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Stability and change of secondary school students' motivation profiles in mathematics: Effects of a student intervention

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A R T I C L E I N F O

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A B S T R A C T

There is high agreement that motivation is an important factor for successful learning processes and outcomes. But how do students differ in terms of motivation and how do these differences affect the effectiveness of a motivation intervention? As an intervention interacts with students' characteristics, students' heterogeneity must be considered and homogeneous intervention effects must be critically examined. This study aimed to identify motivation profiles of a specifically vulnerable student group, namely students in the lowest ability tier in the learning of mathematics. Within the framework of self-determination theory, we investigated how these profiles changed during Grade 7 and Grade 8. Furthermore, the study examined whether a particular intervention setting aimed at promoting positive emotions and motivation in learning had an impact on the patterns of change in the specific motivation profiles compared to students in the control condition. A latent profile analysis based on self-reported intrinsic, identified, introjected, and external regulation of 348 students revealed three motivation profiles, consisting of (a) low-mixed, (b) high-mixed, and (c) self-determined. Results of the latent transition analysis indicated that the majority of students tended to remain in the same profile and also revealed different effects of the intervention on different motivation profiles. The intervention seemed to be better tailored to students in the low-mixed motivation profile than to students in other profiles. This result highlights the nature of differential effects between students.

Individual prerequisites, such as motivation, are important factors in successful learning processes and outcomes. Students' reasons for making the effort to learn can differ between individuals as well as situations. Due to the expectation that both intrinsic and extrinsic incentives can be meaningful for a learning activity, it is anticipated that different forms of regulation may coexist within an individual (Hidi & Harackiewicz, 2000; Murayama, 2019). Although evidence of a generally close relationship between motivation and achievement exists (e.g., Steinmayr & Spinath, 2009), less is known about the motivation profile of vulnerable groups, such as students in the lowest ability tier who display lower performance. Based on self-determination theory (SDT), this paper addresses this gap by examining latent motivation profiles of students in the lowest ability tier in lower secondary education (Grades 7–8). We specifically focused on differences in the development of mathematics motivation over 2 years and to the differential effects of an intervention that was aimed at promoting motivation in mathematics learning. According to ecological theory, behavior is a function of ongoing interactions between students' characteristics and their environments (Sheridan & Gutkin, 2000); therefore, the finding that some interventions do not have robust effects (e.g., students respond differently to treatment) is not surprising (Fuchs & Fuchs, 2019). We investigated whether students within different motivational profiles responded differently to the intervention and, thus, whether

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the intervention was better tailored for specific motivational profiles. This study extends the traditional intervention evaluation by incorporating student characteristics and their interactions with the environment (i.e., intervention) to provide a better understanding of the individual development of motivation. This knowledge is especially important for students in the lowest ability tier in order to minimize achievement gaps due to individual characteristics, maximize individual learning success, and empower these students for lifelong learning (Preacher & Sterba, 2019).

1. Self-determination theory

Different motivational orientations have been defined, such as those in the self-determination theory (SDT) of motivation established by Deci and Ryan (1985). In SDT, the dichotomous distinction between intrinsic and extrinsic motivation was replaced by a continuum of five types of regulation, consisting of (a) intrinsic, (b) integrated, (c) identified, (d) introjected, and (e) external. These regulation forms differ in their level of self-determination (Deci & Ryan, 1985, 2002). According to this model, the lowest level of self-determination is found in *external regulation*, which is when a given behavior is determined entirely by external factors and occurs exclusively because of a reward or punishment. A low self-determination level can also be found in *introjected regulation*, which has a greater level of external control and includes behaviors pursued because they are necessary due to internal pressure, such as a guilty conscience. *Identified regulation* contains a greater level of internal control and is regarded as a self-determined form of extrinsic motivation. In identified regulation, an individual's behavior is considered personally important and the goals have been temporarily or permanently integrated into the individual's self while still fulfilling an instrumental purpose. *Integrated regulation* is characterized by the individual having integrated former external goals into a coherent self. Finally, *intrinsic regulation* is considered the prototype of self-determined behavior in which the act itself is a pleasure (Deci & Ryan, 2009). In the educational context, intrinsic, integrated, and identified regulation are considered to be the desired forms because in these forms the behavior is regarded as self-determined and meaningful and leads to improved learning outcomes (Deci & Ryan, 2000).

Despite the availability of a more differentiated model of motivational orientation, previous research has frequently defined intrinsic motivation as the opposite of extrinsic motivation (e.g., Harter, 2010) or has focused on only one type (e.g., Marcoulides et al., 2008). Based on the SDT assumption that motivation is not dichotomous and both intrinsic and extrinsic incentives can be meaningful for an action, it is expected that a person may be motivated by multiple factors and different forms of regulation may coexist within an individual (Hidi & Harackiewicz, 2000). For example, students may simultaneously learn mathematics because they enjoy mathematics (i.e., intrinsic regulation), good grades are important to them (i.e., identified regulation), they would otherwise feel guilty (i.e., introjected regulation), and they get a reward for earning a good grade (i.e., external regulation). Although these factors may influence learning behavior to varying extents, they all contribute to the activity and thus should be considered. In this assumption of multiple driving forces, the manifestation of all regulation forms is crucial. It can be assumed that one or another regulation form is more pronounced than the others, but all may be present at the same time because they are not mutually exclusive. However, the modelling of this multi-dimensionality, and the fact that students can at the same time have multiple reasons for their learning behavior, has been a challenge for empirical research.

Previous research on motivation based on SDT (e.g., Baard et al., 2004; Ryan et al., 2006) has used predominantly variable-centered approaches that aim to assess the relationship between individuals' positions on latent dimensions or variables (Magnusson, 2003). A variable-centered perspective is useful in understanding how particular types of motivational regulation relate to outcomes, although it does not adequately assess whether some sets of regulations are more common than others or whether an individual's primary regulation changes over time (Moran et al., 2012; Otis et al., 2005). This has led to lack of a more "holistic, interactionistic [sic] view in which the individual is seen as an organized whole, functioning and developing as a totality" (Bergman & Magnusson, 1997, p. 291); however, this can be addressed with a person-centered approach. A person-centered approach is indispensable when aiming to examine the complexity of individual development (Bergman & Magnusson, 1997). Whereas the variable-centered approach identifies variables of interest and assumes that the predictors have a homogeneous effect on the outcomes across individuals, the person-centered approach identifies individuals with common attributes and assumes that the predictors have heterogeneous effects on the outcomes across subgroups (Laursen & Hoff, 2006; Magnusson, 2003; Moran et al., 2012). Therefore, person-centered analyses investigate how variables group within individuals instead of considering how variables are related to each other. Instead of deciding how to combine the variables, the data identify profiles by grouping individuals who demonstrate similar patterns of variables. As being tracked into the lowest ability tier of secondary education might lead to less heterogeneity in motivation profiles, this approach is particularly interesting (Lazarides et al., 2020). Thus, the person-centered approach can serve as a complementary view to the variable-centered approach (Helmke & Weinert, 1997). Furthermore, person-centered approaches can open new perspectives that are useful in discovering possible intervention effects in different subgroups and can reveal more specific results than variable-centered findings. Therefore, the person-centered approach offers an opportunity to explore motivation profiles.

2. Motivation profiles

During the last decade, motivation research has increasingly aimed to identify different patterns of motivational orientation. However, some weaknesses regarding the identification of motivation profiles have to be considered. Based on different theoretical considerations and statistical approaches, existing research has investigated different motivational variables (e.g., self-concept, interest, intrinsic value, goal orientation). Despite the common idea to identify distinct patterns of motivation, this has led to a heterogeneous picture regarding relationships and comparisons between studies (e.g., Lazarides et al., 2019, 2020; Linnenbrink-Garcia et al., 2018).

Regarding motivation profiles within a theory, such as SDT, previous research on motivation profiles has tended to reduce the four types of regulation into two principal categories consisting of autonomous regulation (with composite scores gained by averaging the subscales of intrinsic and identified regulation) and controlled regulation (composite scores average the subscales of introjected and external regulation; e.g., Hayenga & Corpus, 2010; Vansteenkiste et al., 2009). Subsequently, three or four motivation profiles across different school types have been documented according to the intensity of the categories, including (a) high autonomous and low controlled motivation, (b) high autonomous and high controlled motivation, (c) low autonomous and high controlled motivation, and (d) low autonomous and low controlled motivation (e.g., Corpus et al., 2016; Hayenga & Corpus, 2010; Ratelle et al., 2007; Vansteenkiste et al., 2009). In terms of students' learning outcomes, research indicates that high autonomous motivation profiles are linked to better performance, such as increased persistence and achievement (Guay et al., 2008). Additionally, a high autonomous and low controlled profile has been shown to be associated with higher academic achievement (Gillet et al., 2017; Hayenga & Corpus, 2010, $\eta^2 = 0.06$; Wormington et al., 2012, $\eta^2 = 0.06$), and, according to Vansteenkiste et al. (2009), lower test anxiety ($\eta^2 = 0.09$), less procrastination ($\eta^2 = 0.15$), and less tendency to cheat ($\eta^2 = 0.12$). The two profiles with low autonomous motivation (i.e., low autonomous and high controlled motivation, and low autonomous and low controlled motivation) have been identified as unfavorable profiles due to a lack of improvement in learning. Of these two profiles, the low autonomous and high controlled motivation profile is associated with more procrastination ($\eta^2 = 0.15$) and more test anxiety ($\eta^2 = 0.09$) and was, therefore, considered the most disadvantageous profile (Vansteenkiste et al., 2009). The comparison between the two high autonomous motivation profiles (i.e., high autonomous and low controlled motivation, and high autonomous and high controlled motivation) also confirmed that the concurrent prevalence of high controlled motivation is associated with (a) maladaptive strategy use and ability-validation goals (Corpus et al., 2016); (b) more pressure, stress, and procrastination ($\eta^2 = 0.15$); and (c) test anxiety ($\eta 2 = 0.09$; Vansteenkiste et al., 2009).

Variable-centered research has shown a decline in students' motivation throughout schooling, particularly after the transition to secondary education (e.g., Eccles, Midgley, et al., 1993; Jacobs et al., 2002). However, these findings indicate the average development of all students represented in the sample and do not provide information on individual subgroups and their development. Person-centered studies that can provide such evidence have found that motivation profiles are relatively stable (e.g., Corpus & Wormington, 2014; Gillet et al., 2017; Lazarides et al., 2019; Marcoulides et al., 2008; Nurmi & Aunola, 2005). Furthermore, it could be that motivation profiles—regardless of the type of profile—become more stable with age as younger children (age 9 years) have been shown to change more frequently (19.6%–24%) between profiles than adolescents (age 16 years: 0%–5.6%; Marcoulides et al., 2008). Additionally, less favorable profiles (in terms of motivational orientation) are more stable (55.1%–71.6%) than those profiles that are considered more desirable (Hayenga & Corpus, 2010; Lazarides et al., 2019. Specific to changes in motivation profiles, (a) a change to a less favorable profile occurs more often (4.5%–30.3%) than a change to a more desirable profile (0%–11.9%; Bråten & Olaussen, 2005; Hayenga & Corpus, 2010), and (b) a change between two adjacent profiles (e.g., the low motivation profile and an intermediate motivation profile) occurs more often (4.3%–21.4%) than a change between two distant profiles (e.g., from the low motivation profile to the high motivation profile or vice versa [0%–2.6%]; Marcoulides et al., 2008).

Despite the interesting and valuable findings from prior research on SDT-based motivation profiles, it must be noted that the two-by-two structure (i.e., autonomous and controlled motivation) can lead to an underestimation of motivational heterogeneity because different forms of regulation can co-occur. Although this two-by-two structure may ease profile estimation, it may also be associated with a reduction in the depth of the results and a lack of potentially important insights into more complex motivation patterns in academic learning (Howard et al., 2016). This supports the idea of testing a more open strategy to identify motivation profiles. In addition, previous studies within SDT have investigated motivation profiles collectively for entire middle schools, high schools, or colleges; in contrast, the present study examined students in the lowest ability tier in lower secondary education (Grades 7–8) and thus included a particular group of students at risk for poor performance. Due to the highly selective school system in Switzerland, students are assigned to different tiers (i.e., school types) of lower secondary education based on teachers' assessments of academic performance at the end of primary education (Grade 6). Students in the lowest ability tier, who also display lower performance, differ significantly from students in other tiers in their academic self-perceptions, attitudes toward school, and motivation (e.g., McCoach & Siegle, 2001; Van der Beek et al., 2017). Thus, selecting a specific performance level might lead to less heterogeneity in motivation profiles. Therefore, the present study aimed to investigate whether the existing profiles within SDT research can be found in this at-risk group or whether there is a dominant motivation profile among students in the lowest ability tier. Also, interventions in this at-risk group might be of particular importance because the promotion of motivation could enhance academic performance.

3. Motivation interventions

In recent decades, interest in maintaining and fostering students' motivation in education has increased (Lazowski & Hulleman, 2016; Wentzel & Wigfield, 2007). Based on the findings that motivation tends to decrease during secondary education (e.g., Eccles, Wigfield, et al., 1993; Gnambs & Hanfstingl, 2016), researchers have developed intervention programs intending to alter this trajectory. These intervention programs are based on different motivation theories, such as self-efficacy (Bandura, 1977), expectancy-value (Eccles, 1983), self-determination (Deci & Ryan, 1985), and achievement goals (Elliot, 2005), and target the motivation of students to improve their learning outcomes (see Lazowski & Hulleman, 2016, for an overview).

A meta-analysis of 92 intervention programs (Lazowski & Hulleman, 2016) indicated that programs based on motivation theories offer promise in terms of fostering educational outcomes ($d = 0.49$). Interestingly, no systematic effect size differences have been found when comparing different programs. Therefore, it is assumed that by targeting psychological mechanisms, educational outcomes can be improved and motivation intervention programs can be implemented across different subjects and age groups (Lazowski & Hulleman, 2016). Yeager and Walton (2011) examined intervention programs that target students' feelings, thoughts, and beliefs in and about school as well as learning, with a long-term effect on motivation and achievement. They found that brief social-psychological interventions that did not focus on academic content but rather were aimed at changing underlying psychological processes were suitable for enhancing academic achievement. Social-psychological interventions can trigger recursive social, psychological, and intellectual processes that might change the trajectory of perceptions and outcomes in school (Yeager & Walton, 2011). To be effective, social-psychological interventions must be targeted, tailored, and timely (Cohen et al., 2017). In particular, the time after a transition to a new school has been demonstrated to be a favorable window for change (e.g., Cohen et al., 2009; Walton & Cohen, 2011). As research shows motivation to be domain specific (Guay et al., 2010), in the present study we focused on the domain of mathematics to provide a targeted and tailored intervention. Mathematics is one of the main subjects in Switzerland, has high instrumental relevance (Häberlin et al., 2005), and has far-reaching consequences for career choices and trajectories. In addition, mathematics provides useful skills (e.g., problem-solving, logical thinking) for adult life (Gravemeijer et al., 2017).

Regarding mathematics, several social-psychological interventions have already showed promising results (e.g., Rosenzweig & Wigfield, 2016). However, it should be noted that the number of intervention studies that would allow causal interpretations is relatively small when compared to the number of correlation and non-experimental studies (Lazowski & Hulleman, 2016). Furthermore, intervention studies with marginal or no impact are less likely to be published given that promising effect sizes are a significant predictor of the difference between published and unpublished studies ($d = 0.64$), which might lead to a potential bias in favor of overestimated effectiveness (Chow & Ekholm, 2018; Cook & Therrien, 2017; Polanin et al., 2016). Moreover, intervention studies tend to lack robust effects; for example, program efficacy studies have found that in most mathematics programs, some students do not respond to treatments (Fuchs & Fuchs, 2019). Thus, students' preconditions and their responsiveness to intervention, such as the implementation of newly acquired strategies into the individual learning process, may also contribute to intervention effects (Dane & Schneider, 1998). Consequently, in addition to the general effectiveness of an intervention program, differential effects must be considered.

4. Differential intervention effects

Intervention research usually results in homogeneous effects for all participants. However, as an environment interacts with students' characteristics, students' heterogeneity must be considered and thus the idea of a homogeneous effect must be scrutinized. Based on their characteristics, students may differ in their readiness to benefit from a treatment (i.e., intervention program) at a specific time (Snow, 1991). Thus, students' characteristics moderate (i.e., interacts with) the effects of the intervention (Fuchs et al., 2014). For example, in the context of mathematics interventions, Fuchs et al. (2014) indicated that working memory of students in Grade 4 moderated the effects of a fraction intervention. Furthermore, Chow and Wehby (2019) demonstrated that in second-grade students, individual differences in language ability moderated the effectiveness of a mathematics intervention. Specific to motivation as students' characteristics, research is scarce and continues to be a direction for future research (Fuchs et al., 2019; Kalyuga, 2007; Preacher & Sterba, 2019). Initial results encouraging the investigation of the mediating role of motivation are promising; for example, Lapka et al. (2011) demonstrated differential effects of an online self-regulated learning intervention in which psychology students with a competence-oriented profile and students with motivational deficits benefited from the treatment, whereas no effects were found among the motivationally balanced students.

Based on these differential intervention effects, we expected that motivational characteristics represented through various motivation profiles would influence the effectiveness of motivational interventions. Due to differences in motivation, there may be different responses to motivation interventions. For some students, different recursive social, psychological, and intellectual process may be triggered, producing different effects among students. The present study's evaluation of a program's differential effectiveness for subgroups by using a person-centered approach may help provide new insights into intervention success.

5. The present study

Prior research examining the development of student motivation leaves several questions unanswered. Given that motivation has multiple determining factors, a deeper understanding of its structure and development seems crucial. The aims of the present study were threefold. First, we examined students' motivation profiles based on SDT in mathematics of students in the lowest ability tier in lower secondary education by applying latent profile analysis (LPA). Given that previous research has typically found three to four motivation profiles (e.g., Corpus et al., 2016; Hayenga & Corpus, 2010; Ratelle et al., 2007; Vansteenkiste et al., 2009; Wormington et al., 2012), we assumed we would find a similar number of profiles (H1a). Moreover, we expected that these profiles would represent not only different levels of prevalence in motivation, but also various combinations of regulation types (H1b). Second, we used latent transition analysis (LTA) to investigate the patterns of change in the motivation profiles over the first 2 school years in lower secondary education (i.e., Grades 7–8). According to previous research (e.g., Lazarides et al., 2019), profiles were expected to remain relatively stable over time (H2a). Yet, if changes were to occur, it was assumed that students would move from a motivationally favorable with high intrinsic motivation profile to less favorable profiles with low intrinsic motivation (H2b), as this would align with previous evidence that has documented decreases in intrinsic motivation over time (Gottfried et al., 2001). Third, we analyzed the effects of an intervention program implemented to promote positive emotions and motivation to learn and we used LTA to investigate whether students within different motivational profiles responded differently to the intervention. Based on a variable-centered approach, Sutter-Brandenberger et al. (2019) found that a 2-year intervention resulted in an increase in intrinsic motivation in Grade 7 (the first year of the intervention) but not in Grade 8. A shift to a person-centered approach may allow us to extend these findings by considering how an intervention might affect different subgroups (i.e., those with different motivational profiles). Therefore, we expected different transition patterns between the profiles in the intervention groups (H3).

Our study expands previous research on motivation profiles in several ways. Whereas earlier studies primarily used cluster analysis (e.g., Corpus et al., 2016; Hayenga & Corpus, 2010; Moran et al., 2012) and were based on different motivation variables, such as self-concept, task value, or attainment value (e.g., Chow et al., 2012; Lazarides et al., 2018), we applied an LPA based on the motivational variables of SDT. Furthermore, prior studies using an SDT framework (e.g., Hayenga & Corpus, 2010; Vansteenkiste et al., 2009) limited their analyses by the dichotomization of autonomous motivation (i.e., the average of intrinsic and identified regulation) and controlled motivation (i.e., the average of introjected and external regulation). To avoid the potential loss of information caused by such dichotomization, we applied LPAs without restricting the possible combinations of the four forms of regulation. Additionally, data have been z-standardized in prior studies, which may have led to a misinterpretation of the differences between profiles (Moeller, 2015). Moreover, regarding context, previous research on motivational profiles within SDT has focused either on middle school students (Hayenga & Corpus, 2010) or high-school and college students (Ratelle et al., 2007) and addressed general motivation (Vansteenkiste et al., 2009). Aiming to extend current knowledge, we examined the motivation profiles in early secondary education within mathematics, with students in the lowest ability tier considered as a special at-risk group. Additionally, existing research has not yet investigated whether motivation profiles are relevant predictors of the effectiveness of motivation interventions. To help answer this question, we analyzed whether students within motivation profiles responded in different ways to an intervention aimed at fostering self-regulated motivation in the mathematics classroom. In summary, our objectives were to gain a deeper understanding of the prevalence and development of different motivation profiles of students in the lowest ability tier for learning mathematics in early secondary education. Moreover, we examined how motivation profiles affected the response to an intervention aimed at fostering self-determined motivation in school.

6. Method

6.1. Participants

The present study was part of the intervention project "Maintaining and Fostering Students' Positive Learning Emotions and Learning Motivation in Maths Instruction During Adolescence" funded by the Swiss National Science Foundation and conducted in the German-speaking part of the canton of Bern in Switzerland. For the first step of recruitment, school representatives of the so called "cooperation schools" (a school network participating in teacher education) were informed about the project in a meeting at the University of Bern. These representatives invited mathematics teachers from their schools to participate in the study. Interested teachers were personally contacted by a member of the research team who explained the study design to the teachers. To facilitate participation and to minimize possible attrition, committed teachers were able to choose in which setting they wanted to participate ($n_{\text{student-teacher intervention}} = 8$; $n_{\text{student intervention}} = 8$). As none of the committed teachers volunteered to be part of the control group, mathematics teachers of the same ability tier and the same grade from the same school or a school in the same district were separately recruited ($n = 6$) to serve as controls. A comparison of the school social index, which is based on the proportion of non-Swiss students, proportion of unemployed, buildings with low residential use, and sedentariness ($M_{\text{student-teacher}} = 1.24$, range = 1.08–1.48; $M_{\text{student intervention}} = 1.41$, range = 1.12–1.66; $M_{\text{control group}} = 1.31$, range = 1.03–1.55; $F(2,19) = 2.36$, $p = 0.121$, $\eta^2 = 0.01$) between the groups revealed no significant differences. Furthermore, teachers of the three groups did not differ regarding their self-reported enjoyment of teaching mathematics (see Brandenberger et al., 2018).

Participating students were required to have parental or guardian consent for participation. All data provided by the students were anonymized. The final sample consisted of 348 students, with a mean age of 12.75 years ($SD = 0.64$) at the first measurement point, from 22 classes in the lowest ability tier of education in Switzerland. A total of 117 students (33.6%) were classified with immigrant status.[1] Students' mean socio-economic status, as measured by the highest International Socio-Economic Index of occupational status (Ganzeboom et al., 1992) of their parents derived from the International Standard Classification of Occupations (International Labour Organization, 2012), was 42.73 ($SD = 14.26$), which is below the average for Swiss students, but within the expected range for students assigned to the lowest ability tier given that students in this school type typically come from families with lower socio-economic status (Bauer et al., 2014). Of the total number of students, 179 were female (51.4%) and 169 were male (48.6%).

6.2. Procedure

The study utilized a quasi-experimental design consisting of two experimental groups and one control group. It focused on three measurement points during Grade 7 and Grade 8 (i.e., beginning of Grade 7, end of Grade 7, and end of Grade 8). Of the total sample of 348 students, 134 students participated in a combined student-teacher intervention, 122 students participated in a student intervention, and 92 students were in the control group. The 256 students from the two intervention groups attended four identical workshops during two regular consecutive mathematics lessons, including two workshops in the autumn term and two workshops in the spring term. In the student-teacher intervention, mathematics teachers were first invited to attend a 90-min introductory session where they were informed about the goals and structure of the project. Within the 2 school years, teachers attended two 120-min workshops. In these workshops, teachers were informed about the theoretical background of students' workshop contents (e.g.,

[1] A quarter of the students with a migration background were first-generation students (i.e., students and their parents born outside of Switzerland), three quarters were second-generation students (i.e., students born in Switzerland with foreign-born parents).

SDT or control-value theory) and were encouraged to deepen their knowledge of student emotion and motivation. No measures of the outcomes of the intervention among teachers were conducted (e.g., changes in instructional strategies or attitudes).

The student intervention was multicomponent and incorporated different theoretical components of SDT (Deci & Ryan, 2002), control-value theory (Pekrun, 2006), attribution theory (Weiner, 1985), and expectancy-value theory (Eccles, 1983). In each workshop, students' basic psychological needs were considered as necessary to achieve motivation to participate in the workshops. For example, cooperative activities were used to increase social relatedness, competence was promoted by allowing tasks to be completed with varying levels of prior knowledge and ability, and autonomy was promoted through choices within tasks. Each workshop addressed different objectives with the overall goal of promoting learning motivation and positive emotions in mathematics. The contents of the workshops were progressively arranged and related to students' daily lives.

Each workshop consisted of a mix of theory (e.g., theoretical inputs, transfer activities, motivational self-regulation strategies), hands-on activities (e.g., applying proposed learning strategies to real mathematic tasks), group collaboration (e.g., case studies), video examples, and reflection about their learning and the importance and value of mathematics for academic learning, everyday life, and their future professional lives (see Fig. 1; Brandenberger et al., 2018; Sutter-Brandenberger et al., 2019). Consistent with social-psychological interventions (Yeager & Walton, 2011), these workshop contents were aimed at triggering psychological processes, which, in turn, were expected to influence the trajectories of students' experiences and outcomes.

Three trained members of the research team conducted the workshops. In accordance with McKenna et al.'s (2014) recommendations to measure intervention fidelity, the treatments followed a detailed structured implementation plan and were realized with the identical materials developed and tested in advance to ensure the intervention protocol. The experiences from the piloting were discussed among the three trainers and within a larger team of researchers. For each workshop, a well-defined schedule with the corresponding durations of each activity was defined and all instructions were set in advance (i.e., instructional text). The three trainers took field notes in case of discrepancies to the training plan (e.g., students came a few minutes late due to a preceding test). No major discrepancies were recorded and all activities were conducted as planned. After each workshop, the three trainers discussed and reflected on their experiences in their workshops with the wider research team to ensure that the interventions were identical. Furthermore, treatment checks after the workshops revealed no significant differences between the two intervention groups (Augustin, 2018). All students completed a paper-pencil questionnaire three times over the 2 intervention years, including at the beginning of Grade 7 (t0), the end of Grade 7 (t1), and the end of Grade 8 (t2). Research team members collected data during regular mathematics classes.

6.3. *Measures*

6.3.1. *Mathematics motivation*

Consistent with the SDT framework, students' motivation in mathematics was measured using the four motivation styles of the German Self-Regulation Questionnaire (Müller et al., 2007), which is an adapted version of the Academic Self-Regulation Questionnaire (Ryan & Connell, 1989). The original scale was validated with students ($N = 2651$) with a gender distribution similar to the present study. The age of the validation sample ($M = 14.2$ years, $SD = 1.8$) was slightly older than the mean age of the present sample ($M = 12.75$ years, $SD = 0.64$). However, the validation study recommended the use of the scale for students ages 11 years and older (Müller et al., 2007). Validation was conducted with students of all ability tiers. The values of intrinsic and external regulation were lower in our sample, whereas identified and introjected regulation were higher in our sample, which might be explained by the younger sample and the focus on students from the lowest ability tier (Müller et al., 2007). Students rated all items on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) with the introductory "Now it's about you and your learning in mathematic class". Intrinsic regulation was assessed through five items (e.g., "I work in mathematics because I want to learn new things"; $\alpha_{t0} = 0.89$, $\alpha_{t1} = 0.86$, $\alpha_{t2} = 0.88$) and identified regulation through four items (e.g., "I work in mathematics because it will give me better career choices"; $\alpha_{t0} = 0.82$, $\alpha_{t1} = 0.83$, $\alpha_{t2} = 0.83$). Introjected regulation was comprised of four items (e.g., "I work in mathematics because otherwise I would have a guilty conscience"; $\alpha_{t0} = 0.67$, $\alpha_{t1} = 0.69$, $\alpha_{t2} = 0.73$) and external regulation consisted of three items (e.g., "I work in mathematics because otherwise I would get into trouble at home"; $\alpha_{t0} = 0.68$, $\alpha_{t1} = 0.69$, $\alpha_{t2} = 0.73$). The validation study (Müller et al., 2007) and the present data showed similar results in terms of intercorrelation and Cronbach's α values.

6.3.2. *Mathematics achievement*

Based on the relationship between motivation and performance, scores on a standardized mathematics test were included to estimate missing values. The students' mathematics performance was tested during two regular consecutive mathematics lessons (90 min) at the beginning of Grade 7 using a standardized achievement test of the HarmoS project.[2] This achievement test was aligned with the Swiss curriculum and includes 30 tasks on the topics such as numbers and variables, functional relationships, and sizes and measures. The test was piloted and validated with 6500 students in Switzerland (see Konsortium Mathematik, 2009, for more information). The average standard score was scaled to the mean of 500 points ($SD = 100$) in accordance with the HarmoS project. The

[2] In Switzerland, the main responsibility for education lies with the cantons. As a result, each of the 26 cantons has developed its own curriculum. To harmonize compulsory education nationwide, the HarmoS project was initiated to establish comprehensive competency levels and standards in specific core areas (including math) for compulsory schools. Based on these standards and curricular objectives, a mathematics achievement test was designed for students in Grades 2, 6, and 9. For the present study, the achievement test designed for students at the end of Grade 6 was used to assess the participants at the beginning of Grade 7.

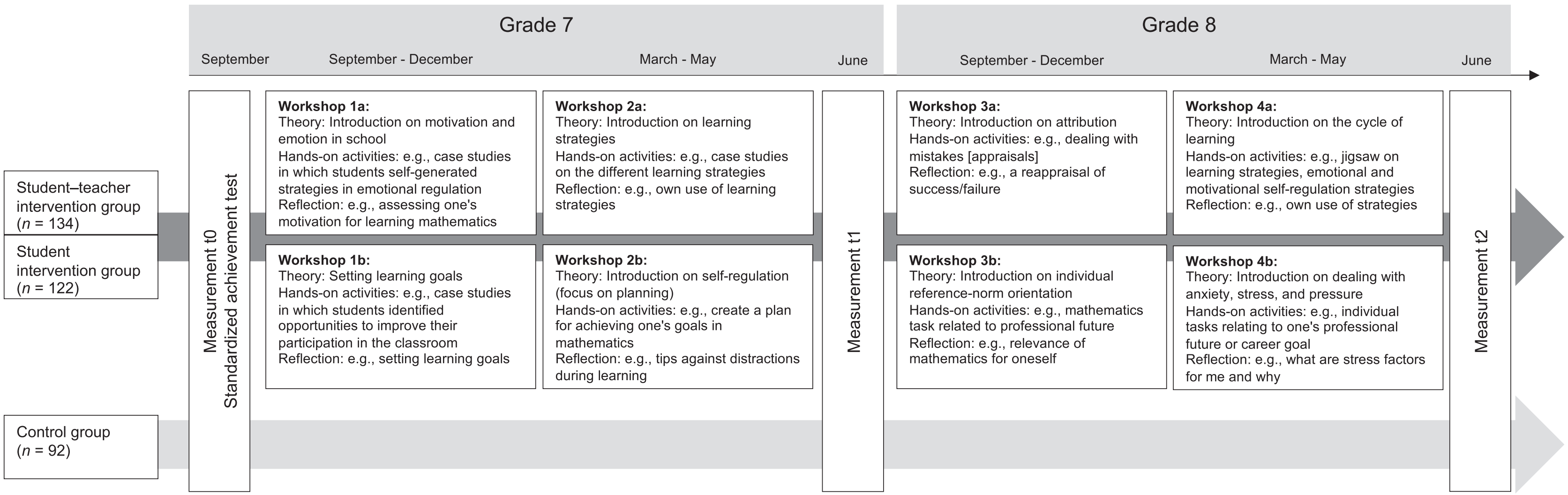

Fig. 1. Intervention Timeline.
Note. t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8.

data from the achievement test were analyzed based on a one parametric item-response model using ConQuest. The mean of the scale was −0.90 (SD = 0.40) and the internal consistency was 0.70. The sample mean at t0 was 432 points (SD = 60.47) and corresponds to the expected range for students in this school type in the canton of Bern in Switzerland (Bauer et al., 2014).

6.4. Data analyses

6.4.1. Missing data

At the end of primary education (i.e., Grade 6), teachers assess students' academic abilities, which then determines student assignment to different tiers (i.e., school-types) of lower secondary education. However, due to the permeability of the Swiss school system, students are still able to move between tiers after this transition. These changes typically occur during the first months of Grade 7. As the present study exclusively focused on students in the lowest ability tier, only those students who remained in this type of school throughout Grade 7 were included in our analyses. Of an initial cohort of 452 students, 348 remained in the lowest ability tier and completed both surveys in Grade 7 (i.e., t0 and t1). At the end of Grade 8 (i.e., t2), 23% of the dependent variables were missing (student absence due to moving to a different tier or change of school during Grade 8, illness, and practical experience as well as trial apprenticeship during data collection in class). Existing research supports the use of methods like multiple imputation and maximum likelihood to treat missing data (Allison, 2010; Schafer & Graham, 2002). Full-information maximum-likelihood (FIML) tends to result in unbiased results, particularly with small sample sizes, and performs well with a moderate amount of missing data (20%–25%; Buhi et al., 2008; Schlomer et al., 2010). Therefore, missing data at the end of Grade 8 were addressed with FIML estimation in Mplus 8.0 (Muthén & Muthén, 1998–2018). For descriptive statistics of the variables, missing values were estimated using the expectation-maximization algorithm in SPSS.

Given the nested structure (N = 22 classrooms) of the data and the nonindependence of observations, the command "Type = Complex" was used for all analyses in Mplus. This approach adjusts standard errors to account for the nested structure of the data (Muthén & Muthén, 1998–2018). Multilevel analytical modelling was omitted because we were solely interested in effects at the individual level (McNeish et al., 2017).

6.4.2. Confirmatory factor analysis

Confirmatory factor analysis (CFA) was conducted with the robust maximum-likelihood estimator (MLR). The MLR estimator has been recommended because it provides better standard errors and is suggested for analyses using "type = complex" (Muthén & Muthén, 1998–2018). The fit indices of root mean squared error of approximation (RMSEA) < 0.07, SRMR <0.08, comparative fit index (CFI) > 0.90, and factor loadings (λ) > 0.50 were used to assess the model fit (Tabachnick & Fidell, 2012). The CFA on the motivational constructs included in the German Self-Regulation Questionnaire (Ryan & Connell, 1989) was conducted in one model for all regulation forms (i.e., intrinsic, identified, introjected, and external) and separately for all three measurement points. For the external regulation scale that originally was comprised of six items, items with low factor loadings (λ < 0.50) were identified. After adjustment, the remaining three items achieved satisfactory to good fit values at all three measurement points.

6.4.3. Measurement invariance

Measurement invariance across time was tested to control whether the latent variables were stable over time and whether the latent constructs could be compared over the three measurement points (Little, 2013). A sequential procedure starting with the least restrictive solution was used. For the first model without constraints (i.e., configural invariance), model specifications were modelled identically at all three measurement points to ensure all parameters were freely estimated. In the second stage (i.e., metric invariance), the factor loadings were equated over the three measurement points. With scalar invariance at the third step, the intercepts were also equated as a comparison of means requires that scalar invariance is ensured (Sass, 2011). To test for measurement invariance, any changes in fit indices (i.e., CFI and RMSEA) were compared between the nested models. The change in ΔCFI <0.01 and the change in ΔRMSEA <0.01–0.015 were set as limits (Chen, 2007). Within this range, it can be assumed that the more restrictive model does not present a significantly poorer fit of the data than the previous model (Little, 2013). The results of the measurement invariance analyses suggested scalar invariance for all variables, thus allowing for the comparison of the mean values over the three measurement points (see Table 1).

6.4.4. Latent profile analysis and latent transition analysis

For the principal analyses (i.e., LPA and LTA), we used a setting of measurement error-corrected factor scores consistent with the method of Little et al. (2006). LTA is a longitudinal extension of LPA and indicates that an underlying grouping variable is not observed but can be derived from several indicators. In the subsequent LTA, the LPA is used to model longitudinal data by estimating the transitions of latent profile membership over time (Lanza et al., 2010). As a person-centered clustering procedure, it allows for a probabilistic assignment of single individuals to a priori unknown subpopulations (with a common latent profile) and enables transitions in latent profile membership to be modelled over time (Collins et al., 2000). Furthermore, grouping variables (i.e., intervention groups) can be included in the analyses (KNOWNCLASS function in Mplus).

Because our sample consisted of three different groups (i.e., student-teacher intervention, student intervention, and control group), we first tested the similarity of profile solutions across these subsamples following guidelines by Morin et al. (2016). The first step tested whether the same number of profiles were identified in each group (i.e., configural similarity) and the second step tested whether the response probabilities were the same (i.e., structural similarity). In the third step, we tested whether the within-profile variability of the indicators was similar across groups (i.e., dispersion similarity), and finally, we tested whether the relative size of

Table 1
Longitudinal Measurement Invariance.

Model	χ^2	df	RMSEA	CFI	ΔRMSEA	ΔCFI
Intrinsic regulation						
1 configural	85.162	72	0.023	0.994		
2 metric	94.919	80	0.023	0.993	0.000	−0.001
3 scalar	111.486	88	0.028	0.989	0.005	−0.004
Identified regulation						
1 configural	45.186	39	0.021	0.995		
2 metric	52.027	45	0.021	0.994	0.000	−0.001
3 scalar	70.978	51	0.034	0.984	0.013	−0.010
Introjected regulation						
1 configural	80.895	27	0.076	0.940		
2 metric	82.675	33	0.066	0.944	−0.010	0.004
3 scalar	89.072	39	0.061	0.944	−0.005	0.000
External regulation						
1 configural	26.249	15	0.046	0.982		
2 metric	28.788	19	0.038	0.984	−0.008	0.002
3 scalar	31.438	23	0.032	0.986	−0.006	0.002

Note. df = degrees of freedom; RMSEA = root mean squared error or approximation; CFI = comparative fit index; ΔRMSEA = change in RMSEA; ΔCFI = change in CFI.

the latent profiles was the same across the groups (i.e., distributional similarity).

Based on the results of the multiple-group similarity, a series of models were tested with the overall sample for each measurement point to identify the model with the best fit over time (Nylund, Asparouhov, & Muthén, 2007). After the number of profiles was selected, the LPA solution was integrated in a longitudinal LPA. We used the methodological framework of Morin and Litalien (2017) to systematically investigate the similarity of latent profile solutions across time. Like the multiple-group approach, this includes a sequential procedure that starts with verifying the number of profiles across measurement points (i.e., configural similarity). Equality constraints were then applied sequentially on the within-profile means (i.e., structural similarity), variances (i.e., dispersion similarity), and relative size (i.e., distributional similarity; Ciarrochi et al., 2017; Morin & Litalien, 2017).

Multiple-group and longitudinal similarity were statistically determined based on a combination of fit indices, including the (a) Bayesian information criterion (BIC); (b) sample-size-adjusted Bayesian information criterion (aBIC); (c) consistent Akaike information criterion (CAIC); (d) Lo, Mendell, and Rubin likelihood ratio test (LMR); (e) Bootstrap Likelihood Ratio Test (BLRT); and (f) entropy value. Smaller values in the BIC, aBIC, and CAIC fit indices indicate a better model fit (Nylund, Bellmore, et al., 2007), whereas a significant *p*-value associated with the LMR and BLRT indicates that the k-1 profile model should be rejected in favor of a k-profile model. The entropy value summarizes the quality of the classification (i.e., precision with which the cases are classified into the profiles), with a measure close to 1 indicating a good fit (Muthén, 2000). Although it is not recommended to use the entropy value as a determinant of the optimal number of profiles (Lubke & Muthén, 2007), it is still informative because it contains a valuable summary of classification accuracy (Morin et al., 2016). Simulation studies have indicated that the CAIC, BIC, and aBIC are particularly effective in choosing a model. However, because the class enumeration procedure may be affected by sample size, the BIC, aBIC, and CAIC may continue to decrease without reaching a minimal point, and thus information criteria are added by a graphical illustration. As suggested by Morin et al. (2016), BIC and CAIC were illustrated by elbow plots that help demonstrate the gains associated with additional profiles. Furthermore, the content level determines the number of patterns by using the interpretability of the individual patterns and the number of persons per pattern as criteria (Boscardin et al., 2008).

Based on the results of the longitudinal LPA, the most similar model was converted to an LTA model, which allowed for estimation of transition probabilities between profiles. Finally, the grouping variable (i.e., intervention group) was included and the transition probabilities were approximated.

7. Results

Applying the outlier labelling rule of Hoaglin and Iglewicz (1987) resulted in no outliers being identified.[3] Across all measurement points (see Table 2), the complete sample showed the highest mean values in identified regulation, with intermediate values for intrinsic and introjected regulation, and low levels of external regulation. The mean values of intrinsic ($t_{t0/t1} = 0.75$, $p_{t0/t1} = 0.452$, $d_{t0/t1} = 0.04$; $t_{t1/t2} = 1.74$, $p_{t1/t2} = 0.083$, $d_{t1/t2} = 0.09$) and identified regulation ($t_{t0/t1} = 0.49$, $p_{t0/t1} = 0.626$, $d_{t0/t1} = 0.03$; $t_{t1/t2} = -0.99$, $p_{t1/t2} = 0.321$, $d_{t1/t2} = 0.03$) in the sample showed no significant change over time. However, the *t*-test for paired samples indicated a significant difference between the first and second measurement points for introjected ($t_{t0/t1} = 5.35$, $p_{t0/t1} < 0.001$, $d_{t0/t1} = 0.29$; $t_{t1/t2} = -0.90$, $p_{t1/t2} = 0.370$, $d_{t1/t2} = -0.05$) and external regulation ($t_{t0/t1} = 4.86$, $p_{t0/t1} < 0.001$, $d_{t0/t1} = 0.26$; $t_{t1/t2} = -0.43$, $p_{t1/t2} = 0.665$, $d_{t1/t2} = -0.02$). Introjected and external regulation declined between the first and the second time points and then remained

[3] The outlier labelling rule relies on calculating the difference between the first and third quartile of the distribution (i.e., interquartile range) and multiplying it by the parameter, *g* of 2.2. The resulting value is added to the third quartile and subtracted from the first quartile values to define the boundaries of the distribution. Any values outside these boundaries are considered outliers.

Table 2
Descriptive Statistics and Correlations for Study Variables.

	Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1	intrinsic regulation t0	3.03	0.91	–	0.42**	0.46**	0.11*	0.52**	0.26**	0.16**	0.02	0.38**	0.20**	0.13*	0.03
2	identified regulation t0	4.04	0.84		–	0.35**	0.08	0.26**	0.43**	0.15**	0.03	0.19**	0.40**	0.07	−0.01
3	introjected regulation t0	2.91	0.83			–	0.47**	0.23**	0.19**	0.41**	0.21**	0.18**	0.13*	0.31**	0.11*
4	external regulation t0	2.41	0.93				–	−0.05	−0.02	0.15**	0.38**	−0.02	−0.08	0.07	0.37**
5	intrinsic regulation t1	3.00	0.92					–	0.43**	0.26**	−0.06	0.54**	0.22**	0.15**	−0.08
6	identified regulation t1	4.01	0.82						–	0.17**	−0.07	0.26**	0.53**	0.02	−0.05
7	introjected regulation t1	2.64	0.89							–	0.43**	0.17**	0.13*	0.49**	0.25**
8	external regulation t1	2.14	0.96								–	−0.01	−0.06	0.24**	0.54**
9	intrinsic regulation t2	2.92	0.85									–	0.33**	0.36**	−0.01
10	identified regulation t2	4.05	0.76										–	−0.11*	−0.08
11	introjected regulation t2	2.69	0.84											–	0.37**
12	external regulation t2	2.16	0.92												–

Note. Range = 1–5. t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8. **p* < 0.05, ***p* < 0.01.

stable. One-way analysis of variance revealed no significant differences between the variables in the two intervention groups and the control group before the intervention ($F(2,344)_{\text{intrinsic regulation}} = 1.66$, $p_{\text{intrinsic regulation}} = 0.07$, $\eta^2_{\text{intrinsic regulation}} = 0.008$; $F(2,344)_{\text{identified regulation}} = 0.25$, $p_{\text{identified regulation}} = 0.78$, $\eta^2_{\text{identified regulation}} = 0.001$; $F(2,344)_{\text{introjected regulation}} = 0.71$, $p_{\text{introjected regulation}} = 0.50$, $\eta^2_{\text{introjected regulation}} = 0.004$; $F(2,344)_{\text{external regulation}} = 0.87$, $p_{\text{external regulation}} = 0.42$, $\eta^2_{\text{external regulation}} = 0.005$). All motivational constructs showed inter-correlation over the three measurement points (see Table 2).

7.1. Motivation profiles

Because previous research generally has yielded three to four motivation profiles, we examined solutions with up to five profiles in each group separately. Table 3 displays fit information (i.e., BIC, aBIC, CAIC, LMR, BLRT, and entropy value) across groups. In the student-teacher intervention group and in the control group, the three-profile solution showed the lowest BIC and CAIC values, whereas aBIC continued to decrease. Also, the significant LMR value suggests a three-profile solution. In the student intervention group, the lowest BIC and CAIC values were in the four-profile solution, whereas the LMR for the three-profile solution was significant and the four-profile solution was not significant, which provides additional support for the three profile-solution. The graphical depiction of the BIC and CAIC values (see Fig. 2) shows a plateau at three profiles in all three groups. Based on the graphical depiction, the significant LMR values in the three-profile solution, and the overall fit, the three-profile solution was retained for all three groups, supporting the configural similarity of the model across groups. Next, a multiple-group three-profile model was estimated in all three groups. From this model of configural similarity, we estimated a model of structural, dispersion, and distributional similarity. Model comparison of configural, structural, dispersion, and distributional similarity revealed decreasing BIC, aBIC, and CAIC values, thereby supporting the similarity of the three-profile solution across groups. Based on the group-similarity, the longitudinal analyses were conducted with the combined sample.

Table 4 displays fit information (i.e., BIC, aBIC, CAIC, LMR, BLRT, and entropy value) for all models over three measurement points. Although the BIC, aBIC, and CAIC values continued to decrease with the addition of profiles, the plotted results indicated a plateau at three profiles, thereby also suggesting a three-profile solution over time as optimal (see Fig. 3). The LMR value at t0 and t2 also suggests a three-profile solution, whereas the BLRT was significant in every model and thus was unable to identify the optimal model. The examination of the three to five profile solutions also revealed that the three-profile solution resulted in well-defined, qualitatively different, and theoretically meaningful profiles, whereas the addition of a fourth or fifth profile resulted in the arbitrary division of the existing profiles into smaller profiles differing only quantitatively from one another. Based on the plotted results, the interpretability of classes, and the fit information, the three-class solution was selected to test longitudinal similarity. Next, we estimated the three-wave LPA of configural similarity including three profiles. Based on this model, a model of structural similarity by constraining the within-profile means to be equal across time waves was estimated. For dispersion similarity, we constrained the within-profile variability to be equal across time waves. Finally, for the distributional similarity model, we constrained the size of the latent profiles to be equal across time waves. Model comparison of configural, structural, and dispersion similarity revealed decreasing BIC, aBIC, and CAIC values, thereby supporting the similarity of the three-profile solution across time waves (see Table 4). Compared with the model of dispersion similarity, the model of distributional similarity resulted in an increase in the value of all information criteria and thus was not supported. This result suggests that the size of the profiles differed across measurement points. Because distributional similarity is not a pre-requisite (Morin et al., 2016), the model of dispersion similarity was thus retained for the following

Table 3
Multiple-Group Similarity.

	k	df	BIC	aBIC	CAIC	LMR	BLRT	entropy
Class enumeration: Student-teacher intervention group								
2 Profiles	2	13	1014.06	972.94	1027.06	0.01	≤ 0.001	0.76
3 Profiles	3	18	983.48	926.54	1001.48	0.04	≤ 0.001	0.83
4 Profiles	4	23	987.44	914.69	1010.44	0.45	0.02	0.82
5 Profiles	5	28	983.59	894.72	1011.29	0.36	≤ 0.001	0.78
Class enumeration: Student intervention group								
2 Profiles	2	13	959.42	918.32	972.42	0.004	≤ 0.001	0.79
3 Profiles	3	18	943.05	886.13	961.05	0.05	≤ 0.001	0.79
4 Profiles	4	23	929.95	857.23	952.95	0.22	≤ 0.001	0.83
5 Profiles	5	28	936.02	847.49	964.02	0.38	0.035	0.84
Class enumeration: Control group								
2 Profiles	2	13	800.48	759.45	813.48	0.01	≤ 0.001	0.85
3 Profiles	3	18	792.51	735.69	810.51	0.05	≤ 0.001	0.83
4 Profiles	4	23	792.77	719.47	815.77	0.51	≤ 0.001	0.80
5 Profiles	5	28	786.85	698.47	814.85	0.05	≤ 0.001	0.89
Cross-Group Similarity								
Configural	3	56	3547.05	3369.40	3603.05	–	–	0.82
Structural	3	32	3459.46	3357.95	3491.46	–	–	0.75
Dispersion	3	24	3422.47	3346.34	3446.47	–	–	0.75
Distributional	3	20	3404.05	3340.61	3424.05	–	–	0.75

Note. k = number of profiles; df = degrees of freedom; BIC = Bayesian information criterion; aBIC = sample-size-adjusted Bayesian information criterion; CAIC = consistent Akaike information criterion; LMR = Lo, Mendell, & Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test.

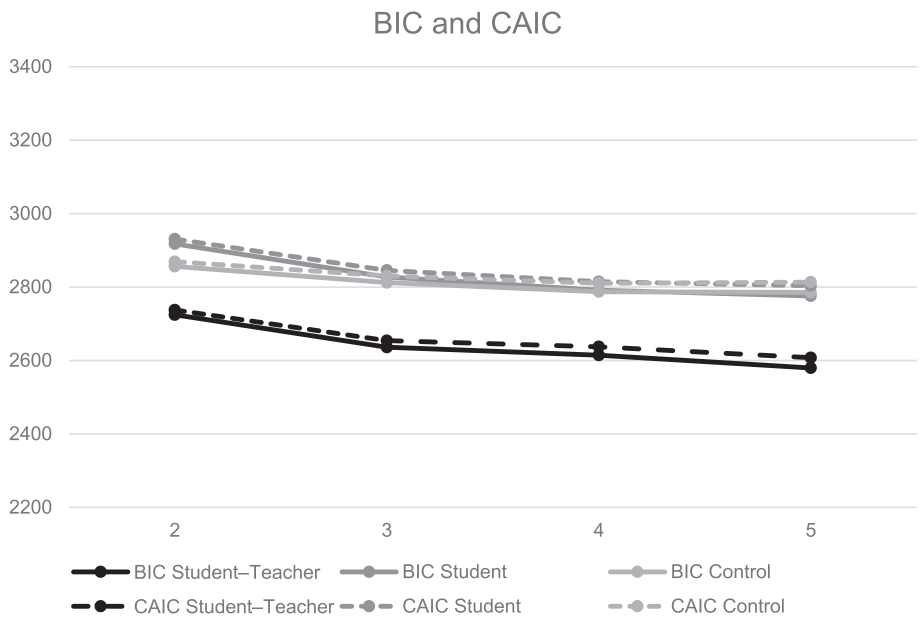

Fig. 2. Elbow Plot for the Information Criteria (BIC, CAIC) for the Two to Five Profile Solutions across Groups.

Table 4
Longitudinal Similarity.

	k	df	BIC	aBIC	CAIC	LMR	BLRT	entropy
Class enumeration: t0								
2 Profiles	2	13	2724.46	2683.22	2737.46	≤ 0.001	≤ 0.001	0.75
3 Profiles	3	18	2636.03	2578.93	2654.03	0.01	≤ 0.001	0.75
4 Profiles	4	23	2614.34	2541.38	2637.34	0.09	≤ 0.001	0.79
5 Profiles	5	28	2579.58	2490.76	2607.58	0.33	≤ 0.001	0.79
Class enumeration: t1								
2 Profiles	2	13	2917.55	2876.31	2930.55	≤ 0.001	≤ 0.001	0.82
3 Profiles	3	18	2827.43	2770.33	2845.43	0.19	≤ 0.001	0.73
4 Profiles	4	23	2791.52	2718.55	2814.52	0.31	≤ 0.001	0.74
5 Profiles	5	28	2775.67	2686.85	2803.67	0.02	≤ 0.001	0.76
Class enumeration: t2								
2 Profiles	2	13	2856.16	2814.92	2869.16	≤ 0.001	≤ 0.001	0.67
3 Profiles	3	18	2812.18	2755.08	2830.18	0.01	≤ 0.001	0.63
4 Profiles	4	23	2787.25	2714.29	2810.25	0.06	≤ 0.001	0.69
5 Profiles	5	28	2785.32	2696.50	2813.32	0.83	≤ 0.001	0.69
Longitudinal Similarity								
Configural	3	78	8253.94	8006.50	8331.94	–	–	0.76
Structural	3	54	8238.25	8066.95	8292.25	–	–	0.74
Dispersion	3	30	8131.93	8036.76	8161.93	–	–	0.77
Distributional	3	26	8146.92	8064.44	8172.92	–	–	0.74

Note. k = number of profiles; df = degrees of freedom; BIC = Bayesian information criterion; aBIC = sample-size-adjusted Bayesian information criterion; CAIC = consistent Akaike information criterion; LMR = Lo, Mendell, & Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test; t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8.

profile interpretation and the LTA (Morin & Litalien, 2017).

Estimates of the motivation regulation of the three profiles are displayed in Fig. 4 and are used to characterize the different profiles. The self-determined motivation profile was characterized by high levels of intrinsic and identified regulation and medium levels of introjected and low levels of external regulation. The low-mixed motivation profile was characterized by low intrinsic, low identified, and low introjected regulation and medium level in external regulation. The third profile, the high-mixed motivation profile, was characterized by medium to high values in all four regulation forms (see Fig. 4). The benchmark for labelling was whether the value of the variable in the profile 0.5 *SD* above (i.e., high) or below (i.e., low) the mean of the variable in the overall sample. In addition to describing the content of the profiles through the mean values of the indicators, the assignment of profile names was also intended to capture the essence of the profiles (e.g., Spurk et al., 2020).

Over time, the number of students within the low-mixed motivation profile remained stable ($n_{t0} = 114$; $n_{t1} = 119$; $n_{t2} = 118$), whereas the number of students in the self-determined motivation profile increased ($n_{t0} = 58$; $n_{t1} = 113$; $n_{t2} = 114$) and the number in

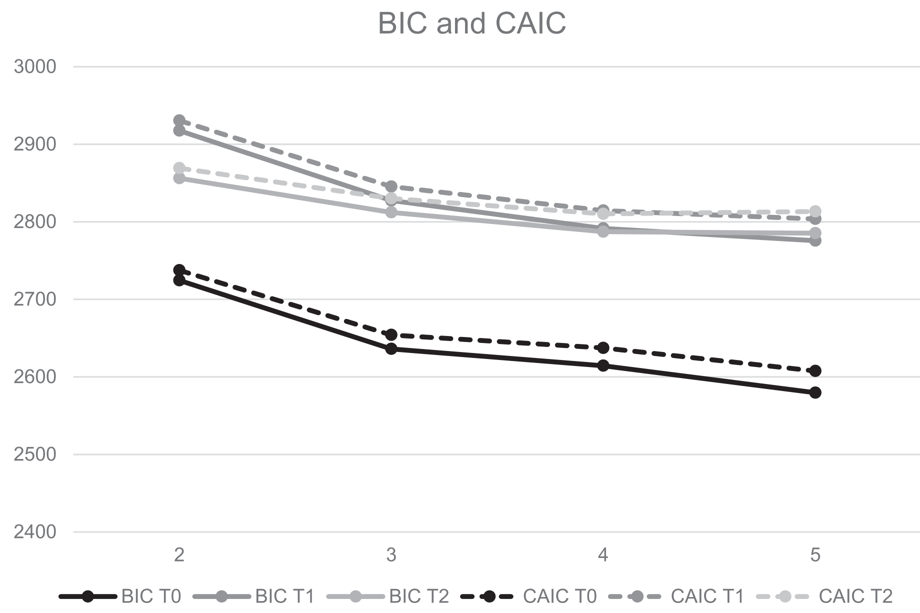

Fig. 3. Elbow Plot for the Information Criteria (BIC, CAIC) for the Two to Five Profile Solutions across Time.
Note. t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8.

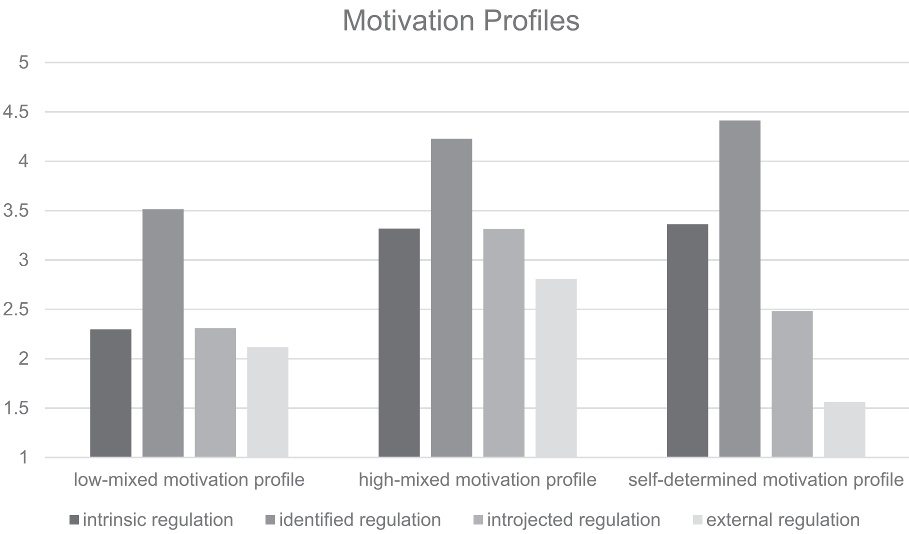

Fig. 4. Motivation Profiles.

Table 5
Transition Probabilities Between Profiles (a) t0 to t1and (b) t1 to t2.

(a)			t1		
			Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile
	t0	Low-mixed motivation profile	0.828	0.054	0.118
		High-mixed motivation profile	0.140	0.602	0.258
		Self-determined motivation profile	0	0.054	0.946
(b)			t2		
			Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile
	t1	Low-mixed motivation profile	0.888	0.112	0
		High-mixed motivation profile	0.079	0.877	0.044
		Self-determined motivation profile	0.032	0.010	0.958

Note. t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8.

Table 6
Transition Probabilities of the Intervention Groups (a) t0 to t1 and (b) t1 to t2.

(a)			t1								
			Student-teacher intervention group			Student intervention group			Control group		
			Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile	Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile	Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile
	t0	Low-mixed motivation profile	0.721	0.098	0.180	0.879	0.000	0.121	0.977	0.023	0.000
		High-mixed motivation profile	0.106	0.657	0.236	0.195	0.659	0.146	0.099	0.599	0.302
		Self-determined motivation profile	0.000	0.022	0.978	0.000	0.123	0.877	0.000	0.010	0.990
(b)			t2								
			Student-teacher intervention group			Student intervention group			Control group		
			Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile	Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile	Low-mixed motivation profile	High-mixed motivation profile	Self-determined motivation profile
	t1	Low-mixed motivation profile	0.892	0.108	0.000	0.892	0.108	0.000	0.900	0.100	0.000
		High-mixed motivation profile	0.149	0.800	0.051	0.081	0.919	0.000	0.000	0.834	0.166
		Self-determined motivation profile	0.035	0.026	0.938	0.052	0.000	0.948	0.000	0.013	0.987

Note. t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8.

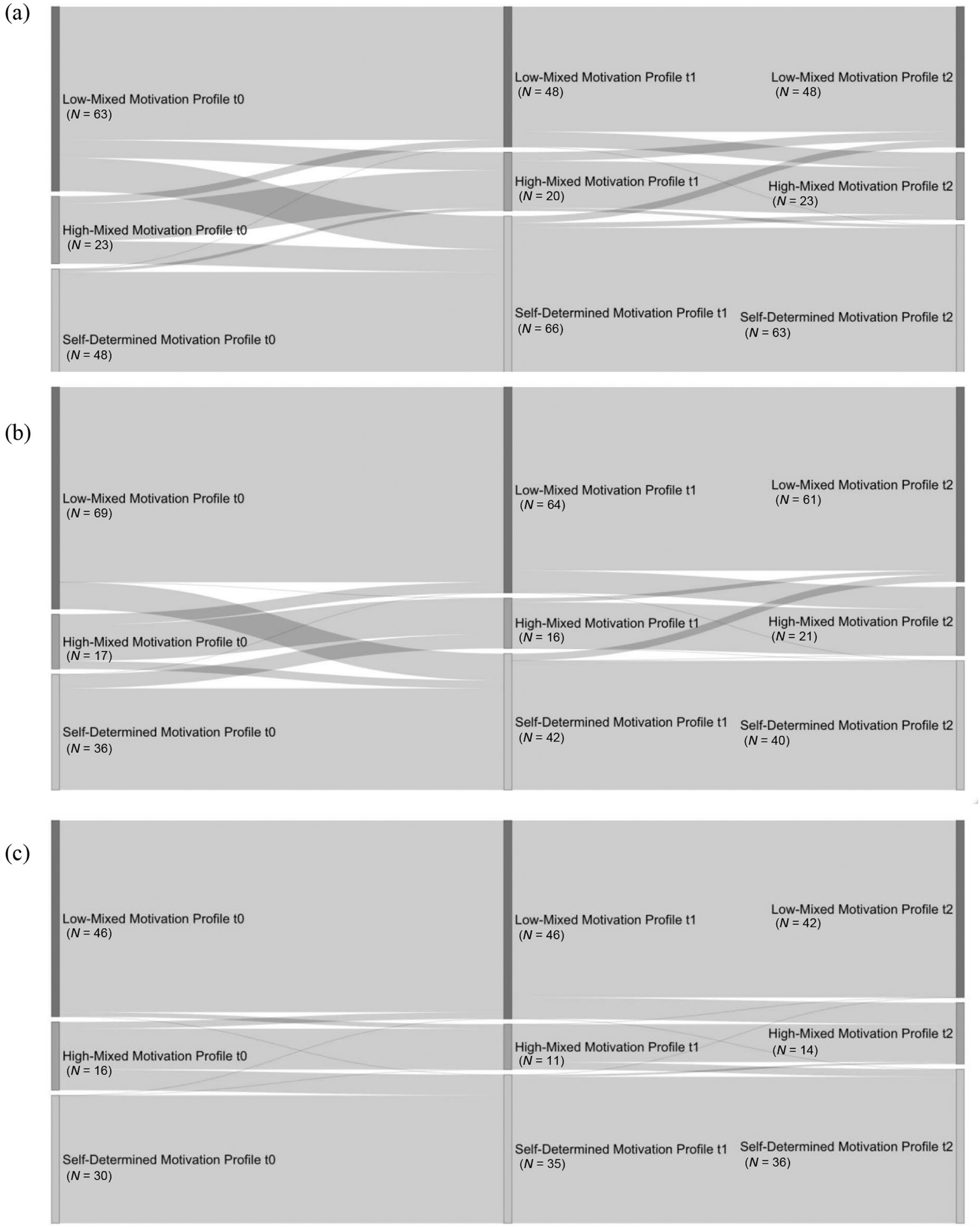

Fig. 5. Latent transitions of (a) the student-teacher intervention group, (b) the student intervention group, and (c) the control group.
Note. Proportions of students for each change between latent profiles across time. The width of the streams is proportional to the quantity represented in the change (number of students). t0 = beginning of Grade 7; t1 = end of Grade 7; t2 = end of Grade 8.

the high-mixed motivation profile decreased ($n_{t0} = 176$; $n_{t1} = 116$; $n_{t2} = 116$).

7.2. Changes in motivation profiles

Estimated transition probabilities for the three measurement points are provided in Table 5. Diagonal values in each matrix show the probability of a student remaining in a motivation profile (i.e., stability over time), whereas values off the diagonal represent the likelihood of change from one profile to another. The results show several trends. First, the most common outcome was to remain within a profile. Second, according to previous research, changes from a more favorable profile to a less favorable profile were less likely than a change from a less favorable to a more favorable profile. Third, more changes in profiles occurred between the first and second measurement points than between the second and third measurement points.

7.3. Differences in changes in motivation profiles between groups

One-way analysis of variance at the first measurement point revealed that there were no statistically significant differences between the two intervention groups and the control group for any of the motivational variables. Therefore, we examined the probability of students' transition between profiles based on their intervention group membership (see Table 6). Again, the diagonal indicates the probability of remaining within a profile, whereas a position adjacent to the diagonal indicates the probability of a specific transition. Similar to the findings above relating to changes in motivational profiles, the probability of students remaining within a profile was highest and changes across all groups occurred more often between the first two measurement points than between the second and the third measurement points (see Fig. 5). Overall, the two intervention groups showed similar changes whereas the control group showed fewer changes (i.e., higher probability to remain within a profile). The probability of a student moving from the low-mixed motivation profile to the high-mixed or self-determined motivation was higher in the two intervention groups than the control group. This effect was found between the first and second measurement points as well as between the second and third measurement points.

8. Discussion

The present study was designed to identify motivation profiles in mathematics of students in the lowest ability tier in lower secondary education. Furthermore, we investigated the patterns of change in the motivation profile during Grade 7 and Grade 8 and whether these changes were associated with the implemented motivation intervention. The major contribution of this study is the application of a person-centered approach within a longitudinal study that aimed to examine the prevalence of changes in motivation profiles in mathematics. Specifically, our focus was on the effectiveness of an intervention for promoting motivation in mathematics across different subgroups and whether it is better tailored to specific students than others. Thus, the present study expands on traditional intervention evaluations by incorporating student motivation and interactions with the intervention to provide a better understanding of the individual development of motivation.

8.1. Motivation profiles

Consistent with our expectations (H1a), we found three motivation profiles that correspond to those found in previous research (e.g., Ratelle et al., 2007). Our findings revealed one profile with medium to high levels and one profile with low levels in all four regulation types. The third profile shows a combination of high levels in intrinsic and identified regulation and medium and low levels in introjected and external regulation (H1b).

Our results differ from other studies that identified four profiles (e.g., Vansteenkiste et al., 2009) as our analyses failed to identify a profile with both a low level of autonomous motivation and a high level of controlled motivation. Given that our study focused on students allocated to the lowest achievement group in secondary education, this result is interesting for researchers and practitioners as according to existing research, a combination of low autonomous motivation and high controlled motivation is the most disadvantageous profile because it is associated with lower achievement, more procrastination, and increased test anxiety (Hayenga & Corpus, 2010; Vansteenkiste et al., 2009). We expected that this profile would be frequent among students in the lowest ability tier; however, our results did not confirm this assumption.

Existing research (e.g., Hayenga & Corpus, 2010; Vansteenkiste et al., 2009) has used composite scores of autonomous and controlled motivation (dichotomization) rather than using all four variables of SDT (i.e., intrinsic, identified, introjected, and external regulation). Although our approach that utilized all four SDT variables provides a more refined picture than using a composite score, doing so limits the comparability with results of other studies. Another advantage and difference compared to prior research is that we explicitly did not apply z-standardization to let the scores within the profiles represent the actual score on the scale instead of the simpler information of above or below average. Thus, for example, the level of external regulation of self-determined motivation profile of 2.0 indicates a low value of agreement (Moeller, 2015). As profile mapping without z-standardization leads to less misinterpretation of differences between profiles, we chose this approach despite the limits in comparability with previous research. In this context, it should be noted that the values of intrinsic regulation ranged in the middle of the scale (≈ 3.3) for the self-determined and high-mixed motivation profiles, but also was noticeably higher than in the low-mixed motivation profile (≈ 2.3). Thus, all three profiles differed regarding intrinsic regulation. Conversely, identified regulation clearly showed a higher agreement than the other forms of regulation in all three profiles and, thus, showed at least partial agreement. All students in the lowest ability tier seemed to be aware of the instrumental purpose of mathematics for their life, which could be helpful information for teachers and school psychologists. This result is also consistent with Ratelle et al. (2007) who demonstrated a similar pattern for intrinsic and identified regulation within the general motivation profiles of high school students.

Overall, it must be highlighted that in this potentially at-risk group of lower secondary education students, the presence of self-determined and high-mixed motivation profiles is an encouraging finding, as existing research has pointed to the advantages (e.g., academic achievement) of these profiles (Vansteenkiste et al., 2009).

8.2. Stability and changes in motivation profiles

Next, we examined the stability and changes in motivation profiles as well as the quality of these changes. Consistent with our expectations (H2a), the results suggested that the three motivation profiles were highly stable over time and that most students remained within their initial lower secondary education profile at the beginning of Grade 7. This finding is consistent with previous person-centered studies (e.g., Lazarides et al., 2019) that have reported rare profile changes. In the present study, when changes occurred, they were more frequent during Grade 7 (between the first and second measurement points) than during Grade 8 (between the second and third measurement points). This result supports the earlier findings of Marcoulides et al. (2008) in that motivation profiles become more stable with increasing age. It seems to be a general trend that motivation stabilizes during secondary education, as a similar trend was found in the development of interest (Xu & Tracey, 2016).

However, our results revealed new patterns of stability and change (H2b) in that in contrast to previous studies from Hayenga and Corpus (2010) and Lazarides et al. (2019), who found profiles with low scores of intrinsic motivation to be more stable than those with high scores of intrinsic motivation, the results of our study showed that the self-determined motivation profile was the most stable profile. This result may be related to the intervention, which was aimed at positive changes in self-determined motivation, and might indicate the effectiveness of the intervention.

Regarding changes in motivation profiles, previous research has documented that changes to profiles with low scores of intrinsic motivation occur more frequently than those in the opposite direction (Bråten & Olaussen, 2005; Hayenga & Corpus, 2010). However, our results showed the opposite development that, according to the SDT theory, can be interpreted as more changes from less favorable to more favorable profiles (4.4%–25.8%) than vice versa (4.2%–14.0%) between the first and second measurement points (H2b). This result might have been expected given that approximately three quarters of the students had received an intervention aimed at promoting motivation in learning, and it may, therefore, be argued that the result cannot be directly compared with previous research.

Interestingly, a closer examination of our results shows that students in the control group also tended to change to the high-mixed or the self-determined motivation profile (2.3%–30.2%). As a possible explanation of this general pattern of changes in our study, the big-fish-little-pond effect (Marsh, 1987) might be a factor as the sample consisted of secondary students in the lowest achievement levels in Grade 7 and Grade 8. Students in Switzerland are assigned at the end of their primary education (Grade 6) to one of three types of school according to teachers' recommendations and student performance in three main subjects (i.e., mathematics, school language, and first foreign language). In a mixed-ability primary class, students with poor performance in mathematics usually orient themselves upwards (i.e., compare themselves with better performing students). After the transition to the assigned secondary school based on ability, students' frame of reference may adapt, and students may perceive themselves as being at approximately the same academic level as their peers. This may lead to less upward comparisons and more positive experiences in the classroom (Becker & Neumann, 2018). This new situation may have contributed to an increase in self-concept, which then can have a positive effect on motivation (Skaalvik & Skaalvik, 2005).

8.3. Effects of the Intervention

In addition to the general development of motivation in mathematics, we investigated whether students with different motivation profiles responded differently to an intervention aimed at fostering self-determined motivation. We expected different transition patterns between the profiles within the two intervention groups (H3) as compared to the control group. Our results showed very similar patterns of change between the student-teacher intervention group and the student intervention group. However, the trends to more favorable profiles, according to the SDT theory, were more pronounced in the student-teacher intervention group (5.1%–33.6%) than in the student intervention group (0%–14.6%). In both intervention groups, most changes occurred for students in the low-mixed motivation profile, which suggests that this group was more sensitive to interventions. During Grade 7 (i.e., between the first and second measurement points) in the student-teacher intervention group, 9.8% of students changed from the low-mixed to the high-mixed motivation profile and an additional 18% of students changed to the self-determined motivation profile. Thus, 27.8% of students in the student-teacher intervention group who were initially in the least desirable motivation profile improved by moving into a more desirable profile (i.e., showing higher motivation or more self-determined motivation) during Grade 7. In contrast, only 2.3% in the control group changed from the low-mixed to the high-mixed motivation profile and no student changed to the self-determined motivation profile during Grade 7. These results provide some limited support regarding the effectiveness of the applied program for students with a low-mixed motivation profile. These findings also support the notion that changes to a more desirable motivation profile can be achieved through an intervention program and that a longer intervention can be valuable in giving more students an opportunity to improve their motivation. As Yeager and Walton (2011) observed, the effectiveness of an intervention depends on the goal to “change students' mindsets to help them take greater advantage of available learning opportunities” (p. 274). This requires not only the use of specific methods (i.e., intervention methods and materials) but also a sufficient time frame of an intervention that allows individual development.

However, the results also illustrate the possible problematic side-effects of an intervention (Zhao, 2018) as some students in the high-mixed and the self-determined motivation profiles showed movement to less-desirable profiles. This finding could be of high importance for educators and school psychologists. For example, between the first and second measurement points, students in the student intervention group had a 12.3% probability to change from the self-determined to the high-mixed motivation profile, thus showing an unintended increase in extrinsic forms of motivation regulation. In addition, a negative trend can also be observed in the high-mixed motivation profile in both intervention groups as during Grade 7, the probability of changing from the high-mixed to the low-mixed motivation profile was 10.6% in the student-teacher intervention group and 19.5% in the student intervention group. These results may be interpreted as an indicator that interventions can be counterproductive if they are not tailored to students' preconditions or are not exclusively implemented with targeted groups.

In sum, students in the low-mixed profile were the most likely to benefit from the intervention as the students in this group had the most potential to increase their intrinsic motivation, whereas the other two groups already displayed higher intrinsic scores. Given the aim of the intervention was to promote self-determined motivation (and not to reduce extrinsic motivation), this suggests successful implementation of the intervention for this subgroup.

9. Limitations and future directions

Although our longitudinal study may extend the knowledge of existing research about motivation subgroups, several limitations need to be considered. First, the identified profiles were based on variables from the SDT framework and our results are, therefore, only partially comparable with other studies. Although an emphasis on SDT might help to better understand the development of forms of motivational regulation, it neglects the fact that student motivation is multifaceted and that other forms of motivation, such as goal orientation, are equally important. Thus, further research is needed that incorporates different motivational forms.

Second, our sample only consisted of students who were placed in the lowest educational tier in Grade 7 and Grade 8 and the study focused on motivation in mathematics, thus no conclusions can be drawn about other academic ability levels or academic subjects because of the domain-specific character of motivation (Wigfield, 1997). Future research that includes a more diverse sample would be needed to validate the profiles identified in this study for other student groups, subjects, and ability levels. Furthermore, existing research has pointed to the advantages (e.g., academic achievement) of the self-determined and high-mixed motivation profiles (Vansteenkiste et al., 2009). However, whether these advantages also hold for different samples, various phases of a learning process, and different forms of learning outcomes (e.g., achievement, positive emotions, self-regulated learning) needs to be explored with further research. In certain situations, being in a low-mixed motivation profile can be positive as it may help to focus on the particular task instead of getting lost in one's interest or to perform better on different task difficulties (effects of goal orientation on performance; e.g., Steele-Johnson et al., 2000).

Third, the transition probabilities between intervention groups are descriptive as no inferential statistical procedures were applied to compare the probabilities of the three groups. Additional research with a larger sample is necessary to determine whether the probabilities statistically differ. In addition, it cannot be completely excluded that other factors than the intervention may have impacted the changes in motivation profiles. It would be interesting for future research to monitor changes in motivation profiles more closely and identify the reasons for change from the students' perspectives using qualitative data (e.g., interviews).

Fourth, the lack of randomization of the three groups must be considered. Although the teachers of the three groups did not differ regarding their self-reported enjoyment of teaching mathematics (see Brandenberger et al., 2018), it is possible that the self-selection of the teachers was correlated with other motivational characteristics (e.g., openness to supporting student engagement) that might have influenced the efficacy of the intervention. By recruiting teachers for the control group from similar environments and focusing on the development of the students, we tried to take the approach to the selection of the teachers into account. Furthermore, the groups did not significantly differ in the dependent variables before the intervention. Nevertheless, teacher effects cannot be excluded. Thus, future studies utilizing sample randomization is needed.

Fifth, it must be pointed out that the motivation profiles were exclusively based on students' self-reported motivation as no other external data were included to validate the profiles (e.g., Lazarides et al., 2019). Thus, more objective data (e.g., teacher evaluation, classroom reports) could be included in future studies to better support the identified profiles. It must be considered that students were divided into subgroups based on selected characteristics; whether this approach reflects authenticity or whether additional characteristics might influence the effectiveness of the intervention in the subgroups remains unanswered.

10. Implications

In terms of theoretical implications, the findings of our study suggest that different motivation regulation forms coexist and that students in the lowest ability tier revealed different motivation patterns. In the present study, students in the lowest ability tier showed motivation profiles similar to students in other ability tiers, such as those identified by Ratelle et al. (2007). Thus, students in this at-risk group in terms of achievement may exhibit motivation profiles with high intrinsic motivation that can be leveraged for academic learning (e.g., self-regulated learning). Consequently, the assumption within SDT that students in the lowest ability tier are less motivated or more extrinsically motivated due to insufficient fulfilment of the basic psychological needs (i.e., needs for autonomy, competence, and relatedness) must be critically discussed (e.g., Garon-Carrier et al., 2016; Poorthuis et al., 2015; Weidinger et al., 2017).

Overall, the identified motivation profiles in this study are encouraging, and educational practice could benefit from knowing students' motivational profiles to better support students in their motivational and academic development. Thus, school psychologists could assist teachers in providing a valid motivational diagnosis, supporting the understanding of differences between profiles, and acknowledging the heterogeneity of learners. The identification of promising motivational patterns and problematic tendencies can help educators more adequately respond to students' needs and provide them with a more supportive learning environment.

The high stability of the identified profiles over time is also relevant for school psychologists as it contributes to a better understanding of student motivation heterogeneity and development. For instance, it can encourage school psychologists to foster an improvement of motivational profiles when students enter secondary education with a problematic motivational profile as well as to support students in maintaining desirable motivational profiles.

The positive trends regarding the change to more beneficial motivation profiles are also encouraging and should be supported in schools (e.g., by providing conducive learning environments). This finding can inspire school psychologists and teachers in promoting student motivation as the results of our study show that motivation may be sensitive to change through a social-psychological intervention program. However, tailored individual support for students might first require additional examination of students' motivation profiles (Walton & Wilson, 2018). This requires, above all, the knowledge and action of school psychologists who can support teachers in understanding and fostering student motivation.

Specific to intervention effects, these findings might indicate the potential of social-psychological interventions for students who are considered to be at risk. The movement toward more favorable profiles, according to the SDT theory, were more pronounced in the student-teacher than in the student intervention group. This finding is consistent with our expectations and underscores the importance of teacher involvement for interventions, which can also encourage school psychologists to closely collaborate with teachers. Students' motivation seems to be best promoted when environmental influences (e.g., in terms of teacher interventions) are combined with interventions targeted directly at students (Schukajlow et al., 2017).

However, as Yeager and Walton (2011) indicated, social-psychological interventions are not “inputs that go into a black box and automatically yield positive results” (p. 293). Rather, they depend on students' and teachers' capacities, mindsets, meanings, and recursive processes of a specific context so they can also lead to undesirable reactions. Along with the publication of positive effects, possible side-effects also need to be reported. Therefore, we would like to encourage a standard in educational contexts that potential adverse effects must be reported in addition to the evidence of expected and desired intervention effects (Zhao, 2018). Moreover, school psychologists' experiences in the schools can better inform research to tailor interventions to specific student groups. Thus, additional research that is informed by empirical evidence, as well as practical experience, is needed to understand this negative motivational development.

11. Conclusions

The results of our study contribute to existing research by identifying relatively stable domain-specific motivation profiles. The findings also extend existing knowledge by showing that students in the lowest ability tier can develop more desirable motivation patterns and, by illustration, that students with different motivation profiles may respond differently to an intervention program. In terms of educational practice, our findings indicate that students in the low-mixed motivation profile in our study seemed to be responsive to interventions that promote motivation. Future intervention could potentially be specifically designed for different target groups within student populations and school psychologists can help to understand and identify these specific needs. Furthermore, the results support the usefulness of a person-centered approach for intervention research as it enables the testing of intervention effects regarding specific subgroups. In summary, the person-centered approach complements the variable-centered results and helps provide a greater understanding of the development of motivation at the individual level. Moreover, it indicates that not all students may equally benefit from instruction and interventions and that instruction should be adapted to the needs of individual students or specific subgroups. A student needs to be respected with their entire personality, experiences, and characteristics, and we must remember that students, each with their own personalities, experiences, and characteristics, may respond differently to learning opportunities and intervention programs. Therefore, specific person-centered diagnostics prior to an intervention provided by school psychologists and a careful implementation that can be supported by school psychologists are required.

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Declaration of Competing Interest

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