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Using Multilevel Mixture Models in Educational Research: An Illustration with Homework Research

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ABSTRACT
The present study illustrates the utility of applying multilevel mixture models in educational research, using data on the homework behavior of 1,812 Swiss eighth-grade students in French as a second language. A previous person-centered study identified 5 homework learning types characterized by different patterns of high or low homework time and effort. Via multilevel latent profile analyses (MLPAs), the dependence of homework learning types on between-classroom differences was investigated. Based on the proportions of homework learning profiles across classrooms, 3 class-level profiles were identified: A "low time", "high time" and an "average" profile. Predictors of the latent profiles at the student and class levels were assessed. The study offers insights into the advantages of multilevel mixture models for educational research.

KEYWORDS
Person-centered methods; multilevel mixture models; homework; teachers; effort; homework time

PERSON-CENTERED APPROACHES HAVE become standard in education and educational psychology because they allow researchers to capture potential differences in a number of interconnected aspects simultaneously and yield a comprehensive picture of interactions between these variables all at once (e.g., Asendorpf, 2014; Collins & Lanza, 2013; Wormington & Linnenbrink-Garcia, 2016). Person-centered methods can be applied to differentiate between clusters of students who show specific patterns on the variables under consideration (Marsh, Lüdtke, Trautwein, & Morin, 2009). This methodology has enabled researchers to target open research questions in education, producing new evidence of meaningful profiles regarding, for example, students' motivation (e.g., Corpus & Wormington, 2014; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009), achievement goals (Pastor, Barron, Miller, & Davis, 2007; Shim & Finch, 2014; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2008), family background (Häfner et al., 2017), and teachers' instructional styles (Klusmann, Kunter, Trautwein, Lüdtke, & Baumert, 2008). A recent person-centered study also showed that students can develop qualitatively different homework behavior patterns, which can be more or less productive in terms of academic achievement (Flunger et al., 2015).

However, situations in classrooms are usually bound to a multilevel context: Students are nested within classes and schools. Thus, it is possible that the distinct types that can be found in

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students' data largely depend on the characteristics of schools or classes (e.g., teachers' attitudes). Differences in students' homework behaviors could stem from what their teachers think about how homework should be carried out and whether it is necessary for parents and teachers to check homework (Trautwein, Niggli, Schnyder, & Lüdtke, 2009).

Variability in student profiles across classrooms or schools has largely been neglected so far, and the impact of teachers, classes, or schools on the development of distinct profiles in students' academic behavior, motivation, or academic achievement remains unclear. The challenge lies in the accurate modeling of the multilevel structure of educational data when applying person-centered methods. To this end, researchers can use multilevel mixture models in which variability in students between classes is modeled with a latent categorical variable at the teacher/class level (Vermunt, 2003). Multilevel mixture models are especially useful because they allow predictors to be considered at both the class and student levels. Thus, they enable researchers to study the dependence of the emergence of specific latent student profiles on teachers' instructional practices or attitudes.

In the present study, we applied multilevel mixture models to homework data to illustrate the value of this method in the educational context. The study thus provides an example of a growing methodological approach (see also Finch & Marchant, 2013) and directs attention to an underrepresented issue in the application of person-centered methods to educational data.

A person-centered approach to assessing students' homework behavior

Homework is understood as "tasks assigned to students by school teachers that are meant to be carried out during non-school hours" (Cooper, 1989, p. 7). Homework time (i.e., the total amount of time spent on homework; Cooper, 2001) and homework effort (i.e., the extent to which students work seriously on homework; Schmitz & Skinner, 1993; Trautwein, 2007) can be considered as the two central variables defining students' homework behavior.

However, not all students are motivated to invest effort or time into completing their homework. A prior person-centered study revealed five distinct homework learning types—namely, *fast learners*, *high-effort learners*, *average students*, *struggling learners*, and *minimalists* (Flunger et al., 2015). *Fast learners* were characterized by high homework effort and low amounts of time spent on homework. *High-effort learners* were characterized by high levels of both effort and time. *Average students* were characterized by medium levels of homework effort and low levels of homework time. *Struggling learners* were shown to have low levels of homework effort and high levels of homework time. *Minimalists* were characterized by low levels of homework effort and time. Given that homework time has been a focus of homework research for decades and that inconsistent findings have been revealed regarding the association between homework time and achievement, the study by Authors (2015) also analyzed whether students' academic achievement depended on specific patterns in students' homework behavior. When prior achievement, gender, and track level were controlled for, *fast learners* showed higher gains in their academic achievement over time, whereas *struggling learners* showed the lowest achievement gains (Flunger et al., 2015).

Characteristics of classes could be driving factors underlying students' differential homework engagement. Teachers who rarely check homework might trigger the *minimalist* style; whereas, teachers who aim to develop interesting homework assignments might promote the styles represented by *fast learners* or *high-effort learners*. However, so far, person-centered homework studies have not addressed the questions of whether and how differences in classes or teachers shape differences in students' homework learning types.

Teacher effects on their students' homework behavior

Homework has been identified as being influenced by more factors than any other learning situation (Cooper, 1989; Xu, 2016). Conceptual models of the homework situation typically propose that a number of aspects and social agents (i.e., students, teachers, and parents) are predictive of students' homework behavior, resulting in a multilevel, multidimensional homework model (e.g., Trautwein, Lüdtke, Kastens, & Köller, 2006; Trautwein, Lüdtke, Schnyder, & Niggli, 2006). Regarding between-teacher differences, on the basis of teachers' reports of their reasons for assigning homework (e.g., Bempechat, 2004; Cooper, 1989; Epstein & Van Voorhis, 2001), different factors concerning what teachers emphasize in their classes regarding homework need to be considered. These factors refer to teachers' homework objectives, teacher implementation and follow-up practices, and teachers' attitudes toward parental involvement (Cooper, 1989; Trautwein, Lüdtke, Schnyder, et al., 2006).

Homework objectives

Teachers' homework objectives can be classified into those that are related to instruction (see Cooper, 2001; Epstein & Van Voorhis, 2001; Rosário et al., 2015), students' personal development (Epstein & Van Voorhis, 2001; Trautwein, Niggli, et al., 2009), or communication (e.g., Cooper, 2001; Rosário et al., 2015; Trautwein, Niggli, et al., 2009). Instructional purposes are usually aimed at improving students' achievement; teachers develop these assignments with the aim of fostering students' skills, knowledge, or practicing of the material (Trautwein, Niggli, et al., 2009). Moreover, teachers also intend to close achievement gaps between their students and try to create a more homogenous achievement level in their class (especially in terms of having fewer low-achieving students). Another major reason for assigning homework is to promote students' personal development, specifically their motivation and self-regulation skills (Hoover-Dempsey et al., 2001; Trautwein, Niggli, et al., 2009; Warton, 2001). Thus, homework should speak to students' areas of interest (Corno, 2000) and improve their ability to manage time and effort (e.g., to be able to carry out homework tasks despite distractions; see Epstein & Van Voorhis, 2001). Finally, the communicative purposes of homework refer to endeavors directed toward strengthening the link between the classroom and the home (e.g., parent-child relationships, parent-teacher communication; Epstein & Van Voorhis, 2001; Trautwein, Niggli, et al., 2009).

Homework implementation practices

Previous findings have suggested that teachers can take two stances toward students' completion of homework tasks, and these are not mutually exclusive: Teachers might regularly check to see that homework is completed (e.g., Núñez et al., 2015) or take a more autonomy-supportive position and emphasize that they perceive homework completion as part of the students' responsibility (Trautwein, Niggli, et al., 2009).

Attitudes toward parental involvement

A body of research has shown that parents' involvement in their children's homework is not per se beneficial for students' outcomes (e.g., Gonida & Cortina, 2014). Rather, the positive effect of parental involvement depends on the quality of the support given to the child (e.g., autonomy support versus interference), and findings on the effectiveness of parental support for students' achievement-related outcomes have been inconsistent (e.g., Hoover-Dempsey et al., 2001; Patall, Cooper, & Robinson, 2008a; Pomerantz, Moorman, & Litwack, 2007). These equivocal meanings of parental involvement and their unclear consequences are reflected in teachers' attitudes: Teachers can be inclined either to hold a positive attitude toward parental involvement or to hold the belief that it is best if students do their homework on their own (Trautwein, Niggli, et al., 2009).

Between-teacher differences and students' homework learning types

Investigating the impact of between-teacher differences on students' homework learning types enables to uncover more evidence for the multilevel nature of homework data. First, homework can be considered a multilevel phenomenon: Homework is assigned at the class level; however, homework-specific outcomes have primarily been explored at the student level. When estimating a single-level model with homework data from both teachers and students, one might produce a less accurate picture of the actual effects of predictors at distinct levels (Pornprasertmanit, Lee, & Preacher, 2014). Specifically, there is strong evidence in homework research using variable-centered methods that the associations between variables differ across levels: Depending on the level of analysis (class or student level), differential associations have been revealed (e.g., Fernández-Alonso, Álvarez-Díaz, Suárez-Álvarez, & Muñiz, 2017; Trautwein & Köller, 2003). A study aiming to disentangle the homework-achievement relation found small associations between homework time and academic achievement at the student level; whereas, homework time at the class or school level was consistently shown to be associated with academic achievement (Dettmers, Trautwein, & Lüdtke, 2009). Another study revealed that whole-class achievement was positively associated with homework assignments; whereas, individual student achievement was negatively affected by high homework time (Trautwein, Schnyder, et al., 2009). Whole-class achievement could also affect the emergence of specific homework types in certain classes. A class-level type characterized by a high frequency of *minimalists* and *fast learners* could be positively predicted by whole-class achievement because students in these classes in general might need less time for homework. By comparison, individual prior achievement might show positive or negative associations with specific student-level homework types (i.e., negative effects on *struggling learners*, positive effects on *fast learners*).

Second, we know from prior research that teachers can have a strong impact on students' homework behavior and learning outcomes. Yet, the pattern of results has been mixed and the associations between teachers' homework practices and students' behaviors have not been consistently confirmed. Xu (2010) investigated the impact of class-level predictors (among others) on students' homework time management in a sample of 1,046 eighth-graders in the southeastern United States, thereby, also studying the role of homework feedback (operationalized as homework checking). In Xu's study, no significant association between homework checking and homework time management was found. By comparison, another study with 454 Spanish students from Grades 5 to 12 showed that teachers' homework feedback predicted homework completion and homework time management but not the amount of time spent on homework (Núñez et al., 2015).

A person-centered study might be able to shed light on the previously inconsistent findings on the association of teachers' homework assignment practices with the time students spend on homework. If teachers ask students to discuss their answers to homework assignments in class in detail, students might invest more time and effort in their homework assignments at home because they know that their homework will be referred to in class, which might lead to a higher frequency of *high-effort learners* in these classes. Thus, it is essential to study the effect of different classrooms and teachers when trying to explain differences between students' homework behaviors.

Extending person-centered analyses to the multilevel context

To target the role of between-classroom differences in students' homework learning types, multilevel mixture models (or multilevel latent profile analyses, MLPAs; e.g., Henry & Muthén, 2010; Vermunt, 2003) can be applied. Next to enabling the investigation of new research questions in homework research—for example, whether contextual effects underlie students' distinct learning types—these models can generally be useful for research in education and educational psychology. That is, it would be interesting to study whether, for example, students' differential motivation types or personality types vary across classrooms and which characteristics of students, teachers or peers are associated with a higher likelihood or higher frequencies of certain types in specific classrooms.

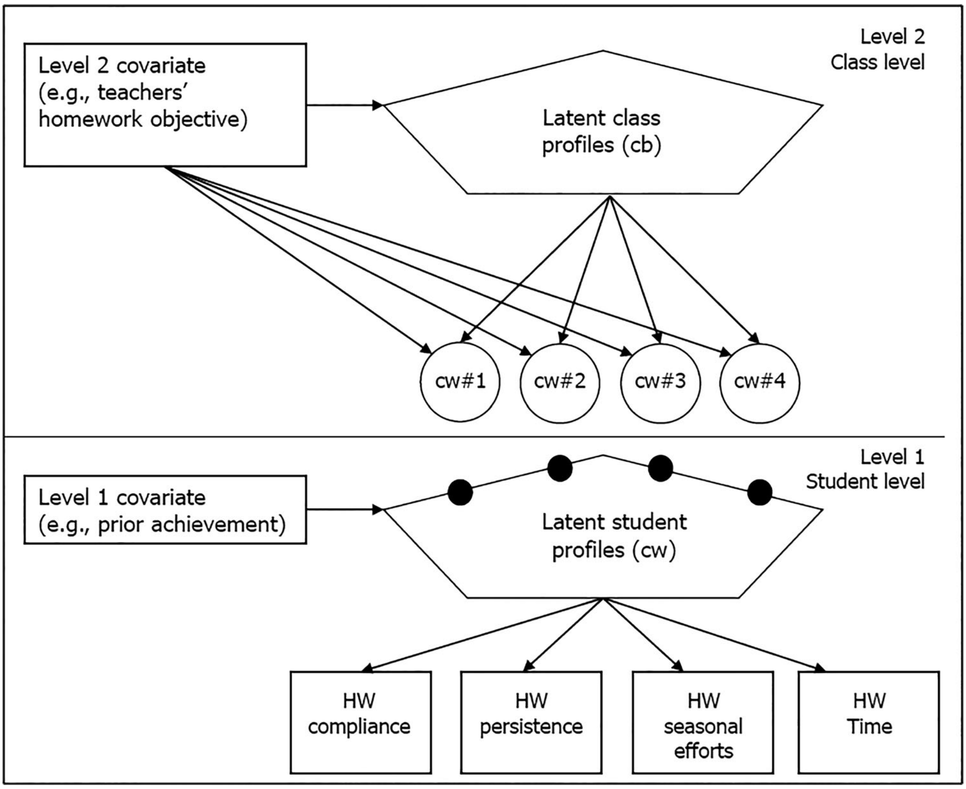

Figure 1. Multilevel mixture model with covariates at the class and student levels.

Concerning multilevel mixture models, one of the essential decisions is to decide how the differences between classrooms can adequately be modeled (e.g., Fagginger Auer, Hickendorff, Van Putten, Béguin, & Heiser, 2016). Via multilevel mixture models, random effects between classes are specified as either continuous or discrete latent variables, representing a random coefficient logistic regression model (see Vermunt, 2003). However, estimating a continuous latent factor requires strict assumptions about the distribution of the random effects and is computationally heavy. Therefore, Vermunt (2003) proposed a nonparametric approach in which a latent profile variable is imposed at the cluster level in addition to the latent profile variable that is imposed at the student level. In a simulation study, Finch and French (2014) showed that the nonparametric approach outperformed the parametric approach with respect to several study conditions. As an example of the nonparametric approach with respect to students' homework behavior, the extent to which students' responses to the homework measures depend on a latent categorical variable at the student level is specified (classifying students into specific learning types at Level 1), and the dependence of these student learning types on their classrooms (identifying latent class-level profiles based on specific distributions of student-level learning types) is additionally modeled with a latent categorical variable at the class level (e.g., Henry & Muthén, 2010; Vermunt, 2003). Figure 1 displays the postulated two-level model for homework research specified with a nonparametric MLPA.

Following suggestions by Mäkikangas et al. (2018), an additional specification of a MLPA could be to investigate latent profiles directly at the class level, using either aggregated measures of student responses or class-level measures, such as teacher reports, without estimating student-level profiles (i.e., "Level 2 only MLPA"). The latent class-level profiles would then be interpreted as classes characterized by divergent class-average profiles of homework-specific behaviors.

The impact of predictors on latent profiles at the student and class level can be investigated with MLPAs with covariates. An important feature of multilevel mixture modeling is that class-level predictors can be specified to predict the random intercepts of latent profiles at the student-level (Van Horn et al., 2016). Thereby, the effects of Level 2 covariates on the variation of Level 1 latent profiles across classes can be investigated. In homework research, next to the question of how teachers' characteristics can influence the profile of their class (e.g., whether the class is characterized by a time-efficient working style), another relevant question is whether "latent classes of students respond differently to their teachers' instructional styles" (Van Horn et al., 2016, p. 259).

The present study

Multilevel mixture models offer new insights for education and educational psychology because they enable researchers to fully capture the multidimensional and hierarchical nature of educational data. In the present study, we aimed to illustrate that multilevel mixture models are useful for targeting open research questions in homework research.

An unresolved issue in homework research is the role of the classroom context in the development of students' differential homework behaviors. Can teachers who intend to promote student motivation with homework foster a distinct homework learning type in students than teachers who see homework simply as a way to practice the learning material? To address these questions, we examined how teachers' homework assignment practices and attitudes toward homework are associated with students' different homework learning types. The present study is part of a research program aimed at exploring the distinct configurations of students' homework behaviors and the impact of these behaviors on academic achievement (Flunger et al., 2015) on the basis of the multidimensional and multilevel model of homework (e.g., Trautwein, Lüdtke, Schnyder, et al., 2006).

We tested two research question in a reanalysis of data collected from 1,915 eighth-grade students (e.g., Trautwein, Schnyder, et al., 2009). First, we applied MLPAs to examine the nature of latent profiles at the class level (e.g., Henry & Muthén, 2010). Thereby, we wanted to explore whether some classes bring about a large variety of homework learning types in students, which can be interpreted as a small effect of classes, or whether there are classes that influence students in such a way that they show quite the same homework learning type (representing a large effect of classes). The second aim was to investigate how teachers' objectives in giving homework, their homework implementation practices, and their attitudes toward parental involvement affected specific homework learning types in students.

We speculated that the patterns of students' differential homework behaviors (i.e., an interplay of low and high levels in homework effort and time) would be mirrored by the nature of meaningful class-level profiles. Our first expectation was that we would find a certain type of classroom in which the probability of learning types characterized by low homework time would be higher (i.e., mainly *fast learners* and *minimalists*), because some teachers would make the efficient regulation of homework time a priority for students. Second, we expected that we would find a type of classroom in which students' learning types would be characterized by high homework effort (i.e., *fast learners* and *high-effort learners*), because some teachers would emphasize homework as a means to motivate their students to learn the material and would aim to develop interesting homework assignments. Vice versa, we also expected that we would find a class-level type with a higher frequency of homework learning types characterized by low effort (i.e., *average students*, *struggling learners*, and *minimalists*), because some teachers would consider independent study time less important than study time in class.

Moreover, we expected that teachers' homework-specific attitudes would be associated with specific class-level profiles and would also play a role in the emergence of certain homework learning types in specific classes. For example, we expected that the teacher attitude that homework should be regulated by the students themselves (at school and at home) would be associated with the "low homework time" class-level profile and respective student-level profiles. By comparison, we expected that teachers who aim to foster student motivation with homework would be more likely to teach "high homework effort" types of classes and students. In addition, we expected that teachers who prefer to give homework so that students have the opportunity for drill and practice of the material through homework or to close achievement gaps with homework would be more likely to create "low effort" types of classes and students.

Method

Sample and design

We applied a secondary data analysis to a longitudinal data set that stemmed from a research project on students' homework behavior in French as a second language in three Swiss cantons (i.e., Fribourg, Valaise, and Lucerne; e.g., Trautwein, Schnyder, Niggli, Neumann, & Lüdtke, 2009). The measures assessed in the research project were selected on the basis of a multilevel conceptual model of the homework process. We drew on data from a student questionnaire that was administered twice to measure students' homework behavior and a teacher questionnaire that was administered to assess teachers' attitudes and behaviors at the first measurement point. These data had already been used in several studies that investigated different research questions with variable-centered methods, such as the role of parents (e.g., Dumont, Trautwein, Nagy, & Nagengast, 2014) or the role of students' characteristics (Trautwein, Niggli, et al., 2009) in determining students' homework behavior.

The sample consisted of 1,915 eighth-grade students (47.96% female adolescents; $M_{age} = 13.63$, $SD = 1.16$) from 112 classes in 27 schools. The average class size was 18.38 ($SD = 4.81$). The time interval between the assessment at Time 1 (October 2003) and Time 2 (June 2004) was 7–8 months. The teacher questionnaire was completed by 79 teachers (41.6% women; mean teaching experience = 16.25 years). Seventeen teachers taught two classes and one teacher taught three classes. Regarding the teacher questionnaire, one teacher with two classes provided ratings for both classes; whereas, 10 teachers with two classes and the teacher with three classes filled out only one questionnaire concerning their homework objectives. Sixteen teachers did not fill out the questionnaire, and seven of these taught two classes. Thus, a total of 79 teachers completed the teacher questionnaires, but measures regarding teachers' homework objectives were obtained for 89 classes with 1,597 students. The MLPAs and the MLPA with covariates for investigating the role of teachers' homework objectives, implementation practices, and attitudes toward parental involvement were estimated with a combined data set that contained the Time 2 student data on students' homework behavior, the Time 1 teacher data, and the Time 1 student data on prior achievement (resulting in a sample with 101 classes and 1,812 students). Thereby, we relied on the "Include All option" in Latent GOLD, which "includes all cases and replications in the analysis regardless of the presence of missing values" (Vermunt & Magidson, 2016, p. 54) and uses two strategies when dealing with data with missing values in indicators and covariates. The model parameters for data with missing values on the indicators of the latent categorical variable were estimated with full information maximum likelihood, considering all available information (e.g., Schafer & Graham, 2002). Regarding any data that were missing in the covariates, a simulation study by Heron, Croudace, Barker, and Tilling (2015) showed that "FIML based mixture modeling can only deal with missing covariate information (incomplete Z) in a rather simple setting and by making potentially undesirable distributional assumptions" (p. 427). The missing values in the covariates were imputed and replaced by the sample mean (see Vermunt & Magidson, 2015a, 2016, for more information). In our syntax examples, we illustrate how to implement FIML for the missing values in covariates in Mplus (see Supplementary Material).

Measures

The items for all scales were answered on a 4-point Likert scale (1 = *completely disagree*, 2 = *somewhat disagree*, 3 = *somewhat agree*, and 4 = *completely agree*) except homework time.

Student questionnaire

Homework time. Homework time was assessed with a single item in an open format: "If you are assigned French homework, how many minutes do you need on average to finish this French homework (without learning vocabulary)?" The students' answers in minutes were recoded into a 7-point Likert scale wherein each point represented a 5-min block such that 1 stood for *0–5 min* and 7 stood for *31 min and more* of time spent on homework. The intraclass correlation (ICC) was .12.

Homework effort. Three aspects of homework effort were assessed—namely, homework compliance, persistence, and seasonal effort (see Flunger et al., 2015) as adapted from Trautwein and Köller (2003). Compliance was assessed with four items (e.g., "I do my best on my French homework"). The ICC was .08. Persistence was measured with three items (e.g., "If I don't find a solution to a certain task quickly, I skip it"; $\alpha = .71$). The ICC was .06. The negatively worded items were recoded. Seasonal effort was also assessed with four items (e.g., "In French, I am a very irregular learner"). The ICC was .07. The Cronbach's alpha values of the manifest measures were satisfactory (homework compliance: $\alpha = .72$; homework persistence: $\alpha = .71$; seasonal effort: $\alpha = .72$).

We tested the factor structure of the homework effort measures via confirmatory factor analysis (CFA). Due to the nested data structure, a design-based correction of standard errors was conducted via the "type is complex" procedure. This analysis confirmed an adequate-to-good fit (CFI = .97; TLI = .96; RMSEA = .038; SRMR = .030). The CFA model with three homework effort factors was compared to a CFA defining homework effort as one latent factor. The CFA with three distinct factors showed a statistically significantly better fit than the CFA specifying one factor (Yuan-Bentler $\chi^2\Delta$ (3) = 231.70, $p < .001$).

Prior achievement. Students' French grades on the final Grade 7 report card were scaled according to a decimal point system, ranging from 1.0 to 6.0, with 6.0 indicating the highest grade.

Track level. Students came from different secondary tracks. For the analyses, we differentiated between two tracks (coded as 0 = lower track, 1 = upper track).

Teacher questionnaire

For more information about all items and the construct validity of the teacher scales, see Trautwein, Niggli, et al. (2009).

Homework objectives. Regarding homework objectives, four scales were measured with the introductory statement "One of my main reasons for giving homework is … "

Drill and practice were assessed with four items (e.g., "that it is very effective to have students practice the material covered in the lesson again at home"; $\alpha = .62$). Closing the achievement gap was assessed with two items (e.g., "that it helps to close achievement gaps between high- and low-achieving students"; $\alpha = .51$). Motivation was assessed with six items (e.g., "that I want to increase students' interest in the subject"; $\alpha = .72$). School-home link was assessed with two items (e.g. "that it encourages parent-child communication about school matters"; $\alpha = .84$).

Homework implementation practices. Homework implementation practices were assessed with two scales. An emphasis on student responsibility was assessed with two items (e.g., "I have explained to my students that they do the homework for themselves and not for the teacher"; $\alpha = .69$). A controlling homework style was assessed with five items (e.g., "I take homework completion into account when assigning grades"; $\alpha = .65$).

Attitudes toward parental homework involvement. Two aspects of teachers' attitudes toward parental homework involvement were measured. Endorsement of parental homework checking was assessed with two items (e.g., "Parents should have their children show them their homework to make sure that it has been done properly"; $\alpha = .66$). Support for student homework autonomy was assessed with four items (e.g., "Students should do their homework without help because that is how they learn the most"; $\alpha = .67$).

Statistical analyses

To assess the dependence of students' homework learning types on the multilevel structure of the data, we first applied MLPAs to the cross-sectional data on students' homework behavior at Time 2. Second, we included covariates (assessed at Time 1) as predictors of the student- and class-level profiles at Time 2.

MLPAs

MLPAs were conducted to simultaneously estimate latent profiles at the class level and at the student level (nonparametric random effects models; e.g., Vermunt, 2003). Just as in standard latent profile analyses, a set of indicators was used to specify a student-level latent categorical variable that consists of a number of distinguishable profiles. Homework compliance, persistence, seasonal effort, and homework time measured at Time 2 were used as indicators of students' homework profiles. For each profile of the latent categorical variable at Level 1 (i.e., homework learning type), classification probabilities and the profile-specific means of the indicator variables were estimated.

In different school classes, there might be a distinct distribution of learning types. This nested data structure was explicitly modeled with another latent categorical variable at the class level by specifying a random-effects multinomial logistic regression analysis (Vermunt, 2003) with the following equation:

$$P\left(Y_{ijt}|W_j = l\right) = \sum_{k=1}^{K} P\left(X_{ij} = k|W_j = l\right) \prod_{t=1}^{T} P\left(Y_{ijt}|X_{ij} = k,\ W_j = l\right). \tag{1}$$

The vector of a response pattern of individual i in Level 2 unit j on a number of Level 1 indicator variables t is denoted by Y_{ijt}. The latent profile variable denoting the latent profile membership at Level 1 is defined by X_{ij}, and a specific latent profile is referred to as k. W_j represents the unobserved latent profile variable at Level 2, and l specifies a particular class-level profile. Thus, in our example, $P(X_{ij} = k)$ is the probability that student i in Level 2 classroom j is classified as latent profile (i.e., learning type) k.

Thus, the class-level profiles are defined by specific distributions of latent student profiles (Henry & Muthén, 2010). The class-level latent profiles are modeled by the extent to which they influence a student's probability of being classified into a specific latent student profile, and student-level profiles are modeled by the extent to which they influence the responses on the four homework behavior measures (Vermunt, 2008; see also Figure 1).

How can the results of MLPA models be interpreted? In the MLPAs, the nature of the effect of classes on students' homework learning types can be evaluated by the variations in the distributions of students' homework learning types and the classification probabilities of the student-level profiles across the class-level profiles. It might be the case that, in specific classes, there is a great likelihood that students are classified into one homework learning profile (e.g., the *high effort learners*); whereas, in other classrooms this learning type might have a small probability;

this can count as an indication of a strong class/teacher effect on the formation of this specific homework learning type. By comparison, if the student homework learning types are assigned in similar numbers to the latent class-level profiles, and there are no great irregularities in the classification probabilities of the student-level profiles across the class-level profiles, this can be interpreted as a small effect of the classroom.

Class enumeration

We first investigated the LPAs (i.e. no specification of random coefficients at the class level) for one to eight student-level profiles and selected the most appropriate model. In the LPAs, the multilevel structure was ignored, and only the measurement model for the student-level profiles was estimated. Thereby, the number of student-level profiles was selected. In the subsequent MLPAs, when we assessed the number of class-level profiles, the class-level profiles were estimated in addition to the student-level profiles. One to six class-level profiles were specified on the basis of the relative frequencies of the student-level profiles.

A set of classification criteria was used to identify the most appropriate model. According to Lukočienė, Varriale, and Vermunt (2010), the group-based BIC is optimal for comparing results of multilevel mixture models. In addition, because the BIC has been shown "to underestimate the number of classes, and the AIC tends to overestimate it, the AIC3 has been recommended as a compromise" (Tay, Diener, Drasgow, & Vermunt, 2011, p. 201). Therefore, the models were compared by considering the AIC3 and the individual-based and group-based BICs. For a comparison of relative fit, the best practice (cf. Morin & Wang, 2016; Petras & Masyn, 2010) involves an inspection of elbow plots. The preferable number of latent profiles is indicated by the point after which the slope flattens and no atypical or extreme deviations from the decreases are depicted. On the basis of suggestions by Collins and Lanza (2013) and Lukočienė et al. (2010), we also considered the parsimony and interpretability of the solution in the process of selecting a model.

Model specification

Concerning the estimation of the latent profiles, we relied on the most parsimonious model (cf. Chen, Bollen, Paxton, Curran, & Kirby, 2001), which had unequal means and class-invariant variances. Before deciding which modeling strategy to apply, we compared models with unequal variances and equal variances because previous findings had suggested that the specification of LPAs with unequal variances yields less biased results (e.g., Kim et al., 2016; Peugh & Fan, 2013). When we allowed the variances to be freely estimated across classes, improper solutions resulted. Moreover, we relied on the conditional independence assumption. Thereby, we assumed that the correlations between the indicators of the latent variables were fully explained by the latent (class) variable (i.e., all shared variance among the indicators was assumed to be explained by the latent class variable, e.g., Schmiege, Masyn, & Bryan, 2018). Morin, Morizot, Boudrias, and Madore (2011) suggested that a relaxation of the local independence assumption "should only be done (…) on the basis of strong theoretical assumption to avoid converging on a model that would reflect capitalization on chance based on atheoretical ex post facto modifications" (p. 65; see also Meyer & Morin, 2016)[1]. For each profile of the latent categorical variable, the profile-specific probabilities of the responses and the profile-specific means of the indicator variables were estimated, and each student's classification into a specific latent profile (i.e., homework learning type) could be derived from these.

We used the default in Latent GOLD with the maximum likelihood estimator (Vermunt & Magidson, 2015b, p. 28) with 1,000 random starts and 200 iterations in all models. To prevent potential problems with profile switching owing to the inclusion of the covariates, we followed Morin, Meyer, Creusier, and Biétry's (2016) suggestions and used the start values from the final unconditional MLPA model in the estimation of the MLPA with covariates.

Investigating the role of covariates with the direct inclusion approach

In a single-level latent profile analysis, the model parameters are assumed to be fixed (i.e., the same for all individuals, see e.g., Vermunt, 2003). In a multilevel model, the intercepts of the latent profiles vary across the Level 2 cluster variable (e.g., Asparouhov & Muthén, 2008). In the nonparametric approach to MLPA, the random intercepts of the latent student profiles at the class level are modeled to be predicted by class-level latent profiles.

In the structural part of the model, Level 2 and Level 1 covariates are considered. The Level 1 variables are modeled as predictors of the latent profiles at the student level, and the Level 2 variables are modeled as predictors of the latent profiles at the classroom level (e.g., Asparouhov & Muthén, 2008). For example, the respective teacher characteristics are modeled to predict the probability that a class will be characterized as a certain class-level type (see also Henry & Muthén, 2010).

In variable-centered approaches, Level 2 covariates are modeled as predictors of the random intercepts of the outcomes at Level 2. In multilevel mixture models, next to the effect on class-level profiles, a Level 2 covariate can also influence the random intercepts of the Level 1 latent profiles (Van Horn et al., 2016). The effects of the Level 2 covariate on the random intercepts of Level 1 profiles refer to the influence of contextual effects on latent profile membership at Level 1. Conceptually, these effects inform about the impact of the Level 2 predictors on the variations in the likelihood of membership in the Level 1 profiles across classes (for more details, see Heck & Thomas, 2015, and Van Horn et al., 2016).

We estimated MLPAs with the direct inclusion approach, which refers to the simultaneous consideration of the Level 1 and Level 2 covariates while estimating the latent profiles. Thereby, the covariates assessed at Time 1 were specified as predictors of the latent student- and class-level profiles identified in the Time 2 data. The teacher variables and students' prior achievement were *z*-standardized prior to these analyses. First, we investigated the effects of the Level 2 covariates on the random intercepts of the latent student profiles in MLPAs without class-level profiles. Subsequently, all covariates were considered jointly as covariates in MLPAs with class- and student-level profiles to explore which classroom/teacher characteristic was most strongly associated with the latent profiles while controlling for the associations with the other covariates. Teachers' behaviors and attitudes were specified as predictors of the class-level latent profiles, which allowed us to evaluate the impact of teachers' homework objectives on the emergence of certain class-level types. In addition, the significant effects of the Level 2 covariates on the random intercepts of the latent student profiles were considered.

To evaluate the effect of a covariate on the probability of classifying a student as belonging to a specific latent profile at the student or class level, we conducted multinomial logistic regression analyses. The syntax we used for the multilevel mixture models with and without covariates is reported in the supplementary material. We used both Mplus and Latent GOLD to analyze our research questions; the reported results were computed with Latent GOLD.

Results

The descriptive statistics (Means, *SD*s) and correlations of the measures of students' homework behaviors and teachers' homework-specific attitudes are presented in Table 1.

Identifying latent profiles at the student and class levels

To determine the optimal specification of the multilevel structure of the data, we estimated LPAs in which the multilevel structure was ignored for one to eight student-level profiles, and then we decided which model was the most appropriate one. Subsequently, we estimated the MLPAs with one to six class-level profiles and selected the most appropriate model.

Table 1. Descriptive statistics and intercorrelations of the study variables.

		M	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Student measures														
(1)	T2 HW compliance	2.75	0.62	–	.70**	−.83**	.24	−.23	−.21	.02	−.24†	.10	−.27†	−.24	.13
(2)	T2 HW persistence	2.63	0.68	.51***	–	−.62**	.01	−.10	−.34*	−.04	−.25†	.13	−.11	−.33*	.11
(3)	T2 HW seasonal efforts	2.45	0.68	−.54***	−.53***	–	−.49*	.06	.15	−.07	.16	−.19	.04	.03	−.10
(4)	T2 HW time	3.45	1.72	.15***	.10**	−.15***	–	.25†	.36**	.39*	.31*	.17	.15	.09	−.12
	Teacher measures														
(5)	Drill and practice	3.28	0.44					–	.42**	.25†	.42**	.17	.48**	.41***	−.19
(6)	Closing achievement gap	2.42	0.68						–	.41***	.56***	.05	.45**	.06	−.14
(7)	Motivation	2.61	0.44							–	.30**	.27†	.46**	.03	.07
(8)	School-home link	2.22	0.68								–	−.01	.33*	.17	−.41**
(9)	Student responsibility	3.32	0.57									–	.40**	.16	.23†
(10)	Controlling HW style	2.85	0.55										–	.34**	−.09
(11)	Student HW autonomy	2.47	0.70											–	−.21*
(12)	Parental HW control	3.11	0.52												–

Note. The correlations were computed with a multilevel analysis in Mplus 7.4. T = time point; HW = homework.
Concerning the student measures, the correlations at the student level are reported below the diagonal and the correlations at the teacher level are reported above the diagonal.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 2. Fit statistics for the LPAs specifying distinct numbers of latent profiles at the student level.

Latent profiles # Student-level	Log-likelihood	Parameters	BIC	AIC	AIC3	SABIC
1	−8143.28	8	16,346.62	16,302.56	16,310.56	16,321.21
2	−7701.02	13	15,499.65	15,428.05	15,441.05	15,458.35
3	−7462.22	18	15,059.58	14,960.44	14,978.44	15,002.40
4	−7379.36	23	14,931.41	14,804.72	14,827.72	14,858.34
5	**−7242.39**	**28**	**14,695.01**	**14,540.78**	**14,568.79**	**14,606.05**
6	−7184.73	33	14,617.24	14,435.47	14,468.47	14,512.40
7	−7153.46	38	14,592.23	14,382.92	14,420.92	14,471.51
8	−7117.13	43	14,557.11	14,320.26	14,363.26	14,420.50

Note. Boldface font indicates the selected model. AIC = Akaike information criterion; BIC = Bayesian information criterion. SABIC = sample-size adjusted BIC.

Results of the LPAs

When we investigated the solutions of the LPAs with different numbers of student-level profiles, the information criteria consistently decreased as the number of classes increased (see Table 2). To inspect the meaning of the information criteria further, we examined elbow plots to identify the point at which the decrease flattened (i.e., became negligible; see Morin, Maïano, et al., 2011; Petras & Masyn, 2010). These elbow plots showed that for the student-level profiles decreases in the information criteria tended to flatten around five profiles (Figure 2). In addition, the solutions with five and six student-level profiles identified five profiles with a similar pattern. The additional sixth profile was considered a subgroup of the student profile *struggling learners* with especially low values in persistence and compliance and an inappropriate working style. In this case, the recommendation is to rely on the more parsimonious solution with fewer profiles. Thus, our criteria suggested a solution with five student-level profiles (also identified in earlier work; see Figure 3 and Flunger et al., 2015).

Results of the MLPAs

The results of the MLPAs using the Time 2 homework measures showed that modeling the latent class-level profiles improved the model fit compared with the results of the LPA (see Table 3).

Identifying class-level profiles on the basis of the relative frequencies of student profiles.

Regarding the MLPAs, the BIC supported the solution with three class-level profiles. The AIC, AIC3, and group-based SABIC kept on decreasing. Although the SABIC and the BIC-G supported a four-profile solution, the difference in the values that resulted for the three-profile

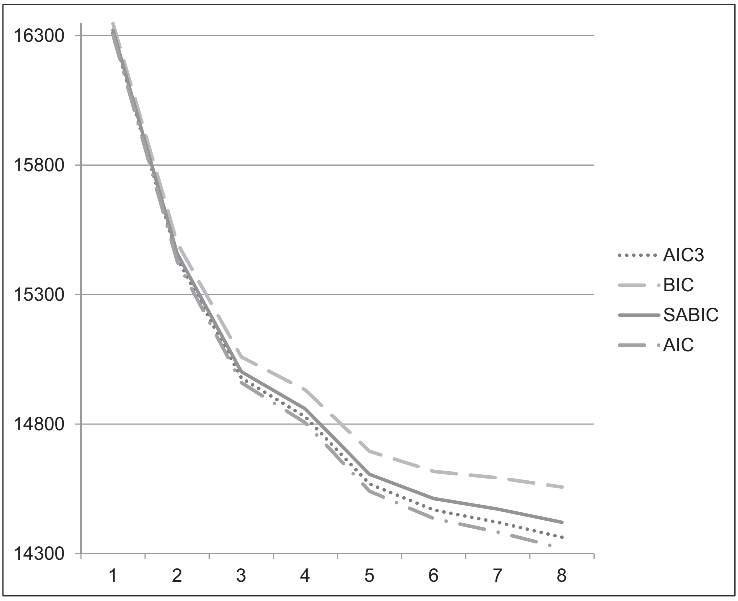

Figure 2. Elbow plot for the information criteria yielded with latent profile analyses.

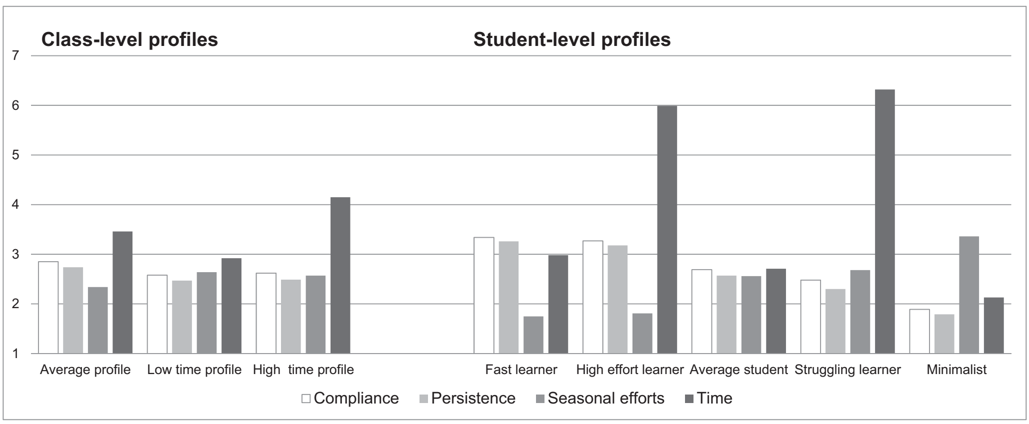

Figure 3. Mean pattern of homework behavior of the class-level and student-level profiles.

Table 3. Fit statistics for MLPAs with 1 to 6 latent profiles class levels and 5 fixed student-level profiles.

Latent profiles							
# Student-level	# Class-level	BIC	AIC	AIC3	SABIC	BIC-G	SABIC-G
5	1	14,695.01	14,540.78	14,568.78	14,606.06	14,616.90	14,528.41
	2	14,672.84	14,491.07	14,524.07	14,568.00	14,580.78	14,476.49
	3	**14,671.48**	**14,462.16**	**14,500.16**	**14,550.75**	**14,565.46**	**14,445.37**
	4	14,681.30	14,444.44	14,487.44	14,544.69	14,561.34	14,425.44
	5	14,697.73	14,433.33	14,481.33	14,545.23	14,563.82	14,412.12
	6	14,719.70	14,427.76	14,480.76	14,551.32	14,571.84	14,404.35

Note. Boldface font indicates the selected model. AIC = Akaike information criterion; BIC = Bayesian information criterion. SABIC = sample-size adjusted BIC; G = group-based.

solution seemed minor. The elbow plots (Figure 4) showed that the AIC3, SABIC, and group-based BIC tended to flatten around three profiles; thus, adding a fourth or fifth profile did not significantly improve the fit of the model. We also inspected the adjacent solution with four

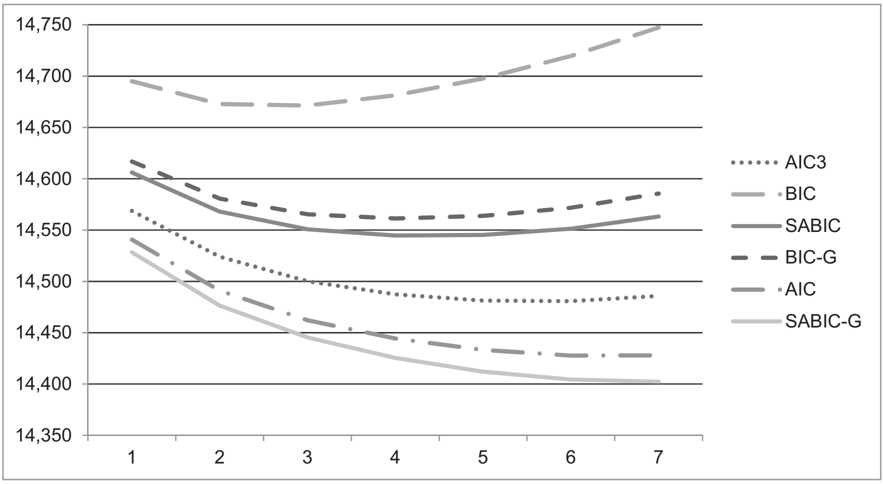

Figure 4. Elbow plot for the information criteria yielded with multilevel latent profile analyses.

Table 4. Frequencies of classes and students (and classification probabilities) for student- and class-level profiles identified at Time 2.

	Class-level profiles identified at Time 2					
	Class-level Profile 1		Class-level Profile 2		Class-level Profile 3	
	Average profile		Low time profile		High time profile	
N students	1167 (.60)		303 (.22)		342 (.18)	
N classrooms	67		17		17	
Fast learner	200	(.21)	48	(.15)	27	(.10)
High-effort learner	144	(.14)	5	(.02)	22	(.09)
Average student	697	(.53)	176	(.50)	111	(.34)
Struggling learner	74	(.08)	21	(.07)	100	(.33)
Minimalist	52	(.05)	92	(.26)	43	(.14)

Note. The latent profiles at the class level were estimated on the basis of the relative frequency of students' homework learning types across different classrooms, based on data on students' homework behavior.

class-level profiles. The solution with four profiles confirmed the three profiles identified in the three-profile solution and yielded an additional profile with very few cases (i.e., $N_{\text{students}} = 31$, $N_{\text{classes}} = 2$, representing only 1.7% of all cases in our sample) and low classification probabilities (.03). The entropy for the solution with three latent profiles at the classroom level was .71, and it was .77 for the solution with five latent profiles at the student level.

Characteristics of the class-level profiles. The three class-level profiles differed in size (see Table 4): The majority of students were classified as class-level Profile 1 ($N_{classrooms} = 67$; $N_{students} = 1{,}167$). The other class-level profiles consisted of fewer students but did not differ greatly from each other in terms of frequencies of teachers and students (class-level Profile 2: $N_{classrooms} = 17$; $N_{students} = 303$; class-level Profile 3: $N_{classrooms} = 17$; $N_{students} = 342$). We used the descriptive statistics for the profile memberships (frequencies of students and classes, classification probabilities; see also Figure 5) to explore whether the class-level profiles were characterized by specific distributions of student learning types. When labeling the class-level profiles, we also considered the estimated class-average mean pattern in students' homework behavior measures (cf. Table 5 and Figure 3).

Regarding the distributions of the student-level profiles, the majority of *fast learners* were assigned to class-level Profile 1 ($N = 200$), with the classification probabilities ranging from .10 to .21 across the three class-level profiles. *High-effort learners* were also mainly assigned to class-level Profile 1 ($N = 144$) and not to class-level Profile 2 ($N = 5$), with the latent student profile

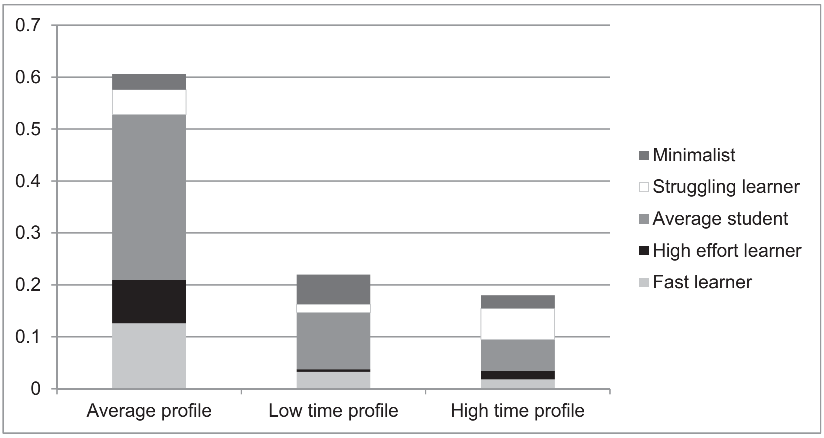

Figure 5. Class-level profiles characterized by the relative frequency of student-level profiles.

Table 5. Mean pattern of homework behavior measures yielded for the student- and class-level profiles and of the covariate students' prior grade.

	Class-level profiles			Student-level profiles				
	Average profile	Low time profile	High time profile	Fast learner	High-effort learner	Average student	Struggling learner	Minimalist
	M	M	M	M	M	M	M	M
Homework compliance	2.85	2.58	2.62	3.34	3.27	2.69	2.48	1.89
Homework persistence	2.74	2.47	2.49	3.26	3.18	2.57	2.30	1.79
Seasonal efforts	2.34	2.64	2.57	1.75	1.81	2.56	2.68	3.36
Homework time	3.46	2.92	4.15	2.98	5.99	2.71	6.32	2.13

probabilities ranging from .02 to .14. The majority of the *average students* were assigned to class-level Profile 1 ($N = 697$), with the classification probabilities ranging from .34 to .53 across all latent profiles at the classroom level. *Struggling learners* were assigned in higher numbers to class-level Profile 1 ($N = 74$) or class-level Profile 3 ($N = 100$) than to class-level Profile 2 ($N = 21$), with the classification probabilities ranging from .07 to .33 across the three latent profiles at the class level. *Minimalists* were assigned to all three latent profiles at the class level, with the highest frequency assigned to class-level Profile 2 ($N = 92$) and the classification probabilities ranging from .05 to .26 across all class-level profiles.

Thus, class-level Profile 1 was characterized by high probabilities of the *average students* profile (.53) and the *fast learners* profile (.21), and comprised considerable frequencies of all five homework learning types, which could be characterized as an "average profile." Class-level Profile 2 was characterized by high probabilities of *minimalists* (.26) and *average students* (.50). This indicates that class-level Profile 2 could be characterized as a "low time" profile. Class-level Profile 3 was characterized by higher probabilities of *struggling learners* (.33) and *average students* (.34). Thus, class-level Profile 3 seemed to consist of higher numbers of students who were characterized by less favorable homework behavior compared with the other learning types (the "high time" profile).

In general, these findings support the role of between-classroom differences in determining students' homework learning types and also highlight the necessity of investigating additional teacher characteristics that can help explain these differences.

Including Level 1 and Level 2 covariates

To test our second research question, we estimated MLPAs with covariates. First, we assessed the impact of teachers' homework objectives on students' homework learning types, through testing whether the Level 2 covariates predicted the random intercepts of the Level 1 latent profiles. Second, all covariates were considered jointly in one model.

We tested all potential profile-specific comparisons for different class-level reference groups (i.e., the "average profile" or the "high time profile") and student-level reference groups (i.e., the *fast learners, high-effort learners, average students, and struggling learners*). The overall statistical significance of the predictors was evaluated with Wald tests. The logistic multinomial regression coefficients from the estimation of the effects of Level 2 covariates on the Level 1 profiles are presented in Tables 6, 7, and 8. The analyses for the joint analyses are reported in Table 9 (results for the class-level profiles) and Table 10 (results for the student-level profiles).

Effects of Level 2 covariates on the random intercepts of the Level 1 profiles

First, we analyzed whether the between-classroom variation in students' likelihood of being classified as specific latent profiles was predicted by the Level 2 covariates (see Tables 6 and 7). Considering the results of the Wald tests (reported in Table 8), teachers' aim to foster students' motivation, teachers' favoring of homework control in class or by parents, the class-average achievement, and students' track level were revealed as significant predictors of the random intercepts of students' homework learning profiles.

Students who were taught by teachers who favored the aim of fostering student motivation through homework had a greater chance of being classified as *high-effort learners* than as *fast learners, average students, struggling learners,* or *minimalists* and had a greater chance of being classified as *struggling learners* compared with the *minimalists*.

Students who were taught by teachers who favored a controlling homework style had a greater chance of being classified as *fast learners* or *average students* than as *struggling learners* and had a greater chance of being classified as *minimalists* rather than as *high-effort students, average students*, or *struggling learners*.

Students taught by teachers who favored parental homework involvement had a higher probability of being characterized as *fast learners* than as *average students*. Moreover, students taught by teachers who endorsed parental homework control were more likely to be classified as *minimalists* than as *high-effort learners, average students* or *struggling learners*.

Students from the upper track were more likely to be classified as *fast learners, average students*, or as *minimalists* rather than as *high-effort learners* compared to students from the lower track.

Prediction of class-level profiles in the joint analyses

We tested the effects of the Level 2 covariates on the Level 2 latent profiles in a joint analysis with all predictors, in which we also specified the significant effects of the Level 2 covariates on the random intercepts of the Level 1 latent profiles. In the joint analysis, teachers' preference of a controlling homework style in class did not affect any classification to student-level profiles. Therefore, we considered teachers' aim to foster students' motivation, teachers' favoring of homework control by parents, the class-average achievement, and students' track level as predictors of the random intercepts of the latent student profiles in the final analysis. An estimated regression coefficient refers to the effect of a covariate (e.g., teachers' homework checking) in predicting the probability that classes or students would be assigned to a class- or student-level profile compared with a reference profile, while the effects of the other covariates were controlled for.

Regarding teachers' homework objectives, the Wald tests revealed two (marginally) significant effects: The aims to foster student motivation and teachers' endorsement of homework checking in class were significant predictors of the probabilities that classes would be classified according to certain class-level profiles. First, teachers' aim to foster students' motivation predicted the likelihood that their classes would be assigned to the "average" profile compared with the "low

Table 6. Effects of the Level 2 covariates on the random intercepts of the Level 1 latent profiles (Part 1, results for the covariates drill and practice, closing achievement gaps, motivation, school-home link, and class-average achievement).

		Level 2 covariates														
		Drill and practice			Closing achievement gaps			Motivation			School-home link			Class-average achievement		
Non-reference profile	Reference profile	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*
Fast learner	High-effort learner	0.10	0.16	0.56	0.12	0.18	0.51	−0.73	0.17	0.00	−0.17	0.18	0.35	0.11	0.36	0.77
Fast learner	Average student	0.13	0.11	0.26	0.00	0.13	0.97	−0.16	0.13	0.20	−0.07	0.14	0.63	−0.28	0.26	0.29
Fast learner	Struggling learner	−0.12	0.15	0.43	−0.33	0.16	0.04	−0.29	0.15	0.06	−0.20	0.16	0.22	0.07	0.35	0.85
Average student	High-effort learner	−0.03	0.14	0.81	0.12	0.15	0.41	−0.56	0.14	0.00	−0.10	0.14	0.49	0.17	0.30	0.57
Average student	Struggling learner	−0.25	0.13	0.05	−0.33	0.13	0.01	−0.12	0.12	0.32	−0.13	0.13	0.31	0.34	0.30	0.25
Minimalist	Fast learner	−0.13	0.15	0.37	0.01	0.17	0.95	−0.07	0.16	0.64	0.41	0.17	0.01	1.26	0.30	0.00
Minimalist	High-effort learner	−0.04	0.17	0.83	0.13	0.19	0.50	−0.80	0.18	0.00	0.24	0.18	0.18	1.15	0.35	0.00
Minimalist	Average student	0.00	0.13	0.98	0.01	0.15	0.96	−0.24	0.14	0.09	0.34	0.14	0.02	0.98	0.26	0.00
Minimalist	Struggling learner	−0.25	0.16	0.12	−0.32	0.18	0.07	−0.36	0.16	0.03	0.21	0.17	0.22	1.32	0.35	0.00
Struggling learner	High-effort learner	0.22	0.19	0.25	0.45	0.19	0.02	−0.44	0.17	0.01	0.03	0.19	0.86	−0.17	0.41	0.68

Note. In these multilevel mixture models, a latent profile variable was estimated at the student level based on students' homework behavior measures assessed at Time 2. The intercepts of the latent profiles varied across the Level 2 cluster variable (the classes). All 10 Level 2 covariates were specified as the predictors of the random intercepts of the Level 1 latent profiles. Students' prior achievement was considered as a Level 1 covariate. The 10 comparisons refer to the potential pairwise comparisons between the five different student homework learning types. The ten pairwise comparisons were yielded with four MLPAs, using different reference groups (i.e., the *fast learners, high effort learners, average students*, and the *struggling learners* served as reference profiles in distinct MLPAs).

Table 7. Effects of the Level 2 covariates on the random intercepts of the Level 1 latent profiles (Part 2, results for the covariates student responsibility, teachers' controlling homework style, student homework autonomy, parental homework control and track level).

		Level 2 covariates														
		Student responsibility			Controlling HW style			Student HW autonomy			Parental HW control			Track level (Upper track = 1)		
Non-reference profile	Reference profile	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*
Fast learner	High-effort learner	−0.08	0.16	0.63	0.11	0.20	0.58	−0.11	0.15	0.47	0.26	0.15	0.09	0.59	0.30	0.05
Fast learner	Average student	−0.03	0.11	0.77	0.02	0.14	0.88	−0.16	0.11	0.16	0.29	0.11	0.01	−0.13	0.23	0.56
Fast learner	Struggling learner	0.00	0.14	0.98	0.38	0.18	0.04	−0.25	0.14	0.06	0.24	0.14	0.08	0.07	0.29	0.81
Average student	High-effort learner	−0.04	0.13	0.74	0.09	0.17	0.59	0.04	0.13	0.74	−0.04	0.12	0.75	0.72	0.25	0.00
Average student	Struggling learner	0.03	0.11	0.80	0.36	0.16	0.02	−0.10	0.12	0.39	−0.05	0.11	0.65	0.20	0.24	0.40
Minimalist	Fast learner	−0.21	0.13	0.12	0.30	0.17	0.08	0.33	0.13	0.01	0.11	0.15	0.45	0.43	0.30	0.16
Minimalist	High-effort learner	−0.29	0.16	0.08	0.42	0.21	0.04	0.22	0.16	0.16	0.37	0.16	0.02	1.02	0.33	0.00
Minimalist	Average student	−0.24	0.12	0.05	0.32	0.15	0.03	0.18	0.12	0.13	0.41	0.13	0.00	0.30	0.28	0.28
Minimalist	Struggling learner	−0.21	0.14	0.14	0.69	0.19	0.00	0.08	0.14	0.58	0.35	0.15	0.02	0.50	0.32	0.12
Struggling learner	High-effort learner	−0.07	0.17	0.67	−0.27	0.22	0.23	0.14	0.17	0.40	0.01	0.16	0.93	0.52	0.33	0.11

Note. In these multilevel mixture models, a latent profile variable was estimated at the student level based on students' homework behavior measures assessed at Time 2. The intercepts of the latent profiles varied across the Level 2 cluster variable (the classes). All 10 Level 2 covariates were specified as the predictors of the random intercepts of the Level 1 latent profiles. Students' prior achievement was considered as a Level 1 covariate. The 10 comparisons refer to the potential pairwise comparisons between the five different student homework learning types. The ten pairwise comparisons were yielded with four MLPAs, using different reference groups (i.e., the *fast learners, high effort learners, average students*, and the *struggling learners* served as reference profiles in distinct MLPAs).

Table 8. Effects of the Level 2 covariates on the random intercepts of the Level 1 latent profiles: results of Wald tests.

	Fast learners		High-effort learners		Average students		Struggling learners	
	Wald ($df = 4$)	p	Wald ($df = 4$)	p	Wald ($df = 4$)	p	Wald ($df = 4$)	p
Drill and practice	4.71	0.32	4.71	0.32	4.71	0.32	4.71	0.32
Closing achievement gap	7.53	0.11	7.53	0.11	7.53	0.11	7.53	0.11
Motivation	26.72	0.00	26.72	0.00	26.72	0.00	26.72	0.00
School-home link	7.74	0.10	7.74	0.10	7.74	0.10	7.74	0.10
Student responsibility	4.63	0.33	4.63	0.33	4.63	0.33	4.63	0.33
Controlling HW style	13.63	0.01	13.63	0.01	13.63	0.01	13.63	0.01
Student HW autonomy	7.25	0.12	7.26	0.12	7.25	0.12	7.26	0.12
Parental HW control	13.37	0.01	13.37	0.01	13.37	0.01	13.37	0.01
Class-average achievement	23.81	0.00	23.81	0.00	23.81	0.00	23.81	0.00
Track level	12.41	0.02	12.41	0.02	12.41	0.02	12.41	0.02

time" profile. Second, teachers' attitudes toward homework checking in class predicted the likelihood that their classes would be assigned to the "low time" profile compared with the "high time" profile.

Prediction of student-level profiles in the joint analyses

Students' prior achievement, teachers' aim to foster student motivation through homework assignment, teachers' favoring of parental homework control, class-average achievement, and track level predicted students' classification as specific homework learning types.

Students' prior French grade, adjusting for the other covariates, positively predicted their classification into the *fast learner* profile and negatively predicted their classification into the *struggling learner* profile. That is, students with higher grades had a higher probability of being classified as *fast learners* and a lower probability of being classified as *struggling learners* compared with the other learning types.

Students who were taught by teachers who favored the aim of fostering student motivation through homework had a greater chance of being classified to learning types characterized by higher time investment in homework or a less advantageous homework style: They were more likely to be classified as *high-effort learners* than as *fast learners* and *average students* and as *struggling learners* than as *average students* or *fast learners* but also as *average students* or *minimalists*, compared with the *fast learners*.

By comparison, teachers' valuing of parental homework control seemed to be associated with a more beneficial homework type: Students taught by teachers who favored parental homework involvement were more likely to be classified as *fast learners* than as *average students* or *high-effort learners*.

Whole-class achievement was mainly associated with a minimalistic homework style in students. Students from classes with a higher class-average achievement were more likely to be classified as *minimalists* than as *fast learners, high-effort learners, average students*, or *struggling learners*.

Finally, students from the upper track were more likely to be classified as *average students* than as *high-effort learners* compared to students from the lower track.

Discussion

The major objective of the present study was to demonstrate how multilevel mixture models can be used to investigate the extent to which students' homework behavior profiles depend on the classroom context. First, unconditional multilevel mixture models were applied to explore the patterns in the distributions of students' homework learning types at the classroom level. Three class-level profiles were identified. The "average" profile was characterized by a profile that was a

Table 9. Results of the MLPA with covariates: association of Level 2 covariates with the class-level profiles.

	High time versus low time profile			Average versus low time profile			High time versus average profile					
Covariates	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Wald (*df*)		*p*
Drill and practice	0.92	0.68	0.170	−0.22	0.52	0.680	1.14	0.64	0.073	3.24	(2)	0.200
Closing achievement gap	0.58	0.58	0.310	−0.31	0.51	0.550	0.89	0.57	0.120	2.48	(2)	0.290
Motivation	0.61	0.60	0.310	1.50	0.62	0.016	−0.88	0.58	0.130	5.93	(2)	0.052
School – home link	0.28	0.52	0.600	−0.31	0.46	0.510	0.58	0.53	0.270	1.25	(2)	0.540
Student responsibility	0.13	0.53	0.800	0.01	0.45	0.990	0.12	0.50	0.800	0.08	(2)	0.960
Controlling HW style	−1.69	0.75	0.025	−0.97	0.61	0.110	−0.72	0.65	0.270	5.21	(2)	0.074
Student HW autonomy	−0.08	0.49	0.860	−0.11	0.42	0.790	0.02	0.49	0.960	0.07	(2)	0.960
Parental HW control	−0.13	0.52	0.800	−0.04	0.46	0.940	−0.10	0.46	0.830	0.07	(2)	0.960
Class-average achievement	−1.54	1.24	0.210	−0.25	0.91	0.780	−1.29	1.16	0.270	1.65	(2)	0.440
Track level	−0.54	0.73	0.460	−0.17	0.60	0.780	−0.37	0.67	0.580	0.55	(2)	0.760

Note. Est. = logistic multinomial regression coefficient yielded from random-coefficients multinomial logistic regression models. *SE* = standard error. In these MLPAs with covariates, both latent student-level and class-level profiles were modeled. The student-level profiles were estimated based on students' homework behavior measures assessed at Time 2; the class-level latent profile variable was specified as a predictor of the random intercepts of Level 1 profiles. Teachers' homework objectives and students' prior achievement were assessed at Time 1. The analyses were conducted with all available data of 1,812 students.

Table 10. Results of the MLPA with covariates: Association of Level 1 and Level 2 covariates with the student-level profiles.

		Level 1 covariate			Level 2 covariates											
		Prior achievement			Motivation			Parental HW control			Class-average achievement			Track level (Upper track = 1)		
Non-reference profile	Reference profile	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*	Est.	*SE*	*p*
Fast learner	High-effort learner	0.54	0.15	0.00	−0.68	0.15	0.00	0.33	0.14	0.02	0.21	0.34	0.54	0.16	0.19	0.40
Fast learner	Average student	0.60	0.11	0.00	−0.19	0.09	0.04	0.30	0.10	0.00	−0.26	0.24	0.28	−0.19	0.12	0.13
Fast learner	Struggling learner	1.03	0.14	0.00	−0.43	0.14	0.00	0.25	0.13	0.06	−0.35	0.37	0.34	0.04	0.18	0.83
Average student	High-effort learner	−0.07	0.13	0.59	−0.49	0.13	0.00	0.04	0.12	0.76	0.46	0.30	0.12	0.34	0.16	0.03
Average student	Struggling learner	0.42	0.11	0.00	−0.24	0.12	0.05	−0.05	0.11	0.63	−0.09	0.32	0.77	0.22	0.14	0.12
Minimalist	Fast learner	−0.75	0.14	0.00	0.40	0.14	0.00	−0.07	0.16	0.66	1.34	0.35	0.00	0.12	0.19	0.54
Minimalist	High-effort learner	−0.22	0.16	0.18	−0.28	0.17	0.10	0.26	0.19	0.16	1.55	0.44	0.00	0.28	0.25	0.26
Minimalist	Average student	−0.15	0.12	0.23	0.21	0.12	0.08	0.23	0.14	0.11	1.08	0.30	0.00	−0.07	0.16	0.69
Minimalist	Struggling learner	0.27	0.14	0.05	−0.03	0.16	0.85	0.18	0.15	0.25	0.99	0.39	0.01	0.16	0.19	0.40
Struggling learner	High-effort learner	−0.49	0.16	0.00	−0.25	0.17	0.14	0.09	0.16	0.57	0.56	0.42	0.19	0.12	0.21	0.57

Note. Est. = logistic multinomial regression coefficient yielded from random-coefficients multinomial logistic regression models. *SE* = standard error.

In these MLPAs with covariates, both latent student-level and class-level profiles were modeled. The student-level profiles were estimated based on students' homework behavior measures assessed at Time 2; the class-level latent profile variable was specified as a predictor of the random intercepts of Level 1 profiles. The ten pairwise comparisons were yielded with four MLPAs, using different reference groups (i.e., the *fast learners, high effort learners, average students*, and the *struggling learners* served as reference profiles in distinct MLPAs). Next to the effects of the Level 1 covariate prior achievement on the student-level profiles, four Level 2 covariates were considered as predictors of the random intercepts of the random intercepts of the student-level profiles, based on the results from the prior MLPAs without class-level profiles (see Table 8).

mixture of all student learning types. The “low time” profile was characterized by low probabilities of *high-effort learners* and *struggling learners*. The “high time” profile was characterized by higher probabilities of *average students* and *struggling learners*.

Second, teachers’ homework objectives were investigated as predictors of the class-level and student-level profiles at Time 2. Teachers’ aim to foster student motivation through homework was shown to predict homework learning types characterized by high homework time investment (the *high-effort learners* and the *struggling learners*). Moreover, we found that teachers favoring a controlling homework style were more likely to teach classes characterized by a time-efficient rather than a time-consuming profile. These findings underscore the potential for extending person-centered research to multilevel analyses.

Identifying latent profiles at the classroom level

Person-centered, typological approaches offer new insights for homework research because they enable researchers to more fully acknowledge the multiple dimensions (and their interactions) according to which the complex nature of the homework context is best characterized (e.g., Flunger et al., 2015). On the basis of the theoretical premises by Trautwein, Lüdtke, Schnyder, et al. (2006), suggesting that a multidimensional, hierarchical model can be used to capture the homework situation, and given the empirical evidence for the necessity of multilevel studies in homework research (e.g., Fernández-Alonso et al., 2017; Fernández-Alonso, Suárez-Álvarez, & Muñiz, 2015), it is essential to conduct research to further investigate the roles that teachers or classes play in affecting the different patterns of homework time and effort invested by their students. Specifically, we expected that the variation in students’ homework learning types across classrooms would show distinct and theoretically significant profiles characterized by different class-average patterns in homework time and effort.

In line with our expectations, we identified meaningful patterns in the between-classroom variation of students’ homework learning types. Most noteworthy, one class-level profile was composed of higher frequencies of the student homework learning types *average students* and *minimalists*, which are learning types characterized by low levels of homework time. Prior homework research has shown that between-teacher differences can affect the effort that students put toward their homework (Natriello & McDill, 1986; Trautwein, Lüdtke, Schnyder, et al., 2006). Our results are in accordance with these findings and indicate that students’ perceptions of teacher involvement regarding homework can affect specific homework behaviors, which correspondingly differ between classrooms. Thus, the differences in the identified class-level profiles underscore the role that contextual effects play in determining students’ homework behavior.

We found a “high time” class-level profile, which seemed to feature students in greater need of support, given that students classified as *struggling learners* were a major part of this group. Therefore, it would be particularly interesting to investigate the association of teachers’ homework objectives and implementation practices with this class-level profile because our finding that class-level profiles can emerge implies that students adapt their homework behavior to whether they perceive adult monitoring (be it by parents or teachers; see also Xu & Wu, 2013). In sum, the results of the MLPAs highlight the necessity to test predictors of the class-level profiles.

The impact of teachers’ homework objectives

Teachers’ homework practices and objectives can play a critical role in determining the latent profiles of their classes and their students. Our findings revealed that teachers’ aim of promoting student motivation and teachers’ attitudes toward homework control in class were significant predictors of specific class-level profiles. Moreover, teachers’ homework-specific objectives and implementation practices were also shown to predict students’ homework behavior profiles: The aim of promoting student motivation and the endorsement of parental homework involvement both had an impact on the classification of students as specific homework learning types.

Contrasting patterns of results were found for the associations between teachers' homework objectives and distinct class-level profiles. Thus, our study confirmed a link between teachers' homework-specific intentions and the effort or time that students in different classrooms considered appropriate for their homework. Thereby, our results extend findings from earlier homework research. Specifically, our study underscores the need to consider differential configurations in both homework effort and time at the student level in homework research and to explore how their distributions across classrooms are affected by teacher characteristics.

First, whereas in prior variable-centered analyses focusing solely on homework effort, a low emphasis of the aim to foster student motivation through homework by teachers was found to be associated with low homework effort in students (Trautwein, Niggli, et al., 2009), our study revealed that—when compared to the "average profile" (characterized by high frequencies of the *fast learners, high effort learners*, and *average students*)—a low emphasis on motivation was rather associated with the "low time" class-level profile, which mainly comprised homework learning types characterized by low homework time (*minimalists*, and *average students*).

Second, teachers favoring a controlling homework style were more likely to teach classes characterized as "low time" profiles compared with classes characterized as "high time" profiles. The "low time" profile was defined by a large proportion of student-level types characterized by low homework time. It might be the case that the teachers whose classrooms are assigned to the "low time" profile foster students' studying and homework skills more resourcefully than the other teachers when checking their homework in their classrooms—for example, by promoting self-regulation or also homework management strategies (e.g., Xu & Wu, 2013).

In educational research, it is particularly interesting to explore whether latent profiles of students are affected differently by their teachers' instructional styles or other Level 2 predictors. Multilevel mixture models enable to assess these "cross-level differential effects" (Van Horn et al., 2016, p. 267), through estimating the impact of Level 2 predictors on the variation of the probability of latent profile membership at Level 1 across classes (Heck & Thomas, 2015; Van Horn et al., 2016). Therefore, in addition to testing the question concerning how teachers' homework objectives were associated with the profile of their class, we also investigated how teachers' homework-specific beliefs were associated with the between-classroom variation of students' probabilities to be classified as specific homework learning types.

Our findings can offer important implications for classroom interventions. First, our findings imply that students taught by teachers who favored the aim of fostering student motivation had a higher probability of being classified as the *high effort learner* and *struggling learner* homework learning types. Thus, the objective to promote student motivation through homework might not be associated with a time efficient working style in students. By comparison, students taught by teachers who more strongly endorsed parental homework involvement were more likely to be classified as *fast learners* rather than as *high effort learners* or as *average students*. That is, regular homework checking in class or by parents might be more beneficial for students' homework skills than efforts to render homework more interesting.

In sum, our study clearly shows the benefits of applying multilevel mixture models in educational research. When theoretical models (as in our homework example) acknowledge a multidimensional, hierarchical model and when prior research has revealed inconsistent findings regarding the associations of factors at the class level and at the student level, multilevel mixture models can be expected to be particularly valuable. In future applications, multilevel mixture models can help to identify which characteristics of teachers and classrooms are associated with specific configurations of student characteristics, such as their academic performance (e.g., Finch & Marchant, 2013), specifically targeting the potential impact of the variation between schools or classrooms and other underlying factors.

Limitations

Although the current study yielded new findings for homework research and also suggested future directions for educational research, some limitations have to be considered. First, although we were able to draw on a large data set with a substantial number of classrooms and teachers (see e.g., Trautwein, Schnyder, et al., 2009), additional longitudinal studies with a comparably broad assessment of students' homework behavior and teacher characteristics, also in other domains, are scarce, giving rise to questions about the generalizability of our findings. Thus, future research is needed to study students' homework behavior in more domains and with other samples.

Second, in this study, we considered data from both students and teachers regarding their general homework-specific practices. In this study design, teachers and students were asked to estimate their average behaviors when answering the questionnaires, an approach that did not allow us to study the daily implementation of homework, communication about and feedback on homework assignments, or the impact of variations over time. Therefore, future studies might benefit from focusing on real-time assessments—for example, by offering online homework assignments with digital tools and in-situ homework monitoring while students work on their homework (see e.g., Roschelle, Feng, Murphy, & Mason, 2016).

Third, the reliabilities of the homework effort measures were acceptable but not overly high. Although behavioral engagement has been defined as a multidimensional construct, previous studies often used one scale to assess behavioral engagement (e.g., Fredricks, Blumenfeld, & Paris, 2004). These measures did not differentiate between the distinct aspects of behavioral engagement, such as compliance, effort, and time investment. Consequently, future research should aim to use improved behavioral engagement measures that consider the unique characteristics and definitions of each aspect of effort (see also Wigfield et al., 2015).

Conclusion

In conclusion, the present study extended recent person-centered research (Flunger et al., 2015) on students' homework behavior by using a multilevel approach. As expected, we found that theoretically meaningful patterns can be identified in the classroom-level latent profiles based on the distribution of students' homework learning types across classrooms and teachers. Most importantly, we were able to identify a risk profile at the class level (the "high time" profile), and our analyses enabled us to acknowledge the role of specific teacher homework implementation practices that are associated with the latent class-level profiles (e.g., regular homework checking in class) and student-level profiles (e.g., teachers' endorsement of parental homework control). It is important to consider these between-classroom influences when exploring the factors that underlie differences in students' homework learning behavior, especially when developing classroom interventions.

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Notes

1. The conditional independence assumption implies that, conditional on the latent profile variable, students' responses on the indicators were uncorrelated. We did not have a theoretical rationale (e.g., same wordings of measures) to specify correlations within classes. Thus, within-class correlations were assumed to be zero, which could lead to the risk of extracting spurious classes. In order to inspect

whether the five identified latent student profiles were in fact meaningful, we followed suggestions by Bauer and Curran (2004) to "embark on a program of construct validation" (p. 26) and evaluated the number of classes also based on their associations with substantively meaningful variables (e.g., Oberski, 2016). For this purpose, we investigated associations of the latent profiles with a number of theoretically connected external variables (Flunger et al., 2015; Flunger et al., 2017), which confirmed unique and meaningful associations between each of the five classes and the considered outcomes and covariates.

2. In preliminary analyses, we investigated the effects of a professional training program on teachers' homework implementation practices on the class-level profiles. More specifically, several teachers ($N = 25$ from five schools) were randomly selected to take part in a professional development training program on homework (Schnyder & Niggli, 2003). We also investigated the effects of the professional development program using a dummy variable (0 = no training received; 1 = training received). The professional development program referred to training for school teams in which the teachers received materials with suggestions for improving their homework implementation practices. The school teams could identify the specific strategies they would implement as obligatory, desirable, or optional. Examples of suggested strategies are the choice of homework assignments regarding French (e.g., letting students write a small text using newly learned vocabulary and commenting on each text or increasing the number of regular listening assignments) and homework checking (e.g., regular homework checking, number of class discussions regarding homework). Within one school year, the selected teams met three times to exchange experiences and could also receive more materials (specific homework assignments on, e.g., vocabulary learning; for more information, see Schnyder & Niggli, 2003). We did not find statistically significant effects of the professional training program.

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