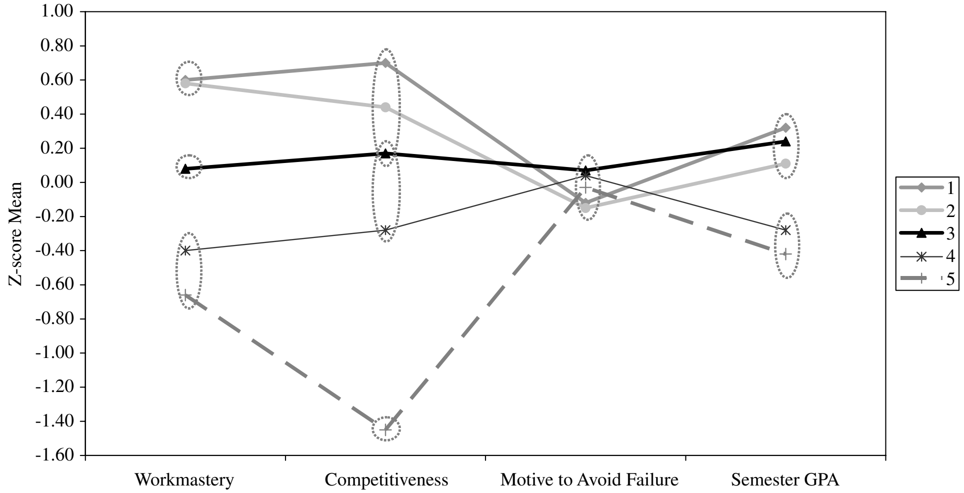

Fig. 4. Z-score means for measures of motivational disposition and semester grade point average by cluster for the 2-factor conceptualization of goals. *Note.* Means in different ellipses are significantly different from one another.

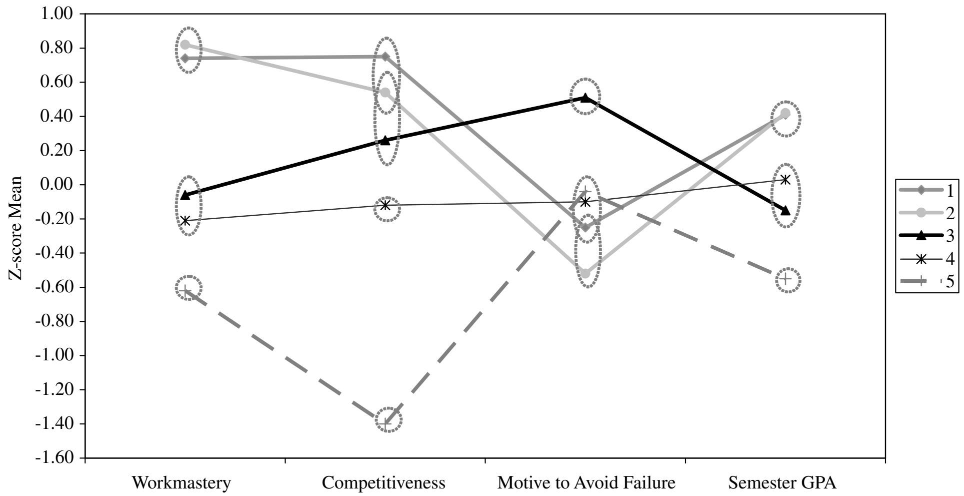

Fig. 5. Z-score means for measures of motivational disposition and semester grade point average by cluster for the 3-factor conceptualization of goals. *Note.* Means in different ellipses are significantly different from one another.

For all conceptualizations of goal orientation, there were statistically and practically significant differences among the clusters in workmastery and competitiveness with the differences being of large practical significance for both variables ($R^2 = .14$ and .23, respectively). The differences among clusters in competitiveness were larger than their differences in workmastery, which corresponds with the larger differences among clusters in their performance-approach means relative to their mastery-approach means. The relative ordering of the clusters in mastery-approach and performance-approach means was similar to their

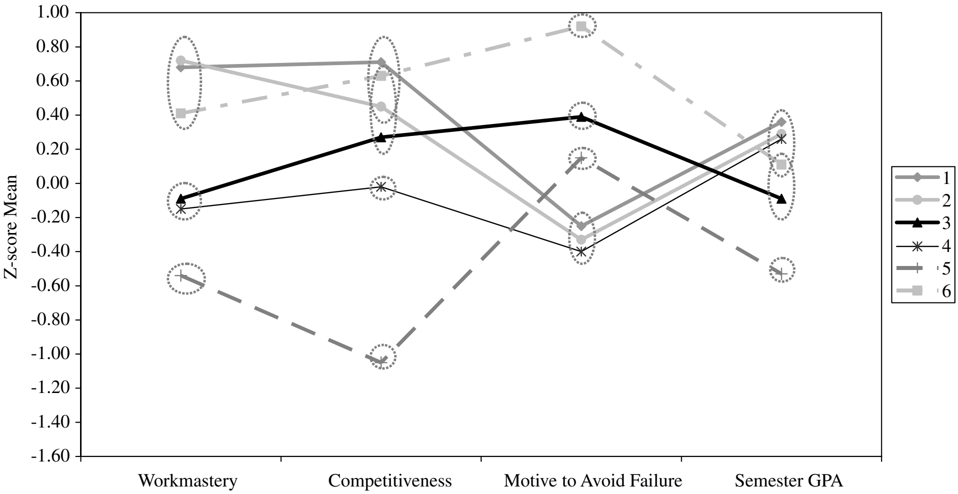

Fig. 6. *Z*-score means for measures of motivational disposition and semester grade point average by cluster for the 4-factor conceptualization of goals. *Note.* Means in different ellipses are significantly different from one another.

ordering in the workmastery and competitiveness variables respectively, offering supportive validity evidence for the cluster solutions.

While the differences among clusters in workmastery and competitiveness were of the same magnitude for all conceptualizations of goal orientation, the differences among clusters in motive to avoid failure increased as the complexity of the conceptualization increased. For instance, in the 2-factor conceptualization the clusters did not significantly differ from one another in motive to avoid failure. However, there were significant differences among clusters in motive to avoid failure for the 3- and 4-factor solutions. The practical significance of this effect was the same for both the 3- and 4-factor solutions, with the R^2 values of .05 and .06 indicating a small to moderate effect. The relative ordering of cluster means on the motive to avoid failure measure are only somewhat related to their ordering on the avoidance measures in the 3- and 4-factor solutions, which is not surprising given the small to moderate relationship ($r \sim .28$) between motive to avoid failure and the avoidance factors in the overall sample (see Table 4).

Controlling for SAT, the clusters also differed from one another significantly in semester GPA for all conceptualizations. For all conceptualizations the differences among clusters in semester GPA, once controlling for SAT scores, was of small to moderate practical significance with the R^2 values remaining fairly consistent across conceptualizations. Clusters 1 and 2 had relatively high semester GPAs while Cluster 5 had relatively low semester GPAs across conceptualizations. The averages of Clusters 3 and 4 changed across conceptualizations and were never the highest or the lowest. The mean semester GPA associated with Cluster 6 was average.

4. Discussion

One of the main purposes of the present study was to compare the different cluster solutions that resulted when the factors of different conceptualizations of goal orientation were used as cluster indicators. To this end, LPA was used to classify college students into different goal orientation profiles using 2-, 3-, and 4-factor conceptualizations of goal orientation. Our results indicated that five different goal orientation profiles were needed to classify college students in the 2- and 3-factor conceptualizations and six different profiles in the 4-factor conceptualization. When examining the profiles that emerged in the different solutions (shown in Figs. 1–3)[6], it is of interest to note that the majority of students are represented in clusters that have moderate to high levels on the goal orientation factors. In all solutions, no profile emerged that was low in mastery-approach, and with the exception of Cluster 6 in the 4-factor conceptualization, no profile emerged that was high on the avoidance measures. It is possible that the failure to find such profiles may be attributable to the use of a college student sample that limits our ability to generalize these findings to other populations.

The finding that the college student population actually consists of several different sub-populations, each with its own set of goal orientation means, variances, and covariances, has important implications for goal orientation researchers. First, it should heighten researchers' awareness that their population of interest may not be homogeneous in respect to the multivariate distribution of the various goal orientation measures. If heterogeneity exists, the sample statistics used to describe the mean, variance, and correlation among the different goal orientation measures may not be reflective of the population. Secondly, the finding that sub-populations exist with their own unique parameters may shed light on why study findings vary. For instance, a researcher using data sampled predominantly from Cluster 5 in the 4-factor solution would make very different conclusions regarding the relationships among the goal orientation measures than another researcher sampling predominantly from Cluster 2.

The remainder of our discussion is organized by first considering whether our findings support the conclusion that more complex conceptualizations are needed to better differentiate among students and to better predict an achievement related outcome; second, by discussing the validity evidence we found for our cluster solutions; third, by considering whether the more complex conceptualizations in our study are the best operational definitions of goal orientation. We then consider the benefits gained in using LPA in the present article in comparison to the traditional cluster analytic techniques we used for the same purposes in a previous article (Pastor et al., 2004) and mention other ways readers might consider using LPA in future goal orientation research.

4.1. Were more complex conceptualizations needed to better differentiate among students and to better predict an achievement related outcome?

To a certain extent, the results of our study supported the idea that more complex conceptualizations of goal orientation were needed to differentiate among students. When the avoidance goal orientations were included in the 3- and 4-factor models as cluster indica-

[6] When considering the Cluster 1 profiles in the 2-, 3-, and 4-factor solution recall that convergence was only possible if the performance-approach mean for this cluster was set to 20.5. The mean for this cluster, as well as the high mastery-approach mean for Cluster 6 in the 4-factor solution, imply that perhaps the particular scale used in this study has a ceiling effect. Perhaps future research can explore different methods for alleviating the ceiling effect for these clusters, such as including more points on the response scale or including items that are written to measure persons who have extremely high approach goal orientations.

tors, greater distinction among the clusters in motive to avoid failure was obtained. Additionally, a unique cluster (Cluster 6) emerged in the 4-factor solution, representing a profile quite different from the rest in avoidance goal orientation.

A somewhat surprising result was the consistency of the solutions across the different conceptualizations of goal orientation. Because similar clusters emerged in the different conceptualizations having similar estimated parameters, it may be argued that more complex conceptualizations are not necessarily needed to better differentiate among students. This is a surprising result since the results of LPA, like cluster analysis, are dependent upon the number and nature of the cluster indicators used. Although there was similarity in the cluster solutions, membership of a person in the same cluster for all conceptualizations was not guaranteed and instead was related to the classification accuracy associated with each cluster. For instance, across solutions classification accuracy was highest for persons in Cluster 1. Accordingly, about 90% persons classified in Cluster 1 in the 2-factor solution, were also classified into this cluster in the 3- and 4-factor solutions. Classification accuracy and thus, the consistency with which a person was assigned to the same cluster in all conceptualizations was lower for the remaining clusters. Even though similar entropy statistics and average posterior probabilities (Table 8) were found in our first and second samples, this only illustrates that our accuracy in classifying students into clusters was consistent, not necessarily that it was good. The average posterior probabilities and entropy statistics obtained in this study were moderate and perhaps could be no larger since many of the clusters were close in distance and had rather large within-cluster variability.

Another purpose of our study was to determine if clusters derived from more complex conceptualizations of goal orientation were better able to predict an achievement-related outcome. For all conceptualizations of goal orientation we found small to moderate differences among the different goal orientation profiles in average semester GPA, controlling for SAT. Because the magnitude of the difference among profiles did not increase as more complex conceptualizations were used, we cannot conclude that the 3- or 4-factor models are better able to differentiate among students in semester GPA. Of course, we only examined how the profiles differed in semester GPA, which is only one measure of success in college, and an imperfect one at that. Future research should examine how the profiles relate to other measures of success in college, such as interest or engagement in the material. It could be that one profile is associated with academic success in college whereas another profile is associated with increased interest, arguing for a specialized goal pattern (see Barron & Harackiewicz, 2001). It would also be of interest to see if and how students' profiles change during their college careers or if different profiles would emerge if students were questioned about their goals for a specific course, rather than their goals for a given semester.

4.2. Was there supporting validity evidence for the cluster solutions?

Across conceptualizations, the magnitude of the differences and the rank order of clusters in mastery-approach and performance-approach averages corresponded to those for workmastery and competitiveness, respectively. As well, differences among clusters in motive to avoid failure were null in the 2-factor conceptualization and much larger for the conceptualizations including the avoidance goal orientations. Because the clusters differed as expected from one another in measures of motivational disposition, supporting validity evidence for the cluster solutions was obtained.

Of course, we only examined three measures of motivational disposition in an effort to acquire validity evidence for our solutions. Because the support for our models is tied to the measures of motivational disposition used in the present study, further validity evidence should be acquired that utilizes different operational definitions of motivational disposition. More importantly, further validity evidence should be acquired using a variety of different variables known to be related to goal orientation. For instance, past achievement goal research has linked achievement goals to a wide range of different affective, cognitive, and behavioral variables (for reviews see Brophy, 2005; and Pintrich & Schunk, 2002). For example, different goals have been linked to the experience of different positive and negative emotions, to different self-regulation processes and attributions for success and failure, and to specific engagement or withdrawal of particular learning behaviors (such as task persistence and help-seeking). In addition, readers would benefit from reviewing work by Elliot and his colleagues (e.g., Elliot & McGregor, 2001) who have evaluated a comprehensive range of other motivational and developmental antecedents as well as potential consequences of achievement goals, while developing the 2×2 model of goal orientation.

The importance of collecting validity evidence for one's cluster solution is highlighted by questioning whether the students in Cluster 6 of the 4-factor solution have truly high achievement goals across the four dimensions or whether these students simply share the same response style. In other words, are the high subscales scores for this cluster a result of their high goal orientations or a result of the style in which they responded to the items (e.g., choosing the highest response for each item)? There are three reasons why a response set is not a plausible reason for these subscale scores. First, many items on the modified AGQ are reverse-scored thus decreasing the likelihood of a response set. Second, evidence exists to support the notion that students at this university put forth adequate effort and view the results of Assessment Day as important (Sundre & Wise, 2003; Wise & Kong, 2005). Third and most importantly, the pattern of means for this cluster on the measures of motivational disposition provides validity evidence for this cluster.

4.3. Are the more complex conceptualizations used in this study the best operational definitions of goal orientation?

In the current article, we evaluated 2-, 3-, and 4-factor conceptualizations of achievement goal orientation, which begs the obvious research question of which conceptualization provides the best operational definition for achievement goals. However, we should note that the number of factors that need to be assessed is still a topic of great theoretical and empirical debate (Brophy, 2005; Harackiewicz et al., 2002; Midgley et al., 2001). While some researchers favor one of the three conceptualizations focused on in the current article, other researchers are expanding the conceptualization to include other possible goal distinctions (e.g., Grant & Dweck, 2003; Pieper, 2003). Although continued expansions may prove to better capture the breadth of the construct as more research evidence is collected, they have not been used as frequently as 2-, 3-, and 4-factor conceptualizations. Therefore, we focused on the 2-, 3-, and 4-factor conceptualizations of achievement goals so that the results of our study would be useful to researchers debating among these conceptualizations. We also were motivated in the current study to evaluate whether the adoption of one of these more complex conceptualizations would allow us to better differentiate among students. We found this indeed to be the case, and therefore our results add support to the idea that more complex conceptualizations utilizing approach and avoidance dimensions in addition to mastery and performance dimensions can be useful in educational practice and research. It was also the purpose of this article to provide instruction on a technique that could be used to assess whether various conceptualizations of goal orientation are useful in differentiating among students. We encourage other researchers to employ LPA techniques to gather validity evidence for their perspective of choice, and as new conceptualizations of achievement goals emerge.

4.4. Do the LPA results differ from our previous study using traditional clustering methods?

There are some similarities between the results found in our current study and in our previous study (Pastor et al., 2004), which used hierarchical and non-hierarchical traditional clustering techniques to examine differences in the goal orientation profiles of college students. The number of clusters we found for each conceptualization was similar: five, five, and six clusters for the 2-, 3-, and 4-factor conceptualizations in the current study and 5, 6, and 7 in the previous study. We have more confidence in the number of clusters found in the current study because we were able to utilize more rigorous criteria when deciding upon our final models. By being able to use the BICs, LMRs, and χ^2 difference tests, we felt the subjectivity associated with choosing a final model was reduced. The retention of Cluster 6 in the 4-factor solution, however, illustrates how subjectivity is not entirely avoided when using LPA. For instance, other researchers may have justified dropping Cluster 6 because of its small sample size and non-significant Lo–Mendell–Rubin likelihood ratio test. However, we felt that the existence of this small, aberrant group of students would be of interest to goal orientation researchers.

Although the number of profiles decided upon was similar in our current and previous studies, the nature of the profiles differed and again, we have more confidence in the LPA profiles because the method allowed us to fit a variety of different models to the data. Recall that while the traditional techniques are most appropriate to use with data whose cluster covariance matrices conform to a constrained Model C specification, LPA can be used with data having a variety of different forms for $\mathbf{\Sigma}_k$. In all our LPA solutions, superior fit was obtained by allowing not only the means, but the variances and covariances among the goal orientation factors to vary across clusters. The fact that a model allowing these parameters to vary across clusters was needed to adequately describe the data makes us question the results of our previous study. With a college-aged population, the present article suggests that a model less restrictive than the one most appropriate for traditional techniques is needed. Related to this point is another reason why we prefer LPA; LPA is not biased towards creating clusters of equal size, a known disadvantage associated with commonly used traditional methods and evident in our previous article.

We also prefer LPA because it allows, unlike traditional clustering methods, fractional cluster membership. LPA results are often used to classify students into clusters and then examine how the students differ on external variables, such as GPA. When LPA results are used in this manner, the researcher can either use modal assignment to classify students into clusters or represent students' fractional cluster membership through utilization of the posterior probabilities. The same decision has to be made when, as illustrated in this study, the model parameters estimated in one sample are used to classify students in another sample. If the classification accuracy of a model is high, either method can be used with little impact on the results. For instance, if the classification accuracy had been extremely high in the present study, it would have made little difference whether dummy-coded variables or posterior probabilities had been used to represent cluster membership in Step 3. However, because the classification accuracy was only moderate in this study, it is likely that different results would have been obtained. We feel that it was important to capture the classification accuracy of the LPA model in our Step 3 analyses and were pleased that we had the choice of using the posterior probabilities for such a purpose. Note that we would *not* have had a choice in how to represent cluster membership in our Step 3 analyses had we used traditional clustering techniques.

4.5. Other uses of LPA

In the present study, we examined differences among clusters in measures of motivational disposition and academic achievement by using the posterior probabilities of cluster membership as predictors in several regression equations. We could have also incorporated these variables directly into the LPA model which would have required defining each variable either as a predictor or an outcome of the latent categorical variable of cluster membership. For instance, the measures of motivational disposition and SAT score could have been used as predictors of cluster membership and semester GPA as an outcome of cluster membership. Had these variables been incorporated into the model, it is possible that different results than those found in the present study would have been obtained. This may seem like an undesirable result, however, many researchers, such as Muthén (2004), actually advocate for the use of these variables in the model when one is trying to decide upon the number of clusters to retain and the particular parameterization of $\mathbf{\Sigma}_k$. The reasoning is that model misspecification, and thus misleading parameters, may result if the variables that are not included in the LPA model have important relationships with the variables that are included in the model. We did not use this approach in the current study because we wanted to keep the illustration of LPA simple. However, it is suggested that future research incorporate these variables into the LPA model to examine if the results differ from those found in the current study.

Although this study illustrated a number of uses and benefits of adopting LPA, it does not fully capture the different ways in which LPA models can be used. For instance, only continuous cluster indicators were used in the present study and it was assumed that the within-cluster distribution of these indicators was multivariate normal. In latent variable mixture modeling, both categorical and continuous variables can be used as cluster indicators, with the within-cluster distribution specified as being the one most suitable for the indicator in question.

We also assumed in our article that the same factor structure applied to all persons in our sample and thus conducted the LPA using subscale scores. Another possibility would have been to use items as input into the analysis and instead of LPA, utilize a factor mixture model to examine population heterogeneity. This approach would have allowed us to explore the extent to which the parameters of a proposed measurement model were invariant across clusters. This is similar to multiple-group factor analysis which is used to assess the measurement invariance of a factor model across groups, but differs in that group membership is not known. If a model in factor mixture modeling is found to be invariant across clusters (with respect to both the factor structure and other restrictions placed on the model), then cluster profiles can be compared at the latent mean level. Further information regarding factor mixture modeling can be found in Gagné (2006), Lubke and Muthén (2005), and Yung (1997).

Readers wanting to use LPA should keep in mind one of the limitations of the procedure, which is that few simulation studies have been done investigating the sample size needed for adequate power and good estimation of parameters as well as the performance of the cluster selection criteria when used with data that may be violating the distributional assumptions that have been made. Until such studies are completed, it is suggested that researchers perform their own simulation study using the Monte Carlo facility in Mplus (Muthén & Muthén, 2002).

5. Conclusions

Researchers desiring to take a more person-centered approach to analyzing their data often turn towards median-split techniques or cluster analysis for the purposes of classifying students into homogeneous subgroups. In this article, we showcased a latent variable technique, LPA, which could be used for such a purpose and illustrated many of the advantages associated with its use. By using LPA, we were able to utilize more rigorous criteria when deciding upon our final cluster solutions, represent students' cluster membership fractionally, and classify students from another sample into clusters. Our primary purpose for applying this technique was to inform the current debate in the goal orientation literature as to whether more complex conceptualizations of the construct were needed to better distinguish among students and to predict achievement-related outcomes. The information provided by our results was mixed. Although the number and nature of the profiles were similar across conceptualizations, our ability to differentiate students in motive to avoid failure increased when more complex conceptualizations were used. However, use of more complex conceptualizations did not increase our ability to predict one achievement-related outcome, semester GPA. Researchers are encouraged to build upon the techniques and approach used in the current study to examine if the cluster profiles from the various conceptualizations of achievement goals not only replicate, but differ in ways not examined in the current study. Such research will not only provide information regarding the consistency and validity of the cluster solutions, but also help us understand what kind of relationships different educational outcomes have with the various profiles.

Appendix A. Mplus syntax for mixture modeling

The following syntax illustrates how to use Mplus version 3.01 for mixture modeling. Numbers to the far left should not be included in the syntax and are only included here to ease instruction. We use as an example the 2-factor conceptualization (line 4; map = mastery-approach subscale score; pap = performance-approach subscale score) and a three cluster model (line 5). The word "mixture" on line 6 indicates that the analysis type is mixture modeling while line 7 is used to define the number of random sets of starting values to use (e.g., 100) as well as the number of those sets associated with the highest log-likelihood values (e.g., 10) to use as starting values in the final optimizations.

Lines 9–20 are used to specify different specifications for $\mathbf{\Sigma}_k$ as shown in Table 1. If left unaltered, the syntax would result in Model E. To obtain Model D, lines 14, 17, and 20 need to be commented out (by placing an exclamation mark at the beginning of the line). Model C can be obtained by additionally commenting out line 11. For Model B, lines 12–20 need to be commented out and Model A can be obtained by additionally commenting out line 11. The syntax below is written for models that allow the means to vary across cluster indicators and clusters. The syntax can be altered to constrain means, provide starting values for means, or to fix means at certain values by including lines that refer specifically to the cluster means (e.g., "[map]; [pap];").

To provide starting values of 5 and 6 for the map and pap variances respectively of Cluster 1, line 13 would need to be altered to read: "map*5; pap*6;". To cross-validate a model as we did in Step 2 of this article, the syntax would need to be altered to read in the Sample 2 data and the parameter estimates would need to be fixed at the Sample 1 values. For example, to fix the value of the Cluster 1 covariance at −3, line 14 would need to be altered to read: "map with pap@-3;".

On line 21, Tech 7 is used to obtain the sample statistics for each cluster (calculated by weighting observations by the posterior probabilities); Tech 11 to obtain the LMR and Tech 13 to obtain the SK tests along with univariate, bivariate and multivariate indices of skewness and kurtosis. Lines 22 and 23 provide plots of the cluster solutions similar to those in Figs. 1–3. Lines 24-25 create an output data set that in this example contains map, pap, the posterior probabilities associated with Clusters 1, 2 and 3 and a cluster membership variable (based on modal assignment).

```
1   TITLE:          LPA for 2-factor conceptualization & 3 Clusters
2   DATA:           FILE IS spr03_AGQ.dat;
3   VARIABLE:       NAMES ARE id map pap pav mav;
4                   USEVARIABLES ARE map pap;
5                   CLASSES = c(3);
6   ANALYSIS:       TYPE = mixture;
7                   STARTS = 100 10;
8   MODEL:
9       %overall%
10      map; pap;
11      map with pap;
12      %c#1%
13      map; pap;
14      map with pap;
15      %c#2%
16      map; pap;
17      map with pap;
18      %c#3%
19      map; pap;
20      map with pap;
21  OUTPUT:         TECH7 TECH11 TECH13;
22  PLOT:           TYPE = Plot3;
23                  SERIES = map pap(*);
24  SAVEDATA:       SAVE = CPROBABILITIES;
25                  FILE IS postprobs.DAT;
```

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