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University and student segmentation: Multilevel latent-class analysis of students' attitudes towards research methods and statistics

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Background. It is often claimed that psychology students' attitudes towards research methods and statistics affect course enrolment, persistence, achievement, and course climate. However, the inter-institutional variability has been widely neglected in the research on students' attitudes towards research methods and statistics, but it is important for didactic purposes (heterogeneity of the student population).

Aims. The paper presents a scale based on findings of the social psychology of attitudes (polar and emotion-based concept) in conjunction with a method for capturing beginning university students' attitudes towards research methods and statistics and identifying the proportion of students having positive attitudes at the institutional level.

Sample. The study based on a re-analysis of a nationwide survey in Germany in August 2000 of all psychology students that enrolled in fall 1999/2000 ($N = 1{,}490$) and $N = 44$ universities.

Methods. Using multilevel latent-class analysis (MLLCA), the aim was to group students in different student attitude types and at the same time to obtain university segments based on the incidences of the different student attitude types.

Results. Four student latent clusters were found that can be ranked on a bipolar attitude dimension. Membership in a cluster was predicted by age, grade point average (GPA) on school-leaving exam, and personality traits. In addition, two university segments were found: universities with an average proportion of students with positive attitudes and universities with a high proportion of students with positive attitudes (excellent segment).

Conclusions. As psychology students make up a very heterogeneous group, the use of multiple learning activities as opposed to the classical lecture course is required.

Both students and instructors believe that students' attitudes towards research methods and statistics affect course enrolment, persistence, achievement, and course climate

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(e.g., Harlow, Burkholder, & Morrow, 2002; Hilton, Schau, & Olsen, 2004). There is some empirical evidence to support this belief. Several studies reported a small to moderate relationship between attitude towards statistics and course achievement, measured by test scores or grades (Gal, Ginsburg, & Schau, 1997; Harris & Schau, 1999; Vanhoof *et al.*, 2006; Waters, Martelli, Zakrajesk, & Popovich, 1988). Further, many students majoring in the social sciences reported experiencing stress and anxiety in statistics classes (Benson, 1989; Zanakis & Valenzi, 1997; Zeidner, 1991). Dillon (1982) went so far as to coin the term 'statisticophobia'.

If student attitudes towards research methods and statistics are so important, then we need instruments to assess them. At present, several inventories are used to assess attitudes towards statistics, such as the Statistics Attitude Scale (McCall, Belli, & Madjidi, 1990), the Attitudes Toward Statistics (ATS; Wise, 1985), the Survey of Attitude Toward Statistics (SATS; Carmona, Martinez, & Sanchez, 2005; Cashin & Elmore, 2005; Chiesi & Primi, 2009; Schau, Stevens, Dauphinee, & Del Vecchio, 1995), and the Statistics Attitude Survey (SAS; Roberts & Bilderback, 1980; Roberts & Saxe, 1982). Up to now, these instruments have been used in the research mainly to assess sex differences in attitudes towards statistics (e.g., Cherian & Glencross, 1997) and changed attitudes towards statistics (e.g., Harlow *et al.*, 2002) or to predict student performance (e.g., Dempster & McCorry, 2009; Lalonde & Gardner, 1993).

However, inter-institutional variability has been widely neglected in the research on students' attitudes towards research methods and statistics (an exception here is Lauer, Rajecki, & Minke, 2006). Particularly from the perspectives of the professional career of young academics and scientists and the design of Bachelor's and Master's degree programmes, it is important for the individual university to discover what beginning students' general attitudes towards psychological research methods and statistics are. But once this is known, the findings can be meaningfully evaluated for the individual university only if comparison figures are also available for other universities, in the sense of benchmarking. Only comparison figures make it possible to qualify the findings at a university as university specific or to regard them as a fact that applies to universities equally (Mutz & Daniel, 2007).

However, previous results in a similar research area in higher education (e.g., postgraduate research experience) are not very promising: The study by Ginns, Marsh, Behnia, Cheng, and Scalas (2009), based on a census survey of research higher degrees (RHD), students, and standard multilevel analyses, provided little empirical support for the use of the Student Research Experience Questionnaire (SREQ), a modified version of the Postgraduate Research Experience Questionnaire (PREQ), for the benchmarking of either faculties or departments. Furthermore, the Ginns *et al.* study replicated the negative results of a previous study using PREQ data (Marsh, Rowe, & Martin, 2002). In fact, Ginns *et al.* (2009) found no reliable individual differences between *single institutions* (or faculties, departments); however, there might be differences between *groups or types of institutions*.

The aim of this paper is to present a theoretical concept, scale, and method for capturing beginning psychology students' attitudes towards research methods and statistics and for identifying the proportion of beginning psychology students that have a positive attitude towards research methods and statistics, taking all university institutes of psychology in Germany as an example. Using multilevel latent-class analysis (MLLCA), our aim was to group students in different student attitude groups and at the same time to obtain university (or institute of psychology) segments based on the incidences of the different student attitude groups. The study based on a re-analysis of a nationwide survey of all incoming psychology freshman at universities in Germany. Specifically, the study focused on the following questions:

(1) Are there different *types* of psychology students with different attitudes towards research methods and statistics? Can these types be placed on a continuum (positive or negative attitude), or do the types differ in qualitative structure (e.g., students desire solid knowledge in research methods and statistics but do not enjoy these subjects at all)?
(2) Do student attitude types vary across universities? Can universities be classified according to the different proportions of certain attitude types (*university segments*)? How might these differences be explained?
(3) How does the probability of being in a particular latent class (attitude type) depend on several student covariates (e.g., age, sex, grade point average (GPA) on school-leaving exam)?
(4) What is the student potential with positive attitudes towards research methods and statistics at the individual universities?
(5) What are the educational-psychological implications of the results of this study for the design of courses on research methods and statistics?

In the next section, which outlines the theoretical framework, the concept of attitude towards research methods and statistics is defined following social psychology. Then MLLCA is shown to be a statistical approach that makes it possible to identify individual attitude types of students and at the same time to segment universities according to the different incidences of these types.

Conceptual Framework

Structure of attitude towards research methods and statistics

Following social psychology, a person's attitude towards research methods and statistics is defined as '. . . a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor' (Eagly & Chaiken, 1993, p. 1). An attitude is an acquired behavioural disposition, a learned state that creates an inclination to respond in a certain manner. As a hypothetical construct, an attitude is not directly observable but can be inferred from observable responses. One of the central functions of attitudes is serving knowledge organization and guiding approach and avoidance (Bohner & Wänke, 2002). Although inter-attitudinal structure describes how attitudes towards different objects are linked to each other (e.g., balance theories), intra-attitudinal structure deals with the central question of how an attitude is represented in memory. This concerns the representation of the attitude as a point on an evaluative continuum (one-dimensional concept) or as a point in a multidimensional space. Regarding the one-dimensional concept of attitudes, the range of the continuum can be examined. An attitude can range along a unipolar continuum; for example, it can range from no enjoyment at all to a lot of enjoyment. Some attitude objects, for example psychology research methods and statistics, might provoke more polar attitudes that can be represented by bipolar dimensions (e.g., negative–positive). In the area of attitudes towards statistics, multidimensional inventories predominate. For instance, the survey instrument ATS scale (Wise, 1985) distinguished two dimensions: *course*, students' attitude towards statistics courses, and *field*, students' attitude towards the use of statistics in their fields of study.

The SATS (Schau *et al.*, 1995) was designed to identify four dimensions of attitudes towards statistics:

> (a) Affect – positive and negative feelings concerning statistics; (b) Cognitive Competence – attitudes about intellectual knowledge and skills when applied to statistics; (c) Value – attitudes about the usefulness, relevance, and worth of statistics; and (d) Difficulty – attitudes about the difficulty of statistics as a subject. (pp. 869–870)

Multidimensional inventories allow students to assess the field of research methods and statistics in a differentiated way: They can express also ambivalence, in that they can report a positive attitude on one dimension (course, for instance) and a negative attitude on another dimension (field, for instance). Furthermore, a multidimensional structure of the questionnaire can mostly be validated empirically using factor analysis or structural equation models.

Nevertheless, in this study we preferred a one-dimensional polar and emotion-based attitude concept for four reasons. First, the dimensions found are correlated, more or less strongly, which tends to speak for fewer dimensions or even one dimension. For example, in a structural equation model Schau *et al.* (1995, p. 874) found correlations between the latent SATS dimensions *Affect* and *Cognitive Competence* (r = .92) and *Affect* and *Difficulty* (r = .69). Chiesi and Primi (2009) showed comparable findings. Second, in social psychology the concept of attitude strength is discussed as an important moderator between attitude and behaviour (Bohner & Wänke, 2002, p. 63): An attitude is strong, if it is persistent over time, resistant to persuasion, and predictive of behaviour. Attitude strength is all the higher, the more accessible the attitude is in memory, the higher the person's confidence is with which the attitude is held, the lower that ambivalence is, and the more polarized and the more extreme the attitude is. This speaks more for a one-dimensional polar construct of attitude towards statistics than for a multidimensional construct. Third, student surveys have come under criticism, such as for example the U.S. National Survey of Student Engagement (NSSE; www.nsse.iub.edu), a survey of student participation in programmes and activities that institutions (colleges) provide for personal and learning development. Among other things, NSSE has been criticized for starting out from the 'file-drawer model' in social psychology (Schmidt, 2009; Schwarz & Bohner, 2001): According to the model, attitudes are mental files that the students use when answering the questions. In reality, students tend to construct their answers temporarily at the time of the survey. This means that attitudes vary very widely over time. However, multidimensional questionnaires with many items are criticized far more for the 'attitude-as-constructions' model than short, one-dimensional polar questionnaires are. Fourth, multidimensional inventories require long questionnaires. The ATS has 29 items and the SATS 32 items. The disadvantage of long questionnaires is that willingness to participate or to complete the full questionnaire decreases considerably (Dillman, Sinclair, & Clark, 1993). For this reason, short, one-dimensional questionnaires are preferable to long, multidimensional questionnaires.

Explaining latent student cluster membership

As several studies underlined the importance of research methods and statistics for successful psychology studies (e.g., Harlow *et al.*, 2002; Hilton *et al.*, 2004), approaches for explaining academic achievement (e.g., mathematical background) can also be used for explaining individual differences in attitude towards research methods and statistics (Carmona *et al.*, 2005). Several studies identified two factors explaining academic achievement, cognitive intelligence, and personality (e.g., Noftle & Robins, 2007; Robbins *et al.*, 2004; Trapman, Hell, Hirn, & Schuler, 2007).

Chamorro-Premuzic and Furnham (2003) examined the influence of personality traits on academic achievement in a longitudinal study. They found that Neuroticism tended to impair academic achievement (on exams, final-year project), whereas Conscientiousness enhanced academic achievement. In a further study, Furnham and Chamorro-Premuzic (2004) found that intelligence (notably spatial ability) explained 3% of the variance in statistics examination grades and that personality traits, especially the Big Five personality traits Extraversion, Openness, and Conscientiousness (Costa & McCrae, 1992), explained 12% of that variance. For Furnham and Chamorro-Premuzic (2004), cognitive ability and personality are two orthogonal constructs in predicting academic achievement. Although cognitive ability represents what a person can do, personality traits provide information on what a person will do (Furnham & Chamorro-Premuzic, 2004, p. 944). Extroversion and Neuroticism are correlated with ability theoretically and empirically (Eysenck & Eysenck, 1985): Individuals with high Extroversion, low Neuroticism, and high cognitive ability, for instance, show high mental speed and are affected less by anxiety. The most important personality factor for academic performance was found to be Conscientiousness – thoughtfulness, goal-directed behaviours with good impulse control (Chamorro-Premuzic & Furnham, 2008; Furnham & Chamorro-Premuzic, 2004; Noftle & Robins, 2007). It can be assumed that careful, hard-working, organized, and achievement-oriented students are also more successful in academic settings and hence form positive attitudes towards research methods and statistics. As a proxy for cognitive ability, the GPA on the school-leaving exam can serve, as it was shown many times to be a strong predictor of academic success at university and of career success (Burton & Ramist, 2001; Trapman *et al.*, 2007).

There is in addition a selection effect that must be considered: Owing to excess demand for university places in psychology in Germany, authorities at the *Zentralstelle für die Vergabe von Studienplätzen* (central office for the allocation of university places) allocated 60% of the places based on GPA on the school-leaving exam and 40% based on time on waiting list and other reasons. This meant that students with poorer GPAs could take up psychology studies via the alternate route of further training and/or working (Süllwold & Stoff, 1990; Witte & Brasch; 1991). It can be supposed that older students with work experience are less interested in research methods and statistics than younger students are, as their school years are further behind them. Older students are also likely to have more difficulty with the mathematical/scientific basic course material in psychology than younger students entering the university straight from school.

In the face of the development of psychology as a 'female dominated profession' (Olos & Hoff, 2006), it is not assumed that there are differences between men and women in attitude towards research methods and statistics (Gundlach, Tröster, & Moschner, 1999; Marsh, Bornmann, Mutz, Daniel, & O'Mara, 2009). As a result of the selection mechanism via grades, the portion of students with higher cognitive ability (and a strong attitude towards research methods and statistics) is higher at very attractive universities with a great surplus of applicants than at universities with a smaller surplus of applicants. The desirability of the university – as the rate of applicants – is thus a determinant of attitude towards research methods and statistics at the level of the universities (see next section).

In Germany, for a long time the main field of work for psychologists was clinical psychology, including psychotherapy and counselling/diagnostics. Students who are not interested in clinical psychology, psychotherapy, and counselling/diagnostics seek out other alternatives, such as industrial and organizational (I&O) psychology or research and teaching. In the last 20 years, I&O psychology has become established as a field of work (Schorr, 2003). The choice of I&O psychology tends to lead to a more positive attitude towards research methods and statistics.

The explanations up to now aim at establishing a student's attitude to research methods and statistics as a construct that has a real effect on study success (e.g., Furnham & Chamorro-Premuzic, 2004; Lalonde & Gardner, 1993). It can be expected that students that develop a positive attitude towards research methods and statistics will be more likely to see themselves as equal to the demands of psychology studies, will be less worried about having chosen the wrong subject of study, and thus will less frequently intend to switch their subject. Further, they will complete their studies faster and achieve better grades on their university examinations (e.g., university intermediate exam).

Explaining latent university classes membership

With regard to a comparison of psychology institutes, up to now only the results of ranking surveys conducted by various German periodicals have been available, such as *Der Spiegel*, *Stern*, or *Die Zeit* (Mutz & Daniel, 2007). Also available is a 2003 nationwide survey of graduates in Germany conducted by the *Deutsche Gesellschaft für Psychologie* (DGPs; German Psychological Society; Schneller & Schneider, 2005), but the results of that survey cannot be used for a theory-based comparison of institutions.

Upon the background of rankings and surveys of graduates, the economic and cultural local conditions of research and teaching become centrally important. Each year the Cologne Institute for Economic Research, a university-external research institute, publishes rankings of the German states with regard to economic performance based on 33 indicators in the areas of labour market, prosperity, site, structure, and enterprise performance. There are two types of ranking: one ranking examines change (dynamic ranking) and the other examines constancy (stock ranking). In the dynamic ranking and especially in the stock ranking, the states in southern Germany, particularly Bavaria and Baden-Wurttemberg, have had especially high rankings for years (Institut der Deutschen Wirtschaft, 2006, 2010). For this reason, we assume that the better economic performance of southern German states impacts the universities in those states in the form of better framework conditions for research and teaching (infrastructure, professors' salaries, research grants, career promotion, cooperation with industry, and so on). This assumption is supported at least for the area of research by the Funding Ranking 2009 of the *Deutsche Forschungsgemeinschaft* (DFG), the German Research Foundation (DFG, 2009). The figures for third-party funding incorporated in the DFG study account for almost 90% of the financial support provided by national and international funding institutions. For instance, of the 10 universities having the highest volume of DFG grants (*DFG-Bewilligungsvolumen*) in the years 2005–2007, six universities are in the southern German states Baden-Württemberg and Bavaria (i.e., 2 out of 16 states; DFG, 2009, p. 54). Therefore, it can be assumed that universities in southern Germany attract more students that have an interest in research methods and statistics than universities in other German states do.

Multilevel latent-class analysis of attitudes (students, universities)

To identify types of students with different attitudes towards research methods and statistics, it is customary in psychology to use cluster analysis procedures (Everitt, Landau, & Leese, 2001). However, a disadvantage of cluster analysis is that it makes a lot of assumptions, for instance the choice of the distance measure or the choice of the cluster method (hierarchical-agglomerative or divisive). These pre-decisions have different effects on the results of a cluster analysis. Unlike cluster analysis, LCA is a kind of statistical model used to detect and test types called 'latent classes'. It requires fewer pre-decisions than common cluster analysis procedures do and bases on efficient algorithms for parameter estimation (maximum likelihood). Further, it offers a broad range of different models (LCA, IRT models, multilevel models, and more; Magidson & Vermunt, 2002). Nominal, ordinal, or interval scale variables can be included in the same model, called a hybrid model. Besides estimating latent classes, latent continuous variables can also be estimated comparable to factor analysis. It is also possible to test whether latent classes are ordered along a bipolar dimension.

Following McCutcheon (1987), LCA in its basic structure can be defined as a statistical procedure comparable to factor analysis that makes it possible to extract groups of individuals ('latent classes') that are homogenous with respect to the observed nominal or ordinal scale variables. Similar to factor analysis, latent classes are extracted in such a way that the correlations between the observed variables ought to vanish completely ('local statistical independence').

As it can be assumed that the universities, due to their images, attract students with differing levels of interest in research methods and statistics, the universities will be included in the LCA as an additional factor. In an MLLCA, not only will students be grouped according to their attitudes but also universities will be segmented according to their different proportions of student types (Bijmolt, Paas, & Vermunt, 2004, p. 326; Mutz & Seeling, 2010; Vermunt, 2003, 2004, 2008; Zhang, 2004). Further, student types will be called *student latent clusters* and university types *university segments* (or GClasses). This representation allows covariates to be included in the model to predict the probability of being in a particular latent class and is called the 'concomitant-variable latent class model' (Dayton & MacReady, 1988; Vermunt, 2010).

Hypotheses

H1: There are student types (student clusters) showing different attitudes towards research methods and statistics, which can be ranked along a polar and emotion-based dimension (positive–negative).

H2: The younger the student and the better the student's GPA on the school-leaving exam, the more that the student will choose I&O psychology, and the more that the student's personality is extraverted, conscientious, emotional stable and open, the more likely it is that the student will belong to a student cluster having a positive attitude towards research methods and statistics.

H3: There are different types of universities (GClasses) having different proportions of the different student clusters. These GClasses and the universities belonging to them can be ranked according to these proportions.

H4: The economic conditions in the German states and the attractiveness of the university explain the difference between the universities: Student clusters having a positive attitude towards research methods and statistics will be found significantly more often at southern German universities and at very attractive universities.

H5: Students having a positive attitude towards research methods and statistics will see themselves as more equal to the demands of psychology studies, have fewer worries about having chosen the wrong subject, and thus less often intend to change subject or university. Further, they will be more successful in their studies (achieve better grade on the university intermediate exam, complete their studies faster).

Method

Participants

This approach was applied to a study on university freshmen's career interests and their motives to choose psychology as a course of study (Mutz & Daniel, 2007, 2008). In the study, all psychology students ($N = 3{,}517$) that enrolled in German universities (German diploma) in the fall semester of 1999/2000 were surveyed in August 2000 (census survey). With 1,490 psychology students from 44 psychology institutes returning their questionnaires, the response rate was 42.3%; 82.1% of the students were women. The average age of the students was 23.5 years (Mdn = 21, *STD* (standard deviation) = 5.56, Min = 19, Max = 64). The Federal Statistical Office in Germany (Statistisches Bundesamt, 2000) provided population data on age and sex, which made it possible to estimate the sample selection effects: Women were slightly over-represented, with 82.1% in the sample as opposed to 76.2% in the population, χ^2 $(1, N = 1{,}480) = 24.6$, $p < .05$. Further, students age 20 and younger were somewhat over-represented, χ^2 $(4, N = 1{,}480) = 203.28$, $p < .05$. In spite of these small deviations from the population distribution, a sampling correction was performed to guarantee representativeness of the sample with respect to sex and age (Biemer & Christ, 2008).

Materials and procedures

The completely standardized questionnaire (omnibus survey instrument) contained 58 items on admission to university, choice of university, motives for choosing to study and for choosing the study programme, studying, life and career goals, previous schooling, and personal information. A set of items contained statements regarding education in research methods and statistics used in psychology.

The participants were asked to rate 10 items on different aspects of psychology research methods and statistics on 6-point rating scales (1 = strongly agree, 6 = strongly disagree; see Table 1). These 10 items capture essentially four dimensions: (a) *affect* – positive or negative feeling (e.g., I4); (b) *value* – attitude about the usefulness, relevance and value of research methods and statistics (e.g., I2, I8); (c) *cognition* – cognitive aspects of attitude (e.g., I1, I3), and (d) *prior knowledge* – information about the importance of research methods and statistics in studies (I7). If the values of the 10 items are summed up to a scale, the reliability (Cronbach's α) of the test scores is approximately $\alpha = .73$, which is slightly lower than the reliability coefficient of the SATS subscales reported in the literature (e.g., Cashin & Elmore, 2005). Two items (I3, I7) were eliminated due to small differentiation of the latent classes with only less improvement of Cronbach's alpha ($\alpha = .76$). Through exploratory factor analysis using MPLUS 6.1 (Muthén & Muthén, 1998–2007), we also tested whether these eight items load on one dimension. Even though the χ^2-test (H_0: one dimension is valid) is statistically significant ($\chi^2(20) = 124.96$, $p < .05$), other model validity criteria showed that a one-dimensional model fits the data quite well (Hu & Bentler, 1999; Rodgers, 2010): Bentler's comparative fit index (CFI) amounts to 0.97, the root mean square error of approximation (RMSEA) is 0.059, and the standardized root mean square residual (SRMR) is 0.033. We also examined the adequacy of the response format (6-point rating scale) of the items via a partial credit model using

Table 1. Item number, item formulation, and mean (*M*), standard deviation (*STD*), and R^2

No.	Item formulation	*M*	*STD*	R^2
I1	Psychology is a science.	2.89	1.21	.11
I2	As a psychologist I need solid knowledge in research methods and statistics.	2.14	1.13	.46
I3	In my psychology study I will have to read a lot of English research literature.	1.63	0.87	.07
I4	I expect that I will really enjoy research methods and statistics.	3.32	1.56	.32
I5	Statistical methods allow pretty good predictions of human behaviour.	3.67	1.20	.26
I6	Quantifying psychological properties may be questionable but necessary.	2.52	1.07	.34
I7	At the start of my study course I was informed that I will have to work hard in research methods and statistics.	2.60	1.64	.09
I8	Without methodological and statistical knowledge, competent analysis of psychological hypotheses and theories is not possible.	2.22	1.89	.37
I9	Statistical methods allow concise illustration of data.	1.87	0.90	.27
I10[a]	I cannot imagine that the complex subjects that psychology is concerned with can be assessed by statistical methods.	3.54	1.40	.22

Note. 6-point rating scale (1 = strongly agree, 6 = strongly disagree); R^2, squared correlation between the respective item and the latent clusters (four-class solution).
[a]Item is reversed.

WINMIRA 2001 (von Davier, 2001). The graphical representation of the item thresholds showed that the students did not differentiate between response categories 5 and 6 (disagree, strongly disagree; small threshold differences), so we combined these two categories.

Statistical analyses

For statistical analysis of the data, we used the multilevel latent-class method as implemented in the software program Latent GOLD 4.5 (Vermunt & Magidson, 2005). Following Rindskopf (2006), in a first step a simple LCA of the items was calculated to get student clusters. To obtain the optimal number of clusters, adjusted likelihood ratio (LR) based statistics were used, such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC). These criteria penalize models for complexity (additional parameters), making it possible to make direct comparisons among models of different complexity, or numbers of parameters. Results of a simulation study by Lukočienė and Vermunt (2010, p. 247) for multilevel latent-class models showed that in all simulation conditions, the BIC(*J*) using the number of higher level units as sample size instead of the total number of lower level units outperformed the usual BIC to identify the true number of higher level latent classes. Therefore, BIC and BIC(*J*) were used for model comparison. Additionally, classification statistics were used (R^2, classification error): This set of statistics contains information on how well the latent classes are separated using the observed variables or certain covariates (Vermunt & Magidson, 2005, p. 47). In the second step, the hierarchical structure of data was taken into account, calculating a MLLCA to obtain classes of universities. This analysis was computed including covariates to predict cluster membership and computed not including covariates. The covariates were student's sex, age, and GPA on school-leaving exam, career interest in I&O psychology, and personality traits. Age correlated with work experience ($r = .63$). For example, 61.3% of students aged 24–29 and 83.0% of students aged 30 and older had prior work experience. The mean value of two items (sociable vs. reserved, active vs. passive, 6-point polar rating scale) provided for the personality trait 'Extraversion', the mean value of three items (balanced vs. sensitive, irritable, concentrated vs. easily deflectable, self-confident vs. anxious) provided for the trait 'Neuroticism'. Additionally, the item 'rational, appraisingly vs. emotional' was used as an indicator of 'Conscientiousness' and the item 'unconventional vs. adaptive' as an indicator for 'Openness'.

The ratio between the number of applicants and the number of actual study places at a university (data available from the central office for the allocation of university places) served as an indicator for the attractiveness of a university. The definition of southern Germany (Bavaria, Baden-Wurttemberg, Hesse, Rhineland-Palatinate, Saarland) was adopted from the ranking of German states by the Cologne Institute for Economic Research (Institut der Deutschen Wirtschaft, 2006, 2010).

To test the predictive validity of the student latent classes found, we selected items from the survey in the year 2000 and items from a panel study of the same individuals in the year 2007 ($N = 577$). In 2000, the students were asked if they worried about being up to the demands of psychology studies and if they were worried that they had chosen the wrong subject (6-point rating scale, 1 = causes me a lot of worry, 6 = causes me no worry). The students were also asked if they intended to change subjects. In the 2007 second survey, the students were asked if they were still studying, had completed their studies, had changed subjects, or had dropped out of studies. In the second survey, the students were also asked to report their grade on the university intermediate exam.

Results

Latent structure of attitude towards research methods and statistics

As compared to the other seven items, the students agreed less with items I4, I5, and I10: 'I expect that I will really enjoy research methods and statistics'; 'Statistical methods allow pretty good predictions of human behaviour'; 'I cannot imagine that the complex subjects that psychology is concerned with can be assessed by statistical methods' (Table 1). On average, the students tended to have a positive attitude towards research methods and statistics.

In the following, we examine what items form the basis of the latent-class structure. Table 2 shows the results of fitting models containing from one to seven clusters. Note that the one-cluster model is not a real latent-class model but is used here as a baseline to compare with the fit of models of real interest. The decline in the log-likelihood ratio (LR) is large, from −16,732.0 (first cluster) to −15,657.8 (seventh cluster). Beyond three or four clusters the improvement of LR is minimal, and the same holds for AIC. The BIC that adjusts for model complexity more conservatively than AIC indicates that a four-cluster solution fits the data well. The proportion of classification errors for the four-cluster solution is 18%, which is slightly worse than the three-cluster solution. To see the implications of choosing a four-cluster model, the plot of the mean values (scale

Table 2. Fit statistics for exploratory latent-class models (student clusters)

Number of clusters	LL	NPAR	AIC	BIC	Classification error
1	−16,732.0	32	33,528.0	33,697.5	0
2	−15,962.7	41	32,007.4	32,224.5	0.09
3	−15,770.6	50	31,641.2	31,905.9	0.12
4	−15,715.9	59	31,549.9	31,862.2	0.18
5	−15,695.8	68	31,527.6	31,887.7	0.18
6	−15,681.7	77	31,517.5	31,925.1	0.25
7	−15,657.8	86	31,487.6	31,943.0	0.27

Note. LL, log-likelihood; NPAR, number of parameters; AIC, Akaike's information criterion; BIC, Bayesian information criterion, $N = 1{,}472$ students.

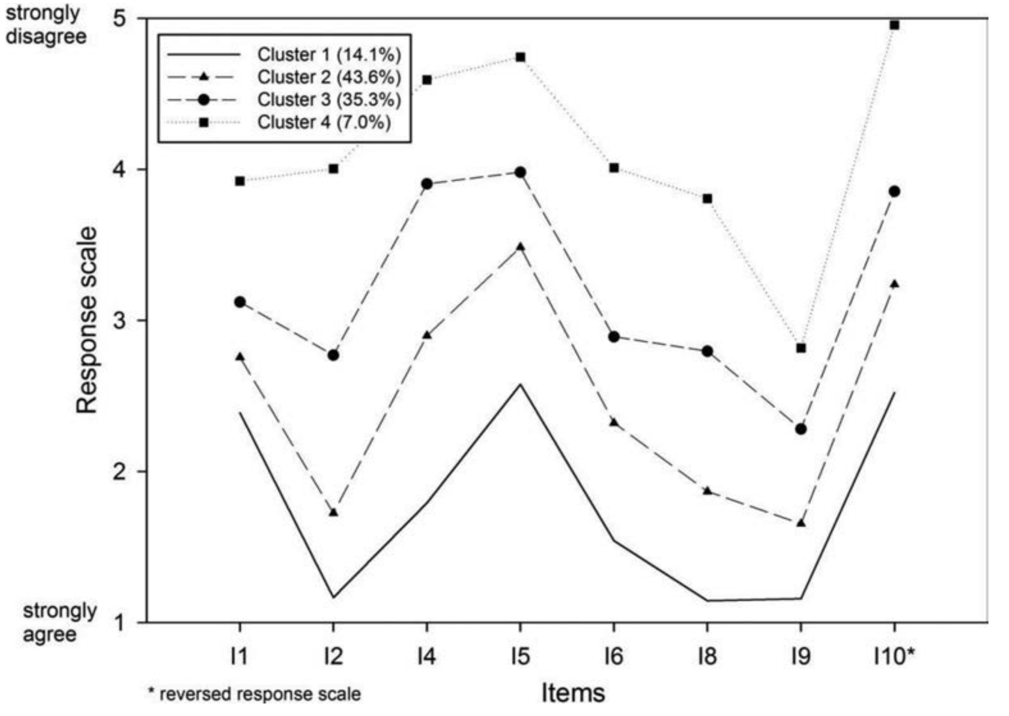

Figure 1. Plot of mean values for each item, given student latent cluster, for the four-class solution, sorted by the mean values (without considering GClasses).

values weighted by the response probabilities) is shown in Figure 1. The four-cluster solution is relatively simple to describe: The first cluster (14.1% of the sample) consists of students who agree very strongly with all items and have a very positive attitude towards psychology research methods and statistics. The students in the second cluster, the largest cluster (43.6% class proportion), also have a positive attitude to research methods and statistics. The students in the third cluster (35.3% class proportion) have a moderately positive attitude towards methods and statistics, and the fourth student cluster (7.0% class proportion) has a rather negative attitude to research methods and statistics. The four clusters can therefore be ranked on an intensity dimension with two poles (from strongly positive to strongly negative attitude towards research methods and statistics) and show no complex response patterns (e.g., a strong demand for solid knowledge in research methods and statistics but no enjoyment at all of research methods and statistics). The item that discriminated the most was item I2 ('As a psychologist I need solid knowledge in research methods and statistics'), with a squared correlation between the item and the latent clusters of $R^2 = .46$ (Table 1). As the proportion of students having a rather negative attitude towards research methods and statistics (cluster 4) is particularly interesting for psychology institutes, in the following a four-cluster solution is preferred over a three-cluster solution, so that the fourth cluster is not omitted.

Multilevel latent structure of attitude towards research methods and statistics

In a multilevel latent structure model, it is assumed that there is variation among the 44 universities of psychology in the *unconditional* probabilities (the probabilities belonging to each latent cluster). In contrast, the conditional probability $P(Y_{ijk}|X_{ij} = s)$, remains the same in each university – that is, the student latent clusters represent the same constructs in each university. For example, a student type that has a very positive attitude towards research methods and statistics responds the same at all universities (same response pattern). But universities can differ in the number of students with a very positive attitude towards methods and statistics (unconditional probability). Further, universities may fall into latent classes, called segments or GClasses, just as students do. These segments represent different types of universities with similar proportions of student latent clusters within each segment.

The results of fitting nine possible models are shown in Table 3. The first four models listed in the table hypothesize that the universities can be classified in one, two, three, or four segments. Of the first four models, the model with one segment (M_2) fits worse (lowest LL, AIC, BIC, BIC(J)) than the other models do. With respect to BIC and BIC(J) the model with two university segments or GClasses fits quite well. Therefore, we prefer the two-segment four-cluster model. According to Hypothesis 3, the finding is that the universities differ in the proportions of students interested in research methods and statistics and can be grouped in two segments.

In addition, we tested whether the student latent clusters can be ranked on an intensity dimension (M_4, '2 GClasses with order restriction of the latent clusters'). There are no differences in LL, AIC, BIC, and BIC(J) between the unrestricted model M_1 and the restricted model M_4. Therefore, the order-restricted model fits the data just as well. In conclusion, the student latent clusters can be ranked on a polar intensity dimension as Hypothesis 1 states.

To illustrate the meaning of these classes of universities, Table 4 shows the distribution of respondents among the four clusters (see Figure 1) of each of the segments of universities. The last row of numbers in Table 4 indicates the proportion of universities that are in each university segment: 69% of the universities are in GClass 1 and 31% in GClass 2. The last column of numbers shows the size of the student latent clusters, which differ only slightly from the results of the simple latent-class analysis, as shown in Figure 1. The remaining columns show the distribution of individuals studying at each type of university who are in each student latent cluster. For instance, among all respondents studying at universities falling into the second GClass, 23% are in cluster 1, 50% are in cluster 2, 26% are in cluster 3, and 1% are in cluster 4. Students having strong positive attitudes towards research methods and statistics (cluster 1) are more likely to

Table 3. Fit statistics of models for variation among universities (GClass) with four student latent clusters

No.	Models for universities	LL	NPAR	AIC	BIC	BIC(*J*)
M_0	1 GClass	−15,715.9	59	31,549.9	31,862.2	31,655.1
M_1	2 GClasses	−15,689.1	63	31,504.3	31,837.8	31,616.7
M_2	3 GClasses	−15,682.4	67	31,498.8	31,853.6	31,618.4
M_3	4 GClasses	−15,681.0	71	31,504.0	31,879.9	31,630.7
M_4	2 GClasses with order restriction of the latent clusters	−15,689.1	63	31,504.3	31,837.8	31,616.7
M_5	M_4 + covariates (cluster, GClasses)	−15,586.6	89	31,351.2	31,822.4	31,510.0
M_6	3 student clusters/2 GClasses + covariates	−15,655.9	71	31,453.7	31,829.6	31,580.4
M_7	2 student clusters/2 GClasses + covariates	−15,869.1	53	31,844.1	32,124.7	31,938.7
M_8	4 student cluster/1 GClasses + covariates	−15,621.5	83	31,408.9	31,848.4	31,557.0
M_9	4 student cluster/2 GClasses + Covariates (Gclass-specific effects)	−15,576.4	113	31,378.9	31,977.1	31,580.5

Note. LL, log-likelihood; NPAR, number of parameters; AIC, Akaike's information criterion; BIC, Bayesian information criterion; BIC(*J*), Bayesian information criterion based on the number of universities ($J = 44$) instead of the total sample size of university students. Covariates on the level of clusters are sex, age, grade point average of school-leaving exam, career interest in I&O, and personality traits. Covariates on the level of GClasses are 'South-German university or not' and 'university attractiveness'.

Table 4. Relative group class sizes and distribution of respondents among latent student clusters (column percent) within each university segment/GClass (M_4)

Cluster	GClass 1	GClass 2	Cluster size
Cluster 1	0.09	0.23	0.13
Cluster 2	0.39	0.50	0.43
Cluster 3	0.42	0.26	0.37
Cluster 4	0.10	0.01	0.07
GClass size	0.69	0.31	

be enrolled at universities in the second segment (GClass 2; 23%) than at universities in the first segment (9%). If we add together the proportions of clusters 1 and 2, then on average, 73% of the students in the second segment (GClass 2) have positive to very positive attitudes towards psychology research methods and statistics as compared to 48% of students in the first segment (GClass 1). With respect to attitude towards psychology research methods and statistics, GClass 2 provides for an excellent segment with a high proportion of students having strong positive attitudes towards research methods and statistics.

Explaining latent cluster and latent GClass membership

If universities differ in the proportions of students in each cluster, it may be because of individual student characteristics or because of characteristics of the universities

Table 5. Parameters of the regression of student latent clusters on covariates and Wald test (M_5)

Covariates	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Wald
Age	−0.05*	−0.00	0.02*	0.03	10.15*
Sex – female	−0.18	0.22	0.21	−0.25	5.11
Grade point average on school-leaving exam	−0.55*	−0.04	0.19	0.40*	13.57*
Career interest – I&O psychology	0.73*	0.49*	−0.39*	−0.83*	44.34*
Neuroticism	0.10	−0.01	0.17*	−0.26*	6.71
Extraversion	0.30*	0.01	−0.07	−0.24*	11.71*
Conscientiousness	0.27*	0.15*	−0.11*	−0.31*	31.96*
Openness	0.05	−0.15*	−0.10	0.21*	12.41*

Note. z-Test for single parameters (H_0: $\beta = 0$); Wald, Wald test for testing the restriction that all parameters of the covariates are zero; entropy R^2 (cluster) = .09 (covariate classification).
$^*p < .05$.

per se. For instance, if women more likely belonged to the strongly positive-minded student cluster than men, and some universities had more women than others, then the universities would differ in the proportion found in the strongly positive-minded cluster (Rindskopf, 2006). The variation of universities can be estimated after taking into account the differences among them in special individual covariates. Therefore, age, sex, and GPA on the school-leaving exam, career interest in I&O psychology, and personality traits are added as covariates in order to explain student cluster membership and the variation between universities. GPA ranged from 1 = excellent, 2 = good, 3 = satisfactory, 4 = sufficient or minimal pass, 5 = deficient to 6 = insufficient. Additionally, we added two covariates on the level of university: university in southern Germany or not, and university attractiveness.

Model M_5 in Table 3 shows a sharp decline of LL, AIC, and BIC(*J*) in comparison to the other models (M_0–M_4). First, it must be noted that the program Latent GOLD uses 'full information maximum likelihood estimation' in the case of missing values; that is, all available information is used in parameter estimation (Vermunt & Magidson, 2005, p. 44). This requires the assumption that the missing data are missing at random (MAR). Second, if covariates are included in a latent-class model, what is modelled is no longer the probability of the response vector P(**Y**) but the probability of the response vector given the covariates P(**Y**|**Z**) (Vermunt, 2010). Therefore, the model choice must be repeated. Table 3 shows that even if three or two student clusters (M_6, M_7) or one university segment (M_8) is used, the standard model M_5 (four student clusters, 2 GClasses plus covariates) remains the best-fitting model. A further model (M_9) is added that allows the parameter of the covariates vary across the GClasses, which is comparable to a random slope concept in parametric multilevel analysis. However, model M_9 is worse than M_5 in all criteria except for the LL. Therefore, the parameters of the covariates do not vary across GClasses. In other words, the influence of the covariates (e.g., age, sex, and GPA on the school-leaving exam) on the student clusters remains constant across universities.

The results of the regression of student latent clusters on student covariates are summarized in Table 5. Age, GPA on the school-leaving exam, career interest in I&O psychology and personality traits (Extraversion, Conscientiousness, Openness) predict the student cluster membership statistically significantly (Wald test); 9% of the differences between student clusters are explained by the covariates (entropy

$R^2_{\text{Cluster}} = .09$). The best predictors are the personality trait 'Conscientiousness' and career interest. A comparison of the regression parameters of the clusters shows whether the probability of being in a certain cluster increases as the predictor value goes up (positive coefficient) or down (negative coefficient): The younger the student ($\beta = -.05$) and the better their GPA ($\beta = -.55$) is, the more they are interested in I&O psychology ($\beta = .73$), extraverted ($\beta = .30$), conscientious ($\beta = -.27$), and the more likely the student belongs to latent cluster 1 (very positive attitude). The worse the students GPA on the school-leaving exam ($\beta = .40$), the lower their career interest in I&O psychology ($\beta = -.83$), the lower they score on Neuroticism ($\beta = -.26$); that is, the more emotionally stable they are, the lower their Conscientiousness score ($\beta = .31$) and the more open and unconventional they are ($\beta = .21$), the more likely it is that they belong to latent cluster 4 (negative attitude towards research methods and statistics). The regression coefficients of GPA on school-leaving exam, career interest in I&O psychology, and Conscientiousness show via the student latent clusters an increasing or decreasing gradient of positive to negative or vice versa. Except for Neuroticism, Hypothesis 2 can thus be confirmed empirically. As predicted, no differences were found for sex.

At the level of the universities, the two covariates 'university is in southern Germany or not' and 'university attractiveness' explain overall 26.9% of the variability of the universities (entropy $R^2_{\text{GClass}} = .269$). However, only the binary variable 'university is in southern Germany or not' is statistically significant (Wald test = 7.3, $p < .05$), with a regression parameter of -1.38 for GClass 1 and 1.38 for GClass 2. This confirms Hypothesis 4 in part: Universities in southern Germany are over-represented in the excellent segment (GClass 2). The attractiveness of the university has no effect, however.

Profiling of universities

For the individual universities it is also important to know how large the different student latent clusters are in their student body. These proportions can be estimated for each university using MLLCA. The universities can be clearly differentiated based on the different proportions of student cluster 1 ('strongly interested in research methods and statistics') in the study body at a university. Figure 2 shows the proportions in decreasing order by size of the proportion of student latent cluster 1. The figure shows that at the Universities of Wurzburg, Giessen, Erlangen-Nuremberg, Constance, Mannheim, Trier, Marburg, Cologne, Berlin (named TU Berlin), Braunschweig (named TU Braunschweig), Freiburg, and Osnabruck (second segment, GClass, 2), 30% and more students are in student cluster 1, students with a very positive attitude towards research methods and statistics. The proportion of students in student cluster 2 is also high at these universities. Nine of 13 universities in GClass 2 are universities in southern Germany (69.2%). The overall proportion of southern German universities among the 44 universities is 43.2%. The proportion of students with a less positive or a negative attitude (clusters 3 and 4) is high at the Universities of Magdeburg, Halle, Saarbrucken, Bamberg, and Wuppertal – universities that belong to the last five universities in the first segment (GClass 1).

If the variation between the universities is corrected for the influence of the covariates, the student cluster proportions are distributed as shown in Figure 3. The number of universities that belong to the excellent segment (GClass 2) increases from 13 to 15 universities. Now, 12 of 15 universities in GClass 2 are universities in southern Germany (80.0%). Except for TU Braunschweig, all universities in the ranking without covariate adjustment still remain in GClass 2 of the ranking with covariate adjustment.

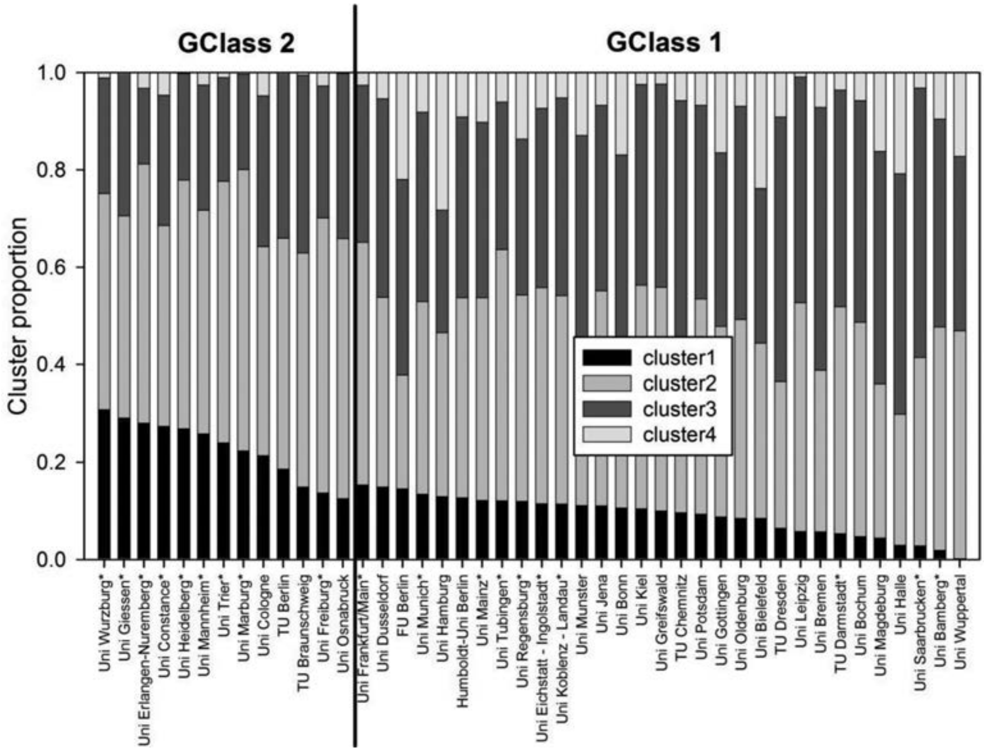

Figure 2. Estimated proportions (class probabilities) of the four student latent clusters (clusters 1–4) for each university with the two segments of universities (GClass1, GClass 2), sorted for the proportion of the first cluster within each GClass *without considering covariates* (*, cities in southern Germany).

Additionally, the University of Munich, Goethe University Frankfurt, and the University of Tubingen rise from GClasses 1 to 2.

Predicting student outcomes by latent classes

In a further step, we calculated the predictive validity of the student latent clusters with regard to criteria of study success. We used the same procedure as for the prediction of the latent classes: The criteria of study success were entered in three independent regression models as 'covariates' in the MLLCA model (M_4, Tables 4 and 6) to obtain pure effects of latent clusters that are not adjusted for all other 'covariates'. For all the criteria of study success, we found statistically significant differences between latent classes (Wald test). As expected according to Hypothesis 5, students having a very positive attitude towards research methods and statistics (student cluster 1) were not worried that they might not be equal to the demands of psychology studies ($\beta = .24$) or that they might have chosen the wrong subject of study ($\beta = .20$). Although students in student cluster 2 were more worried that they might not be equal to the demands of psychology studies ($\beta = -.18$), students in student cluster 4, with a rather negative attitude, were very worried that they might have chosen the wrong subject ($\beta = -.18$). When asked if they intend to change subjects, students having a very positive attitude towards statistics (student latent cluster 1) had statistically significantly less intention to change ($\beta = .78$), whereas students having more negative attitudes (clusters 3 and 4)

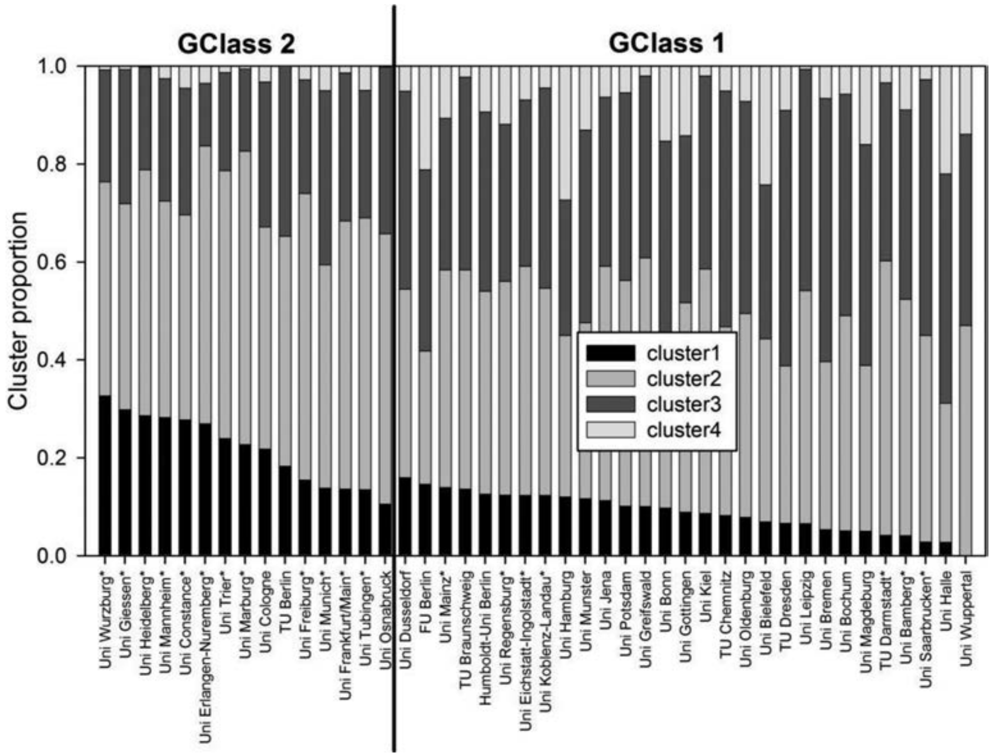

Figure 3. Estimated proportions (class probabilities) of the four student latent clusters (clusters 1–4) for each university with the two segments of universities (GClass1, GClass 2), sorted for the proportion of the first cluster within each GClass *considering all covariates* (*, cities in southern Germany).

less frequently answered 'no' ($\beta = -.33, -.78$) and 'do not know' ($\beta = .41$, cluster 3) or reported the intention to change subjects ($\beta = .77$, cluster 4). This means that 0.6% of students in cluster 1, 1.3% in cluster 2, 2.2% in cluster 3, and 5.9% in cluster 4 intended to change their study subject.

When the data from the 2007 survey are also included, students having positive attitudes (clusters 1 and 2) reported more frequently that they had already completed their studies ($\beta = .37, .48$) or had not changed their subject ($\beta = -.93$), whereas students having more negative attitudes (clusters 3 and 4) reported less frequently that they had already completed their studies ($\beta = -.36, -.49$) or reported that they had changed their subject ($\beta = 1.05$, cluster 4). As for grades on the university intermediate exam (1 = excellent, 2 = good, 3 = satisfactory, 4 = sufficient or minimal pass, 5 = deficient, 6 = insufficient) students having a very positive attitude (student cluster 1) also had better grades ($\beta = -.65$) than students having a more negative attitude towards research methods and statistics ($\beta = .74$). This confirms Hypothesis 5.

Discussion

Inter-institutional variability has been widely neglected in the research on attitudes towards research methods and statistics. Especially, in view of promoting young academics and scientists, and designing Bachelor's and Master's degree programmes,

Table 6. Parameters of three regressions (separated by a horizontal line) of student latent clusters on student outcomes and Wald test

Covariates	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Wald
I worry about being equal to the demands of psychology studies.	0.24*	0.05	−0.18*	−0.11	35.85*
I worry that I may have chosen the wrong subject.	0.20*	0.06	−0.08	−0.18*	18.45*
Do you intend to change your subject?					
Yes	−0.54	−0.14	−0.09	0.77*	32.77*
No	0.78*	0.33	−0.33*	−0.78*	
I do not know yet	−0.24	−0.19	0.41*	0.07	
Have you graduated by 2007?[a]					
I am still studying	0.55	0.15	−0.14	−0.55	34.96*
I have graduated	0.37*	0.48*	−0.36*	−0.49*	
I changed subjects/I dropped out	−0.93*	−0.62*	0.50	1.05*	
Grade on intermediate exam[a]	−0.65*	−0.28	0.18	0.74*	13.35*

Note. z-Test for single parameters (H_0: $\beta = 0$); Wald = Wald test for testing the restriction that all parameters of the covariates are zero; the first two items are rated on a 6-point rating scale (1 = causes me a lot of worry, 6 = causes me no worry).
[a]Panel study in the year 2007 ($N = 577$, 1 = excellent, 2 = good, … 6 = insufficient).
*$p < .05$.

it is decisive for universities to know the extent to which and how many students have positive attitudes towards psychology research methods and statistics.

This study found the following answers to the four research questions and empirical support for the five hypotheses:

- Four student clusters can be identified that can be ranked on a bipolar intensity dimension (from a very positive attitude to a negative attitude towards research methods and statistics). Hence, the structure of attitudes towards research methods and statistics shows no complex response patterns. Hypothesis 1 is confirmed.
- The universities can also be divided into two segments based on the different proportions of the student latent clusters: 69% of the universities with a medium proportion (segment 1) and 31% of the universities with a high proportion (segment 2) of students having positive attitudes towards methods and statistics (excellent segment). On average, 73% of the students in the second segment have positive to very positive attitudes towards psychology research methods and statistics as compared to only 48% of the students at universities in the first segment. Hypothesis 3 is confirmed.
- Membership in the different student latent clusters can be explained in part by covariates: The younger the students and the better their GPA on the school-leaving exam is, the more they are interested in I&O psychology, extraverted and conscientious, the more likely it is that the students belong to latent cluster 1 (very positive attitude). And vice versa, the worse the students' GPA on the school-leaving exam, the less they are interested in I&O psychology, the lower their score on Neuroticism – that is, the more emotionally stable they are, the lower their score on Conscientiousness, and the more open and unconventional they are, then the more likely it is that the students belong to latent cluster 4 (negative attitude towards

research methods and statistics). In latent cluster 3, there are more students who are older and who have work experience before entering university. Working before studying leads to academic interest getting pushed into the background in favour of career-practical orientations. This confirms Hypothesis 2. Besides career interest, the personality trait 'Conscientiousness' is one of the best predictors. This finding agrees with the findings of studies on predictors of academic outcome (e.g., Noftle & Robins, 2007).

- Owing to their more favourable economic framework and to their high-ranking positions in the Funding Ranking 2009 of the German Research Foundation (DFG, 2009), it is plausible to say that universities in southern Germany do better than universities in other German states and are thus over-represented in the excellent segment (GClass 2). About 23% of the variability between universities can be explained by the binary variable 'university is in southern Germany or not'. The attractiveness of the university had no effect, however. Hypothesis 4 is confirmed in part.
- The proportions of the different student latent clusters can be determined for each university. These proportions reflect the potential for students with an interest in research methods and statistics at the university. For instance, at least 30% of the psychology students at the Universities of Wurzburg, Mannheim, Heidelberg, Erlangen-Nuremberg, and Constance have very positive attitudes towards research methods and statistics. If all covariates are included, 80% of the universities in the excellent segment (GClass 2) are universities in southern Germany.
- The student latent clusters show predictive validity: In contrast to students having a negative attitude towards research methods and statistics, students having a positive attitude more often see themselves as equal to the demands of psychology studies, worry less that they may have chosen the wrong subject and less often intend to change their subject or university. They are more successful at their studies all in all (complete their degrees, grades on university intermediate exam). Hypothesis 5 is confirmed.

Previous research concentrated on investigating attitudes towards statistics using various instruments (such as SATS or ATS). In the studies using SATS, four different dimensions were identified (Schau *et al.*, 1995): (a) affect, (b) cognitive competence, (c) value, and (d) difficulty. In contrast, this study on general attitudes towards research methods and statistics found a one-dimensional bipolar attitude structure (positive, negative). However, our questionnaire (omnibus survey questionnaire) contained considerably fewer items and tapped fewer facets than the SATS does (10 items as opposed to 28 items in the SATS). Despite the lower reliability (Cronbach's $\alpha = .76$) of our eight-item inventory than the reliability of the SATS, it was possible to discriminate between students as well as universities. In contrast to the study by Ginns *et al.* (2009) using a sample of RHD students, the present study provides empirical support for benchmarking universities. The reasons for this discrepancy are, for one, the quite different research topics, and, for another, the different statistical multilevel approaches. It might be easier to detect differences between groups or types of universities using MLLCA than to differentiate between single universities using standard multilevel procedures (Mutz & Daniel, 2007).

This study has some limitations: The analyses are based on data from a study that was conducted in the year 2000 (re-analysis), and they do not provide information on the present-day distribution of the attitude types. Nevertheless, there are four reasons why this secondary analysis is justified: First, also in comparison to current surveys, the data used here are unique: They are from a nationwide consensus survey of one cohort, whereby in addition, the representativeness of the sample could be examined at least with regard to age and sex. Second, next to primary analysis and meta-analysis, secondary analysis is a recognized method of hypothesis testing in the social sciences (Dale, Arber, & Procter, 2009). It can be assumed that the cluster of students has remained more or less stable in the last 10 years. Chiesi and Primi (2009), for instance, essentially replicated the factor structure of the SATS by Schau *et al.* (1995) 14 years later, which clearly underlines the thesis of the stability of attitude structures. Third, as newer rankings of the German states show, not much has changed in the framework conditions of university research and teaching. The states in southern Germany still hold the leading position in the stock ranking (Institut der Deutschen Wirtschaft, 2010). Compared to that, in the last 10 years academic psychology has undergone standardization and homogenization (standard framework for the conduct of diploma examinations, Bologna Process). And fourth, the clear findings of this study justify the choice of the study design, in particular the findings on the predictive validity of student latent clusters.

It should also be mentioned that the estimation of the proportions of student latent classes at each university was based on a never-before used but legitimate trick: The variable for identifying the universities that is already in the model is included in the model again as a copy. It is included as a covariate but a covariate that is inactivated – that is, the frequencies of the student clusters are computed for the universities, but the variable is not used as an explaining covariate in the model estimation algorithm. Unfortunately, the procedure does not allow determination of standard errors or confidence intervals of the estimates.

Conclusions

Students' learning success in a course depends in general on their cognitive abilities and their studies-related attitudes and motivations (demand side) and on the course contents and how they are taught (supply side; Bloom, 1976; Helmke, 2009). As to the demand side, students taking psychology methodology courses, in particular statistics courses, in Germany are a very heterogeneous group made up of proportions of the four student types outlined above that differ across universities and university segments. This means that the supply side, as also Harlow *et al.* (2002) recommend, must offer multiple learning activities, such as peer monitoring, consult corner, applied projects, and online experiments in order to do justice to the different ability levels and attitudes of the student groups. Specialized journals, for example *Statistics Education Research Journal* (SERJ, www.stat.auckland.ac.nz/serj) or *Journal of Statistics Education* (www.amstat.org/publications/jse), present possibilities for teaching and learning in many areas of statistics (see also Garfield & Ben-Zevi, 2007). Online offerings especially, in the form of scripts, quizzes, wikis, and blended learning make it possible to broaden the range of methods and to differentiate and adapt them to different groups of students, which in the end accords with the didactic shift from 'teaching to learning' (Welbers & Gaus, 2005) of the Bologna Process. Online offerings (quizzes, scripts, problems with feedback) can help older students to review and refresh the mathematics and science they learned at school. Statistics courses that rely on the lecture course as the only form of teaching are not able to do that.

Beyond that, education in research methods and statistics should start at the beginning of university studies, to allow latent polar attitudes towards research methods and statistics to become salient. This will give the group with very negative attitudes and rather negative study success prospects the opportunity to change their field of study at an early time point. The other way around, this strategy can also result in strengthening the interest of students with positive attitudes towards methods and scientifically oriented research. Very important here is the possibility of self-assessment already during the phase of choosing one's field of study (Camara & Kimmel, 2005): Persons interested in studying or potential psychology students can use an anonymous online tool to test their suitability for psychology studies. The short scale developed here could be used within an online tool of that kind. The use of such tools is all the more urgent in the northern and eastern German states, which have a higher proportion of students with rather negative study success prospects.

Behind the strong predictor career interest – I&O psychology for attitude towards research methods and statistics is in the end a basic career decision of the students that is made very early in university studies and has consequences for learning motivation. Traditionally in Germany, the psychology profession was and is still dominated by the field of clinical psychology (psychotherapy, counselling/diagnostics; Schneller & Schneider, 2005). Students who are mostly interested in clinical psychology view their studies mainly as a means to an end (professional training) and are not easily motivated by methods and statistics or general research-related courses (e.g., cognitive psychology).

The fact that attitude towards research methods and statistics in our study predicted study success (length of time to complete, successful degree completion, grade on university intermediate examination) shows that research methods and statistics is an important subject not only from the point of view of the curriculum. This importance should be reflected in the allocation of resources for teaching this subject.

And finally, in the data set a group of students stood out that are very young – meaning that they began university studies immediately after graduating from high school. They show rather high Extroversion and Conscientiousness. They show the high mental ability and high self-efficiency needed to complete studies successfully. It is from this group that the next generation of academics can be won. Targeted offerings for these students (such as student participation in research projects, leading student tutorials and discussion groups, advanced course offerings, mentoring, fellowships) can promote the academic careers of these students in an early phase of their studies, especially the careers of women students, as our study results revealed no gender differences.

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