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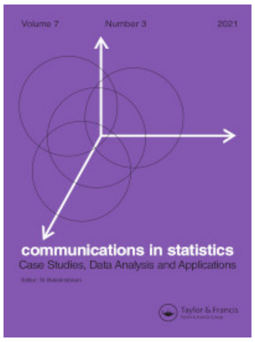
Published in:
Communications in Statistics Case Studies Data Analysis and Applications

DOI:
10.1080/23737484.2021.1911719



Communications in Statistics: Case Studies, Data Analysis and Applications

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ucas20

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To cite this article: Denise M. Blom, Matthijs J. Warrens & Meike Faber (2021) School motivation profiles of Dutch 9th graders, Communications in Statistics: Case Studies, Data Analysis and Applications, 7:3, 359-381, DOI: 10.1080/23737484.2021.1911719

To link to this article: https://doi.org/10.1080/23737484.2021.1911719

Published online: 01 May 2021.

COMMUNICATIONS IN STATISTICS: CASE STUDIES, DATA ANALYSIS AND APPLICATIONS
2021, VOL. 7, NO. 3, 359–381
https://doi.org/10.1080/23737484.2021.1911719

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ABSTRACT

The aim of this study was to identify school motivation profiles of Dutch 9th grade students in a four-dimensional motivation space, including mastery, performance, social and extrinsic motivation. Multiple clustering methods (*K*-means, *K*-medoids, restricted latent profile analysis) and multiple indices for selecting the optimal number of clusters were applied. The statistical selection methods did not completely concur on the optimal number of clusters, but a clear common denominator was provided by the Calinski-Harabasz index and the minimum and mean Silhouette values. All three indices indicated two clusters as the optimal number, regardless of the clustering method used: one cluster of 9th graders with high average scores on all dimensions and one cluster with low mean scores on all dimensions. In addition, we explored the substantive interpretation of multiple cluster solutions. It was discovered that most students are in clusters that can be classified into one of three profile types that may differ in level: (1) approximately equal mean scores on all dimensions, (2) relative high mean scores on mastery and social motivation, and (3) a relatively low mean score on performance motivation. The latter profile type is believed to be a new discovery.

ARTICLE HISTORY
Received 11 November 2019
Accepted 24 March 2021

KEYWORDS
Mastery motivation; performance motivation; social motivation; extrinsic motivation; *K*-means; *K*-medoids; latent profile analysis; profile type

1. Introduction

1.1. School motivation dimensions

Motivation in students is an important research topic in educational research. Students can show different levels and orientations of motivation. Where some children aim to master a new skill, and are mastery oriented, others aim to receive high grades, and thus are more performance oriented (Elliot and McGregor 2001). Specifically, a mastery goal orientation is often related to students' engagement with school tasks (Gonida, Voulala, and Kiosseoglou 2009), high levels of metacognitive activity (Schmidt and Ford 2003), and their self-efficacy beliefs (Pajares, Britner, and Valiante 2000; Coutinho and Neuman 2008), whereas performance goal orientation generally is related to high levels of effort (Elliot and Church 1997) and school performance, such as grades (e.g.

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Table 1. The four school motivation dimensions and their descriptions considered in this study.

Dimension	Description
Mastery motivation	Relates to task interest and degree of willingness to work hard in school
Performance motivation	Relates to individual goals to outperform others and assume leadership roles
Social motivation	Relates to individuals' preference for cooperation with other students and seeking group success
Extrinsic motivation	Relates to individuals' goals to seek social recognition and tangible rewards

Elliot and Murayama 2008; Pintrich 2000; Giota 2010). School motivation has been found to be a significant predictor of educational outcomes such as school grades (Schunk, Pintrich, and Meece 2008), and self-efficacy beliefs (Pajares, Britner, and Valiante 2000).

Besides mastery and performance goal orientation, Maehr (1984), and Mcinnerney and Ali (2006) proposed two additional goal orientations, namely a social goal orientation and an extrinsic goal orientation. Students with a social goal orientation focus on the social gains of academic achievements, meaning that they have social grounded reasons to study (McInerney and Ali 2006; Urdan and Maehr 1995). Furthermore, students with an extrinsic goal orientation aim to gain rewards or praise through their studying (Ryan and Deci 2000). Theoretical work on goal orientations usually differentiates between avoidance and approach versions of mastery and performance goal orientation. This means that children either aim for mastery or high performance (approach), or see tasks as threatening instead of challenging and avoid learning (Elliot and Church 1997; Elliot and McGregor 2001). Maehr's theoretical framework of four motivation dimensions only includes approach goals and no avoidance goals. Therefore, in this paper, our focus is on the four approach tendencies of mastery, performance, social, and extrinsic motivation (see Table 1).

Research found that students rarely show on just one goal orientation. Usually, students show a mixed profile of the different orientations that motivate them to achieve in school. For instance, some students score high on all motivation dimensions, whereas other students score high on some dimensions and low on others (e.g., Elliot and McGregor 2001; Giota 2010; Van Yperen 2006). Because the different dimensions are not taken into account in many studies, researchers may be drawing incomplete conclusions. Exploring how the different goal orientations are interlinked and represented in the students' motivation profiles could help researchers get a more complete picture of how motivation influences school outcomes.

Korpershoek, Kuyper and Van der Werf (2015) gave an extensive overview of variable-oriented research on mastery and performance motivation in children. Variable-oriented methodology focuses on relations between variables, changes in these variables over time, and assumes that the population follows universal laws of human behavior (Von Eye and Bogat 2006). This means that inexplicitly, the assumption is that the population is homogenous and that trends on the group level can thus be aggregated to the individual level (Von Eye and Bogat 2006).

Various authors have looked for profiles of mastery and performance motivation dimensions using cluster analysis, a person-oriented methodology (Wilson et al. 2016). Person-oriented research, besides the focus on (groups of) individuals instead of variables, explicitly assumes the population is heterogeneous. Applying a person-oriented methodology to the students' motivation dimensions means we are taking a holistic interactionist perspective, wherein a student is viewed as the unit of analysis, with all motivation dimensions considered simultaneously (Von Eye and Bogat 2006; Wilson et al. 2016).

School motivation profiles that have been found in research on mastery and performance goal orientations consist of (1) mastery students, i.e., students that score above average on mastery goals and below average on performance goals, (2) multigoal students, i.e., students that score above average on mastery and performance goals, and (3) low-motivated students, i.e., students that score below average on both goal orientations (Korpershoek et al. 2015). Mastery students have the best profile for school adjustment, while low-motivation students usually have the worst adjustment profiles (Wilson et al. 2016).

Korpershoek et al. (2015) were the first to use cluster analysis to study dimensions of school motivation in the context of the four goal orientations. More precisely, these authors used latent profile analysis (LPA) to identify distinct motivation profiles within a sample of the 9th-grade secondary school students based on the four motivation dimensions (mastery, performance, social, and extrinsic). LPA is a model-based method of clustering that is frequently applied. However, it is unclear whether this particular clustering method is the best choice for studying school motivation dimensions. In this study we build on the research by Korpershoek et al. (2015): we further explore profiles of school motivation and we apply multiple clustering methods, namely K-means, K-medoids, and LPA (Hennig, Meilă, Murtagh, and Rocci 2016).

1.2. Cluster analysis

Classifying objects (individuals, products, and animals) is an important part of scientific practice. Cluster analysis is a commonly used person-oriented methodology that can be used to find clusters (groupings) in multivariate data (Köhn, Steinley, and Brusco 2010). There are many different clustering methods and performing a cluster analysis involves making a number of choices (Jain 2010; Hennig and Liao 2013; Tan, Steinbach, and Kumar 2014) including, selecting the clustering method, selecting the variables as input for the clustering method, whether or not to standardize variables, how to handle outliers, and selecting the number of clusters. The various decisions are important because different choices usually lead to different clusters (Hennig et al. 2016).

Clustering methods may be based on different cluster concepts (Anderlucci and Hennig 2014; Hennig et al. 2016). In the traditional distance-based paradigm clusters are subsets of the dataset that have small within-cluster distances and are well separated from other clusters. In contrast, in model-based clustering clusters are defined by parametric probability distributions that can be interpreted as to generate homogeneous groups of objects. The complete dataset is usually modeled by a mixture of these distributions. Clustering methods based on different cluster concepts usually serve different aims (Anderlucci and Hennig 2014). One may be interested in finding well-separated clusters with small within-cluster distances, or one may be interested in finding the "true" clusters as if the data were actually generated from a model. It is therefore important to define the aim of the cluster analysis and make appropriate choices (e.g., selecting the clustering method) accordingly (Hennig et al. 2016).

In this study we will investigate school motivation of students in Dutch secondary education using clustering methods. School motivation profiles have not been comprehensively studied and there is no literature guiding users what clustering method to use for this type of research. Multiple clustering aims, either from the distance-based, model-based paradigms or another paradigm, may be legitimate for studying these profiles. Some statisticians claim the true aim of a cluster analysis should always be to find the "true" clusters in the data (Anderlucci and Hennig 2014). However, this aim may be unattainable for our study, because it is unclear if there is a true model for school motivation data. Any choice of a particular model is basically arbitrary.

From discussions with researchers on potential clustering aims, we have learned that small within-cluster distances is an important aim. That is, in behavioral and social sciences researchers commonly want the individuals (or other objects) in the groups produced to have very similar scores on the input variables. Clear separation of the clusters would be a nice feature of a clustering as well, but often separation seems not feasible given that the data points form a continuous cloud in the variable space if the variables are composites of questionnaire items and educational (performance) measurements. Small within-cluster distances also seems an important clustering aim in person-oriented motivation research. Thus, our clustering aim will be small within-cluster distances.

1.3. The current study

The aim of the present study is to identify school motivation profiles among Dutch students in the 9th grade. Since it is unclear what clustering method is best suited for studying school motivation dimensions, we will apply multiple clustering methods. More precisely, in line with our clustering aim (of finding clusters with small within-cluster distances) we will apply three clustering methods that tend to produce groups with small within-cluster distances. Two methods are distance-based, namely K-means and K-medoids (Kaufman and Rousseeuw 1990; Steinley 2006; Jain 2010), and one method is model-based, namely LPA with restrictions on the parameters. Korpershoek et al. (2015) also used LPA to study profiles of school motivation, but they did not use restrictions on the parameters.

In the cluster analysis literature, a large number of methods to help select the number of clusters have been proposed (Hennig and Liao 2013; Kim 2014; Hennig et al. 2016; Warrens and Ebert 2021). However, there is no consensus in the literature on how to select the number of clusters can best be justified. A best practice is to compare multiple selection methods in order to decide how many clusters is appropriate (Hennig et al. 2016). Therefore, we apply six (commonly used) indices for selecting the number of clusters, namely the Dunn index (Dunn 1974), the Calinski-Harabasz index (Calinski and Harabasz 1974), the WB-index (Zhao and Fränti 2014), the Silhouette coefficient (Rousseeuw 1987; de Amorim and Hennig 2015), Akaike's information criterion (AIC; Akaike 1987; Burnham and Anderson 2004), and the Bayesian information criterion (BIC; Schwartz 1978; Burnham and Anderson 2004).

The paper is organized as follows. In the method section, we present the real-world dataset, descriptions of the measurements, the three clustering methods, and the indices for selecting the number of clusters. In this section, we also present the statistical analysis plan. After this section, we present the results. We first discuss the outcomes based on the indices for selecting the number of clusters. This is followed by a substantive interpretation of the clusters. The final section contains a discussion.

The authors have no interest invested in the methods studied nor the software used. As far as the authors can judge, the present study is a neutral benchmarking study, as described in Van Mechelen et al. (2018).

2. Method

2.1. Sample

The data originate from the large-scale longitudinal research study COOL5-18 performed in the Netherlands between 2007 and 2016 (http://www.cool5-18.nl; Timmermans et al. 2017). This research study followed students from aged 5 to 18 in their school career. In school year 2007/2008, 80 secondary schools with in total 21,384 9th graders participated in COOL5-18.

For 1,451 students one or more motivation scores were missing, which is an issue since K-means and K-medoids analyses require complete data. We did not replace these scores, for example, with imputation methods. Instead, we ignored all students with at least one motivation score missing. Although this

Table 2. Means and standard deviations (between brackets) of motivation dimensions and age across gender.

Variable	Male ($n = 6,702$)	Female ($n = 7,115$)	Total ($N = 13,933$)
Mastery	3.28 (0.60)	3.29 (0.61)	3.28 (0.60)
Performance	2.30 (0.78)	1.94 (0.76)	2.12 (0.79)
Social	3.09 (0.61)	3.24 (0.62)	3.17 (0.62)
Extrinsic	2.74 (0.76)	2.63 (0.78)	2.69 (0.77)
Age	15.2 (0.59)	15.1 (0.54)	15.1 (0.57)

was not investigated, we do not expect that list-wise deletion of students with missing data will have a major impact on representativeness of the sample and the clustering results. The final sample consists of N = 13,933 students. There are 6,702 boys (48%) and 7,115 girls (51%), and for 116 students their gender was not recorded (1%). Information on age is presented in Table 2.

2.2. Population

The study COOL5-18 provided a representative reference sample for students aged 5 to 18 in the Netherlands by using different criteria of sampling (e.g., direction, province, degree of urbanization of the school, and the school performance relative to other Dutch schools) and created an additional sample especially for schools with social-ethnic deprivation (Timmermans et al. 2017). In this study, the population of interest consists of all 9th graders in the Netherlands.

2.3. Measurements

We will use four measurements of school motivation. The four constructs were assessed with the Dutch version of the Inventory of School Motivation (ISM; McInerney and Ali 2006). This inventory consists of 32 items with a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). A high reliability in terms of Cronbach's alpha (Cronbach 1951) was found for all subscales of the inventory: mastery motivation (9 items, $\alpha = .77$), performance motivation (7 items, $\alpha = .84$), social motivation (7 items, $\alpha = .74$), and extrinsic motivation (9 items, $\alpha = .86$). Together, the four subscale scores form a school motivation profile of a student.

2.4. Clustering methods

In line with our clustering aim (of finding clusters with small within-cluster distances), we will consider three clustering methods that tend to produce groups with small within-cluster distances: K-means, K-medoids and LPA.

K-means

K-means is the most widely applied clustering method of the 20th century. It is a so-called partitioning method: for a set of N objects the method will assign each object to one of K nonoverlapping clusters. K-means has been applied in many different research disciplines and researchers have found many meaningful groupings with K-means (Steinley 2006; Jain 2010). In the clustering literature, it has been shown that other clustering methods will provide better clustering results than K-means in a variety of situations (Fränti and Sieranoja 2019). Nevertheless, K-means is still a popular method. First of all, the method is rather easy to implement. Furthermore, it is a multipurpose method in the sense that it can be applied to any data for which the distance measure makes sense. The default distance measure is the squared Euclidean distance, but other distance measures may be used as well. Moreover, K-means is an extensively studied method, and it may be preferred to use an extensively studied method which limitations are known, rather than a less-studied method that is potentially better, but may have hidden limitations (Fränti and Sieranoja 2019).

The K-means algorithm is characterized by the following steps: (1) pre-define the number of clusters K to be found in the dataset; (2) select random K of N data points as potential means (centroids) of the clusters; (3) assign each object to the cluster whose mean has the least-squared Euclidean distance; (4) calculate the new means of the objects in the new clusters; (5) repeat steps 3 and 4 until the assignments no longer change. The algorithm can get stuck in a local optimum. A common way to deal with local optima is to consider multiple random starts (Steinley 2006).

For the application of K-means it is not required to assume that clusters have a particular shape. The K-means algorithm minimizes the squared Euclidean distance between objects in a cluster and the centroid of that cluster. The centroid of a cluster is not necessarily one of the objects (data points) designated to the cluster. In general, K-means will produce homogeneous clusters of spherical shape (Hennig et al. 2016). If variables have different ranges, and if it is desirable that all variables contribute evenly to the clusters found, then the variables need to be standardized before performing the analysis.

If a ground truth is known, K-means usually performs well when the number of clusters is not too large, and when the clusters are well separated (Steinley 2006). For a relatively small number of clusters K-means may exhibit good performance even with overlapping clusters. Furthermore, when the number of clusters is large the performance of K-means may depend to a large extent on the initialization method that is applied (Fränti and Sieranoja 2019).

K-medoids

K-medoids is, similar to K-means, a partitioning method: it assigns each of the N objects to one of K nonoverlapping clusters. The K-medoids algorithm is quite similar to the K-means algorithm, but in contrast to K-means, K-medoids uses objects as centers (medoids) of the clusters. Furthermore, the K-medoids algorithm can be used with arbitrary distances. K-medoids allows for deviations from the spherical cluster shape and the clustering method is more lenient regarding outliers (Hennig and Liao 2013).

Latent profile analysis
In model-based clustering, it is assumed that the data are generated from a mixture of underlying probability distributions (Fraley and Raftery 2002; Hennig et al. 2016). The particular form of model-based clustering used in this study will be referred to as latent profile analysis (LPA) and assumes that the clusters in the data can be described by mixtures of normal distributions. This assumption allows the user to use various statistics for making decisions (e.g. for deciding on the number of clusters). The form of a cluster can be defined by its parameters, i.e., means, variances, and covariances, and each cluster has its own parameters independent from other clusters.

LPA is a probabilistic clustering method that produces posterior probabilities. These probabilities specify for each object the degree of membership to the clusters. Objects can belong to multiple clusters with varying degrees of membership. We will obtain a partition from the LPA analysis by assigning each student to the cluster with the highest associated posterior probability.

In this study, we consider a relatively large number of clusters. With many clusters there are also many parameters that need to be estimated. It may be desirable to use restrictions of class-specific variance–covariance matrices, for example, because this may lead to more parsimony and stability of the parameters in the variance–covariance matrices. Furthermore, we want to find groups that have small within-cluster distances. For the version of LPA used in this study we will constrain the covariances to be zero and the variances to be equal across clusters.

2.5. Software

For applying the clustering methods, we used the R language and software environment (R Development Core Team 2008). For performing K-means we used the R function ClusterR with all default settings. For performing K-medoids we used CLARA (Clustering Large Applications; Kaufman and Rousseeuw 1990) which is an extension of K-medoids that can be used with a large number of objects to reduce computing time. CLARA applies the K-medoids algorithm to multiple subsamples of the dataset and keeps the best results. We used CLARA with all default settings. For performing LPA, we used the R package tidyLPA. We considered normal mixture models with zero covariances and equal variances across clusters.

2.6. Standardization of input variables

Distance-based algorithms like K-means and K-medoids calculate a number of distance measures. Variables that have a larger range tend to contribute more to these distance measures. If it is important that all motivation scores contribute equally to the analyses, it makes sense to put them on the same range, or standardize them before applying the clustering methods. All variables have the same range, since they are averages of scores on 5-point Likert scales. In this study we prefer to use the original scores and the variables will not be standardized.

2.7. Indices for selecting the number of clusters

Internal validity indices

The Dunn index, Calinski-Harabasz index, WB-index and Silhouette coefficient are so-called interval validity indices that can be used for evaluating clustering solutions (Saitta, Raphael, and Smith 2008; Jain 2010; Meilă 2016). The calculation of the coefficients requires the original data and a partition of the objects. For all four coefficients, the procedure for selecting the number of clusters is as follows: (1) obtain multiple clustering solutions with the same clustering method that differ in the number of clusters; (2) calculate the value of the index for all clustering solutions considered; (3) choose the solution (i.e. the number of clusters) for which the index value is highest (Dunn, Calinski-Harabasz, Silhouette) or lowest (WB-index). The aim of this procedure is to identify a solution with clusters that are well separated and have small within-cluster distances.

Suppose we have N objects and K clusters. Let the size of cluster C be denoted by $|C|$, and let the (Euclidean) distance between clusters C_i and C_j be denoted by $d(C_i, C_j)$. The Dunn index is defined as

$$\text{Dunn index} := \frac{\min\limits_{1\leq i<j\leq K} d(C_i, C_j)}{\max\limits_{1\leq k\leq K} |C_k|}, \tag{1}$$

that is, the Dunn index is equal to the minimum inter-cluster distance divided by the maximum cluster size. The Dunn index is an internal validity measures that is commonly used (Saitta et al. 2008).

Furthermore, let $d(r, s)$ denote the Euclidean distance between two data points $r, t \in C_i$ (students r and t in cluster C_i). Define for data point $r \in C_i$ the quantity

$$a(r) := \frac{1}{|C_i| - 1} \sum_{t\in C_i, t\neq r} d(r, t), \tag{2}$$

that is, the mean distance between student r and all other students in the same cluster, the quantity

$$b(r) := \min_{j\neq i} \frac{1}{|C_j|} \sum_{t\in C_j} d(r, t), \tag{3}$$

that is, the smallest mean distance of student r to all students in any other cluster, of which r is not a member, and the silhouette value

$$s(r) := \frac{b(r) - a(r)}{\max\{a(r), b(r)\}} \quad \text{if } |C_i| > 1, \tag{4}$$

and $s(r) := 0$ if $|C_i| = 1$. Using Eq. (4), the Silhouette coefficient is then defined as the mean $s(r)$ over all data points (students). Below, we will also consider the minimum and maximum $s(r)$ values for different number of clusters.

Next, let SS_B and SS_W denote, respectively, the overall between-cluster sums of squares and the overall within-cluster sums of squares (based on the Euclidean distance). The Calinski-Harabasz index is then defined as

$$\text{Calinski-Harabasz index} := \frac{SS_B/(K-1)}{SS_W/(N-K)}, \tag{5}$$

that is, the Calinski-Harabasz index is equal to the ratio of overall between-cluster to the overall within-cluster variance. Moreover, the WB-index is then defined as

$$\text{WB-index} := K \cdot \frac{SS_W}{SS_B}, \tag{6}$$

that is, the WB-index is equal to the number of clusters times the ratio of the overall within-cluster sums of squares to the overall between-cluster sums of squares. Some support for the use of the Calinski-Harabasz index was provided by Guerra et al. (2012), who compared various methods for selecting clusters. In their study, the Calinski-Harabasz index was overall the second best option, and the best option if the data contained no noise and there were not too much dimensions. In this study, the data are low-dimensional, since we have only four motivation variables.

Likelihood-based indices

The AIC and BIC are likelihood-based statistics that are basically standard tools in model-based data analysis (Burnham and Anderson 2004). They are commonly used to estimate the relative quality of each model in a collection of models. In model-based clustering, they are commonly used for selecting the number of clusters of mixture models. For both coefficients, the procedure for selecting the number of clusters is as follows: (1) estimate the parameters of a collections of models; (2) calculate the value of the index for all models considered; and (3) choose the model (i.e., the number of clusters) for which the index value is lowest. The aim of this procedure is to identify a model that has the highest quality relative to the other models.

Let p denote the number of estimated parameters in the model, and let L denote the maximum value of the likelihood function of the model. The AIC is then defined as

$$AIC := 2k - 2\log(L), \tag{7}$$

where log denotes the natural logarithm. Furthermore, the BIC is defined as

$$BIC := p\log(N) - 2\log(L). \tag{8}$$

Both the AIC and BIC have been studied extensively in the context of statistical model selection (cf. Burnham and Anderson 2004). The AIC is the best choice for model selection if effects between models are tapering effects, whereas the BIC is the best choice if one expects large effects between models (Burnham and Anderson 2004). We are not sure what effects to expect for the motivation data in this study, and therefore we will use both. In the context of cluster analysis, Nylund, Asparouhov and Muthén (2007) showed in simulation studies with small numbers of true clusters and without model error that the BIC is generally the best choice. Furthermore, a drawback of the AIC seems to be that it tends to select models with too many parameters (Hennig et al. 2016).

2.8. Statistical analysis plan

We first consider means and standard deviations of the motivation variables. This is followed by pairwise scatter plots of and correlations between the four motivation dimensions. Next, we consider the cluster solutions with 1 to 80 clusters of K-means, K-medoids, and LPA, respectively. The clusters identified by the clustering methods can be described by a profile of four mean scores (calculated over all students in a cluster) for the four motivation dimensions. We first attempt to identify school motivation profiles using statistical selection methods. For the K-means and K-medoids solutions, we consider the values of the Dunn index, Calinski-Harabasz index, WB-index, and Silhouette coefficient. For all LPA solutions, we determined the values of the Dunn index, Calinski-Harabasz index, WB-index, Silhouette coefficient, AIC and BIC.

After considering the statistical selection methods, we try to identify school motivation profiles using substantive arguments. Not all cluster solutions will be considered in detail. After considering a large number of cluster solutions we found that most cluster profiles of the motivation data in this study can actually be summarized by a relative small number of profile types, that can differ in level. There are four profile types that occur quite frequently. These will be referred to as the wave, flat, square root and bowl profile. Figure 1 presents these four profile types: wave (top left), flat (top right), square (bottom left), and bowl profile (bottom right). The naming of the profile types is related to the order of the motivation dimensions, being mastery, performance, social and extrinsic motivation. The definitions of the profiles are as follows.

1. Flat profile: all mean scores are approximately equal. A profile is classified as a flat profile if the (four) mean scores of a cluster on the motivation dimensions do not differ more than 1 point (on a 5-point Likert scale).
2. Square root profile: a relatively low mean score for performance motivation. A profile is classified as a square root profile if it is not a flat profile, if the

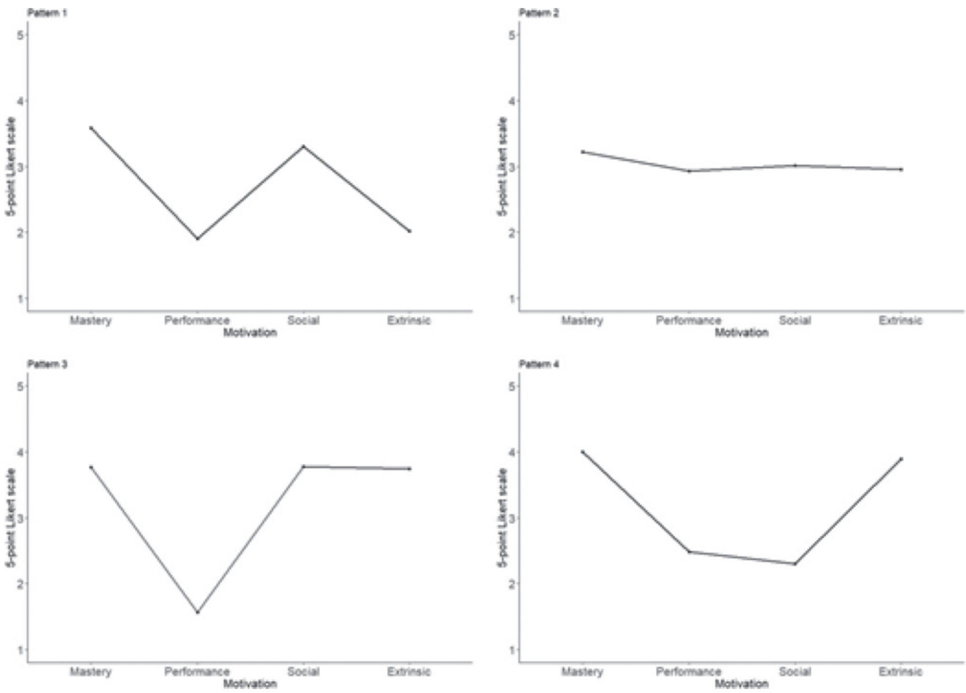

Figure 1. The four profile types used for classifying the profiles.

mean scores of mastery, social and extrinsic motivation are approximately equal (within .50 point), and if the mean score for performance motivation is at least .75 point lower than the highest mean score of mastery, social or extrinsic motivation.

3. Wave profile: high mean scores for mastery and social motivation. A profile is classified as a wave profile if it is not a flat profile, and if the mean scores for both mastery and social motivation are .50 point higher than the mean score for performance and extrinsic motivation.
4. Bowl profile: high mean scores for mastery and extrinsic motivation. A profile is classified as a bowl profile if it is not a flat profile, if the mean scores for mastery and extrinsic motivation are both higher than the both mean scores for performance and social motivation, and if either the mean score for mastery or extrinsic motivation is at least .75 point higher than the mean scores of performance and social motivation.

Not all profiles could be classified into the four profile types defined above. All other profiles were classified into a residual category. For each clustering solution, we determined how many of its clusters belonged to the profile types defined above. The cluster solutions are summarized using the percentages of students in each profile type.

It should be noted that by summarizing the cluster solutions into profile types we throw away the information on the level of the profiles. For instance, the distinction between high or low levels of a flat pattern are removed. Furthermore, the definitions of the above patterns are in a way arbitrary. One may consider alternative definitions. Nevertheless, we think using the profile types defined above provides a useful and meaningful way of classifying the profiles. The profile types were not defined too narrow since it turns out that the residual category in most studied cases contained less than 20% of the students. In other words, the four profile types in most studied cases classify the clusters of more than 80% of the students.

Considering many (i.e., more than the commonly considered 6–8) solutions allows us to select the number of clusters for both a commonly used range, i.e., solutions with 1–8 clusters, but also for a range that has been studied less, i.e., solutions with 9–80 clusters. Studying this many clusters is a possibility due to the size of the data set (N = 13,933). Even with a large number of clusters, all clusters may still contain a substantial number of students. Considering the range 1–80 clusters may provide new insights into the performance of clustering methods and indices for selecting the number of clusters that have not been found in studies that were limited to 2–8 clusters. Furthermore, in model-based clustering it is frequently found that the lowest values of the AIC and BIC correspond to the solution with the maximum number of clusters considered, usually a number between 5 and 8. Studying solutions with many more clusters may also provide new insights into the performance of the AIC and BIC.

3. Results

3.1. Descriptive analysis

Table 2 presents the means and standard deviations of the four motivation scores, for the total sample and for genders separately. The fourth column of Table 2 shows that the students on average scored lowest on performance motivation (2.12) and highest on mastery motivation (3.28). Two sample t-tests between boys and girls on all four motivation scores yielded significant results on the $\alpha = .001$ level for performance motivation ($t = 27.5$, $p < .001$), social motivation ($t = -15.3$, $p < .001$), and extrinsic motivation ($t = 8.66$, $p < .001$).

Figure 2 presents the six pairwise scatter plots of the four motivation dimensions. The plots show that there are no extreme outliers, at least not per two dimensions. No students were omitted from the subsequent analyses. Furthermore, the plots show that the point clouds are connected and dense. There are no well separated clusters, at least not in the two-dimensional subspaces, nor clear (overlapping) bivariate normal distributions.

For performance motivation the scatter plots show a floor effect. Students scored mostly at the lower range of the 5-point Likert scale on performance motivation. Therefore, variability on performance motivation will most likely

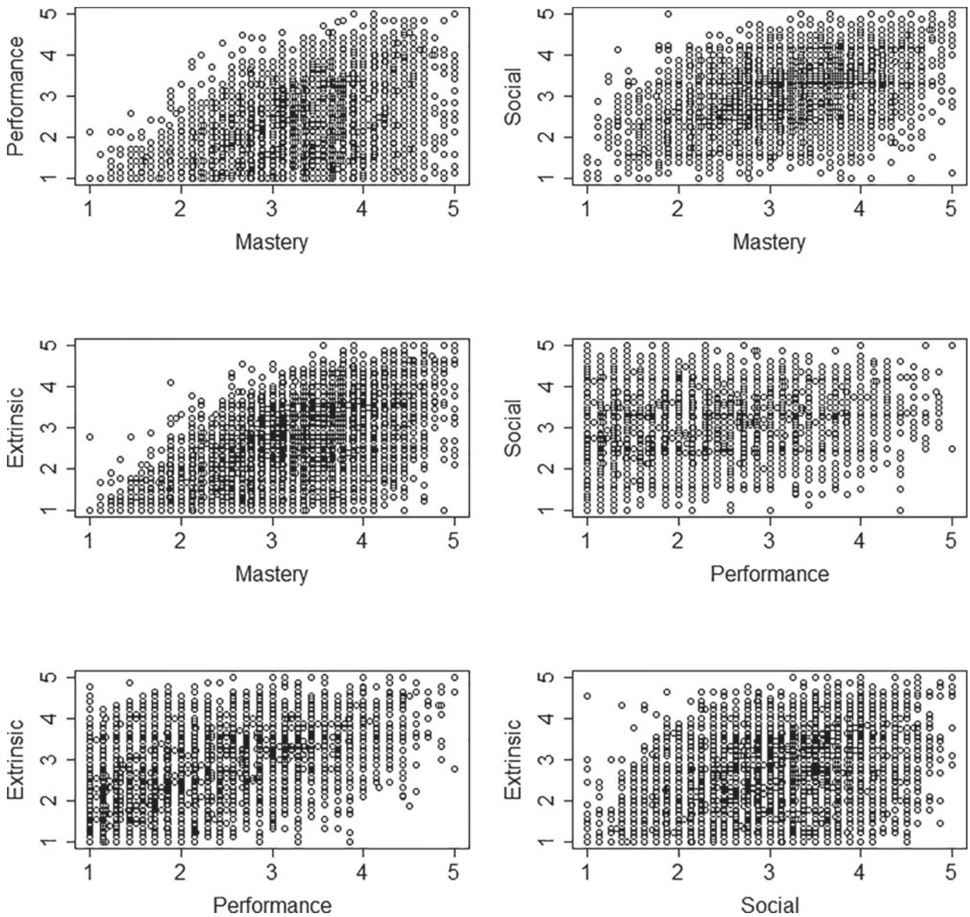

Figure 2. Pairwise scatter plots of the four motivation dimensions.

Table 3. Pearson correlations between the motivation variables.

	Mast. mot.	Perf. mot.	Soc. mot.
Performance motivation	.38		
Social motivation	.47	.16	
Extrinsic motivation	.53	.57	.36

be small across clusters and mean scores will generally be lower for all clusters.

Table 3 presents Pearson's correlations between the four motivation dimensions. All correlations differ significantly from 0 on the $\alpha = .001$ level. In concordance with previous studies, moderate correlations were found between performance and mastery motivation ($r = .38$), between social and mastery motivation ($r = .47$), and between social and extrinsic motivation ($r = .36$). Furthermore, for these data, we have high correlations between mastery and extrinsic motivation ($r = .53$) and between performance and extrinsic

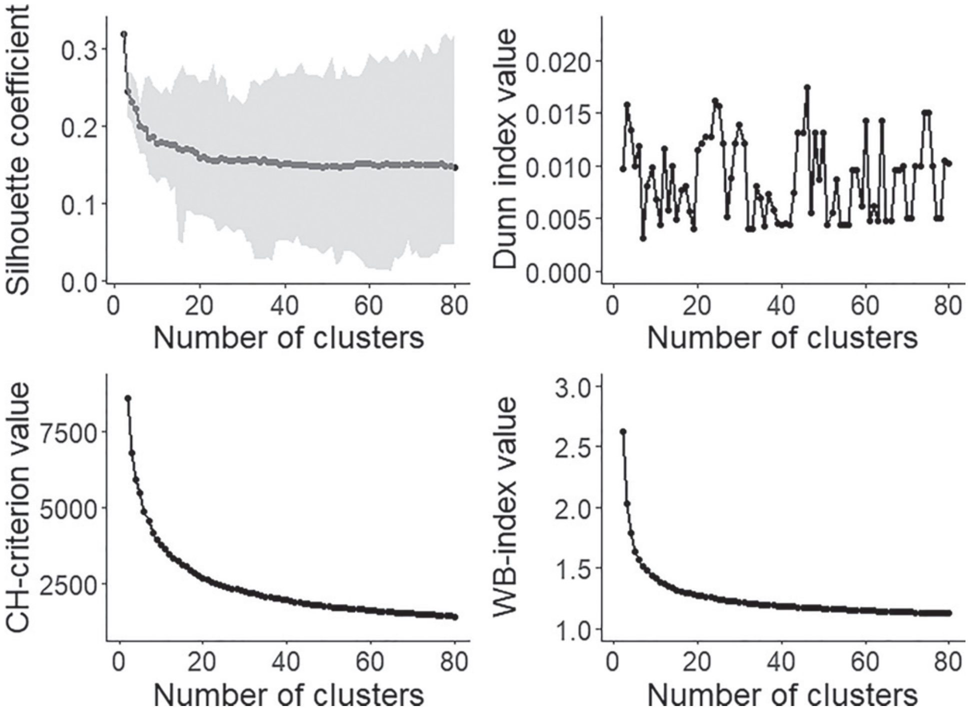

Figure 3. Plots of the index values for the K-means solutions.

motivation ($r = .57$), and a low correlation between performance and social motivation ($r = .16$).

3.2. Number of clusters based on indices

We obtained cluster solutions with 1–80 clusters using K-means, K-medoids and LPA. For each cluster solution with 2–80 clusters we determined the values of the Dunn index, Calinski-Harabasz index, WB-index, and Silhouette coefficient. For all LPA solutions we also determined the AIC and BIC. Plots of the index values as a function of the number of clusters are presented in Figure 3 (K-means), Figure 4 (K-medoids) and Figure 5 (LPA). The plots associated with the Silhouette coefficient also contain for each cluster solution the interval formed by the minimum and maximum value of $s(r)$ in Equation (4) of all data points (students) in gray.

For all three clustering methods, the values of the Calinski-Harabasz index and WB-index are concave upward and roughly decreasing functions of the number of clusters, with a steep drop at the start followed by a steady decline. Using the Calinski-Harabasz index to select the number of clusters, we find for all three clustering methods that two clusters are optimal. For all three clustering methods, the values of the Dunn index and Silhouette coefficient

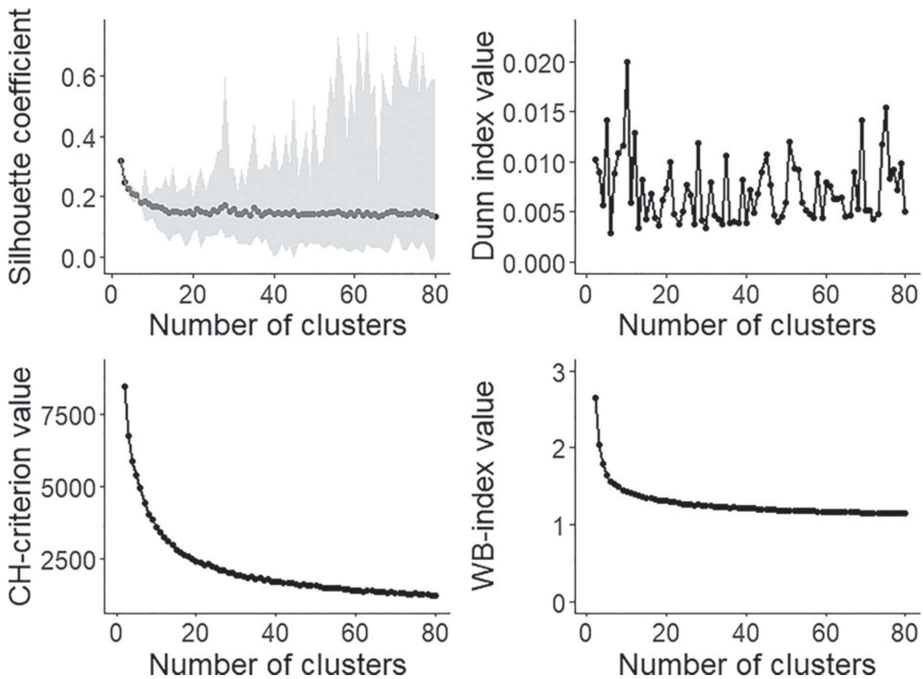

Figure 4. Plots of the index values for the *K*-medois solutions.

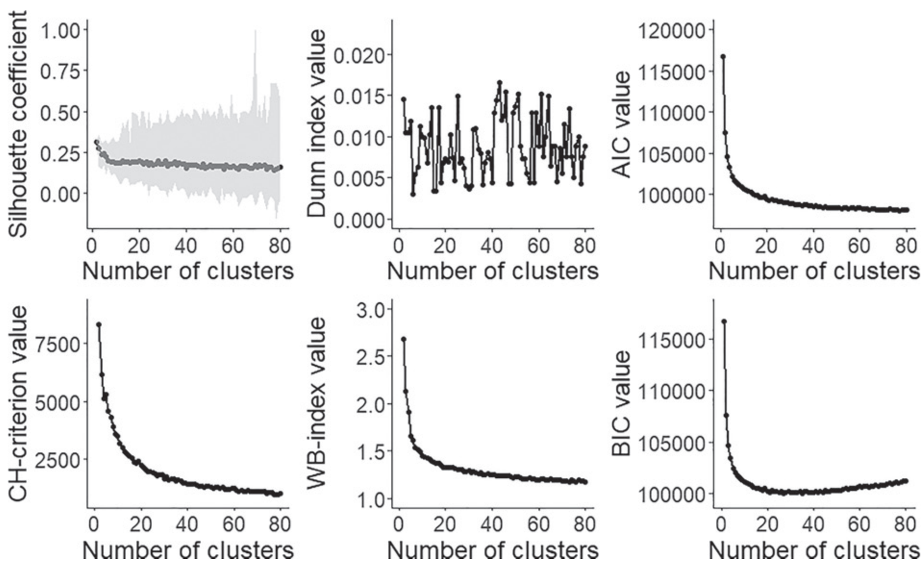

Figure 5. Plots of the index values for the LPA solutions.

exhibit nonspecific patterns that are not clearly increasing or decreasing in the number of clusters.

Figure 5 also presents the AIC and BIC values of the LPA solutions. The AIC and BIC are also concave upward and roughly decreasing functions of the number of clusters. The AIC has a steep drop at the start followed by a steady

Table 4. Minimum and maximum index values and corresponding number of clusters K across clustering methods.

	K-means		K-medoids		LPA	
Index	Value	K	Value	K	Value	K
Maximum Dunn	.0174	46	.0129	77	.0166	43
Maximum CH	8566.38	2	8462.83	2	8301.66	2
Minimum WB-index	1.126	80	1.145	10	1.174	73
Minimum Silhouette	.3109	2	.2961	2	.3032	2
Mean Silhouette	.3178	2	.3172	2	.3146	2
Maximum Silhouette	.3248	2	.7465	62	1.00	68
Minimum AIC					98021.30	77
Minimum BIC					99999.56	35

decline. LPA solutions with more clusters tend to have lower AIC values. In contrast, the BIC value first drops steeply but at some point slightly increases with the number of clusters.

Table 4 presents the minimum and maximum index values and the corresponding number of clusters K for all three clustering methods. As may be expected with this many cluster solutions, the different clustering methods combined with the various indices do not completely agree on the optimal number of clusters. When working with multiple clustering methods and multiple methods for selecting the number of clusters, a best practice is to compare the selection methods and find a common denominator (Hennig et al. 2016). In this study, there is a clear common denominator provided by the Calinski-Harabasz index and the minimum and mean Silhouette values. These three indices consistently point to two clusters as the optimal number, regardless of the clustering method used.

The characterization of the three 2-cluster solutions is as follows. All three cluster solutions consist of a cluster of students with high motivation and one with low motivation on all dimensions. Using the profile types in Figure 1, the high motivation clusters exhibit a flat (K-means, K-medoids) or a square root profile (LPA), and the low motivation clusters all exhibit a wave pattern. The cluster sizes of the high motivation clusters are $n = 7065$ (50.7%), $n = 6482$ (46.5%) and $n = 7912$ (56.8%), and the cluster sizes of the low motivation clusters are $n = 6868$ (49.3%), $n = 7451$ (53.3%) and $n = 6021$ (43.2%) for, respectively, K-means, K-medoids, and LPA.

3.3. Substantive interpretation of the clusters

To enhance the interpretation of the cluster solutions, all clusters of the K-means, K-medoids and LPA solutions with 1–80 clusters were classified into one of the four profile types in Figure 1 or the residual category. Figure 6 is a stacked bar plot which presents for each K-means solution the percentages of students contained in each profile type. For solutions with two, three and four clusters, the flat and wave profiles are the only patterns that occur. Furthermore,

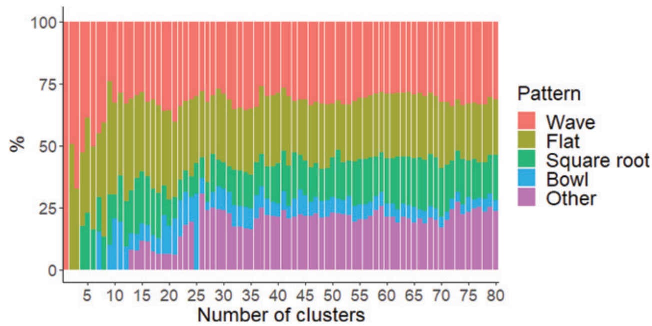

Figure 6. Stacked bar plot with percentages of students per profile type for all *K*-means solutions.

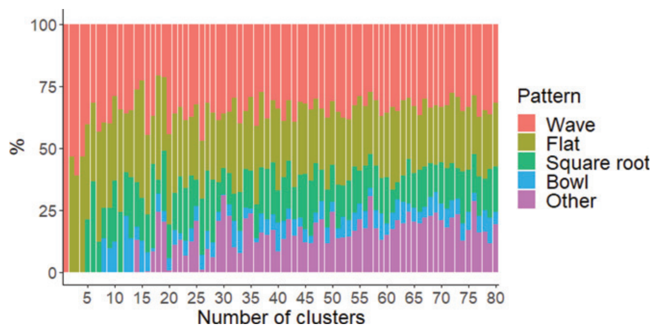

Figure 7. Stacked bar plot with percentages of students per profile type for all *K*-medoids solutions.

for consecutive solutions with a small number of clusters Figure 6 exhibits some oscillation. For solutions with 30 or more clusters the oscillation is much less extreme and the patterns are clearer. For solutions with 30 or more clusters, the dominant pattern is the wave profile (associated with approximately 30% of the students), followed by the flat profile (associated with approximately 25% of the students). To a lesser extent, the square root profile is also relevant for all solutions with five or more clusters. The bowl profile is quite rare in general. Moreover, most clusters of the K-means solutions (approximately 75%) can be classified using only three categories (flat, wave, and square root profiles).

Figure 7 presents for all K-medoids solutions with 1–80 clusters the percentages of students associated with each profile category. Figure 7 shows a similar picture as Figure 6, but in this figure, there is more oscillation for consecutive clustering solutions. Again, the dominant pattern is the wave profile (associated with approximately 30–35% of the students), followed by the flat profile (associated with approximately 25% of the students). Furthermore, for solutions with two, three, or four clusters, the flat and wave profiles are the only profile types that occur. The square root is relevant for all solutions with six or more clusters, and the bowl profile is quite rare. Like the clusters of the K-means solutions, most clusters of the K-medoids solutions (approximately 80%) can be classified using only the flat, wave and square root categories.

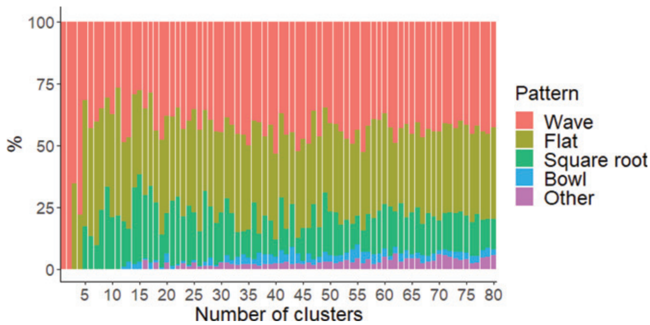

Figure 8. Stacked bar plot with percentages of students per profile type for all LPA solutions.

Figure 8 presents for all LPA solutions the percentages of students associated with each profile type. Figure 8 exhibits a similar degree of oscillation from left to right as Figure 7. The dominant patterns are, again, the wave profile (associated with approximately 35% of the students) and the flat pattern (associated with approximately 30% of the students). On average, there are more square root profiles (associated with approximately 25% of the students). For the LPA solutions, the bowl pattern is generally also quite rare.

There are several higher order similarities between the clustering solutions of K-means, K-medoids and LPA. For all three methods the flat and wave profiles are dominant profiles among the cluster solutions. Furthermore, for all three methods, the majority of profiles can be summarized by three types of profiles, that may differ in level, namely wave, flat and square root profiles. In addition, the bowl profile is quite rare for all three methods.

Combining the results of the three clustering methods, we may conclude that for solutions with 30 or more clusters 30–35% of the students belong to clusters that have a wave profile, 30–35% of the students are in clusters that have a flat pattern, and 20–25% of the students are in clusters that exhibit a square root pattern. Some solutions with less than 20 clusters fit into this description as well (i.e., have approximately the same composition of profile types), while other clustering solutions have different compositions of profile types.

4. Discussion

The aim of the present study was to identify school motivation profiles of the 9th graders in a four-dimensional motivation space, including mastery, performance, social, and extrinsic motivation. Since it is has not been comprehensively studied what clustering method is best suited for studying school motivation dimensions, we applied three clustering methods (K-means, K-medoids, and restricted LPA) that tend to produce groups with small within-cluster distances (in line with our clustering aim). Furthermore, since there is no consensus in the literature on how to select the number of clusters can best be justified, we used and compared six selection methods in order to decide how many clusters is appropriate.

We considered clustering solutions with different number of clusters (1 to 80). We first considered statistical methods to identify school motivation profiles. As may be expected with this many cluster solutions, the different methods did not completely agree on the optimal number of clusters. When working with multiple clustering methods and multiple methods for selecting the number of clusters, the best practice is to compare the selection methods and find a common denominator (Hennig et al. 2016). In this study, a clear common denominator was provided by the Calinski-Harabasz index and the minimum and mean Silhouette values. All three indices indicated two clusters as the optimal number, regardless of the clustering method used.

The characterization of the three 2-cluster solutions was as follows. All three cluster solutions consisted of a cluster of students with high motivation and one with low motivation on all dimensions. The high motivation clusters had approximately equal mean scores on all motivation dimensions, whereas the low motivation clusters all exhibited relative high mean scores on mastery and social motivation. The high motivation clusters contained 50.7%, 46.5%, and 56.8% of the 9th graders, and the low motivation clusters contained 49.3%, 53.3%, and 43.2% of the students, for, respectively, K-means, K-medoids, and LPA.

Next, we explored the substantive interpretation of multiple cluster solutions. We discovered that the data were structured in such a way that all profiles could be summarized by a relatively small number of profile types. In many solutions, most students are in clusters that can be classified in one of three profile categories, that may differ in level: (1) approximately equal mean scores on all motivation dimensions, (2) relative high mean scores on mastery and social motivation, and (3) approximately equal mean scores on mastery, social, and extrinsic motivation, and a relatively low mean score on performance motivation.

Regardless of the clustering methods, all clustering solutions consisted of three main profile types that have analogues in the motivation literature. The profile type that is characterized by relatively high mean scores on mastery and social motivation compared to the mean scores on performance and extrinsic motivation, corresponds to previous findings in the literature that students can pursue social goals next to academic goals (King and McInerney 2012). The profile type that is characterized by equal mean scores on all motivation dimensions corresponds to students that handle a multigoal approach. These two dominant profile patterns also occurred in the particular 6-cluster solution considered in Korpershoek et al. (2015).

We found a third common profile type that is characterized by equal mean scores on mastery, social, and extrinsic motivation, but a relatively low mean score on performance motivation. This profile type was not mentioned in Korpershoek et al. (2015) and is believed to be a new discovery. In addition, we found another new but rarer profile type which is characterized by high mean scores on mastery and extrinsic motivation and relatively low mean scores for performance and social motivation. The latter new profile types is only encountered when one considers clustering solutions with more than 10 clusters.

Our results support the statement by Korpershoek et al. (2015) that higher scores on extrinsic motivation are related to higher scores on performance motivation. This is emphasized by the correlation of size .57 for these data. Furthermore, it can be concluded that the findings support a multidimensional framework of school motivation. Stated differently, students differ in the type of motivation they pursue in order to achieve in school context. Typically, students tend to have mastery and social goal orientations and, in some cases, also extrinsic motivation. Performance motivation was relatively low for a large number of students.

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