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Effectiveness and Sustainability of the ViSC Social Competence Program to Prevent Cyberbullying and Cyber-Victimization: Class and Individual Level Moderators

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We investigated whether the general anti-bullying program ViSC sustainably prevents cyberbullying and cyber-victimization. A longitudinal randomized control group design was used to examine (i) program effectiveness immediately after a 1 year implementation phase and (ii) sustainable program effects 6 months later taking several moderators on the class level (class climate and ethnic diversity) and on the individual level (gender, age, internet usage, traditional bullying/victimization) into account. Effectiveness (e.g., the change between waves 2 and 1) was examined in 2,042 students (47.6% girls), aged 11.7 years (*SD* = 0.88) enrolled in 18 schools and 103 classes. Sustainability (e.g., the change between waves 3 and 2) was examined in a sub-sample of 6 schools and 35 classes comprising 659 students. The self-assessment multiple-item scales showed longitudinal and multiple group invariance. Factor scores were extracted to compute difference scores for effectiveness (*Posttest minus Pretest)* and sustainability (*Follow-up test minus Posttest)* for cyberbullying and cyber-victimization. Multilevel Modeling was applied to examine (i) the effectiveness and (ii) the sustainability of the ViSC intervention controlling for several individual and class level variables. Controlling for covariates, it was demonstrated that the ViSC program is effective in preventing cyberbullying and cyber-victimization and that the effects are sustainable after 6 months. The consequences for cyberbullying prevention are discussed. Aggr. Behav. 42:181–193, 2016.

Keywords: cyberbullying; cyber-victimization; prevention; effectiveness; sustainability

INTRODUCTION

The ViSC Social Competence Program has been developed, implemented, and evaluated as one component of the Austrian national strategy to prevent violence in schools (Spiel & Strohmeier, 2011, 2012). The ViSC program is a primary preventive anti-bullying program that does not include specific anti-cyberbullying elements (Strohmeier, Hoffmann, Schiller, Stefanek, & Spiel, 2012). It has been demonstrated that the ViSC program is effective in preventing cyberbullying and cyber-victimization after 1 year of program implementation indicating that traditional bullying and cyberbullying share similar mechanisms (Gradinger, Yanagida, Strohmeier, & Spiel, 2014). What has not been investigated yet is whether a general anti-bullying program without a specific cyberbullying component is able to prevent cyberbullying even after program implementation, e.g., over a 1.5-year period. Moreover, several individual and class level variables which might moderate short- and long-term program effectiveness of a general anti-bullying program have also not been examined. For a large scale application of programs it is important to know whether class level variables, such as class climate or ethnic identity, and individual level variables, such as gender, age, internet usage, and traditional bullying and victimization, moderate the effectiveness and sustainability. Such knowledge is important (i) to better understand mechanisms of cyberbullying and cyber-victimization and (ii) to provide the evidence that allows practitioners to make

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evidence-based decisions regarding the most promising prevention approach in schools (Flay et al., 2005).

PREVENTION OF BULLYING AND CYBERBULLYING

Meta-analyses show that general anti-bullying prevention programs are on average effective in reducing traditional bullying and victimization (e.g., Farrington & Ttofi, 2009; Ttofi & Farrington, 2011). In contrast, research regarding cyberbullying prevention is rather sparse. Many terms have been used for cyberbullying (e.g., cyber aggression, cyber harassment) but most often the term cyberbullying is used for bullying through electronic means. Based on Smith et al. (2008), cyberbullying can be defined as “An aggressive, intentional act carried out by a group or individual, using electronic forms of contact, repeatedly and over time against a victim who cannot easily defend him or herself.” Recently, several programs that specifically tackle cyberbullying have been developed and evaluated (e.g., Menesini, Nocentini, & Palladino, 2012; Ortega-Ruiz, Del Rey, & Casas, 2012; Pieschl & Porsch, 2013; Schultze-Krumbholz, Zagorscak, Wölfer, & Scheithauer, 2014). At the same time, some general anti-bullying programs also showed short-term effects regarding the prevention of cyberbullying and cyber-victimization (e.g., Gradinger et al., 2014; Williford, Elledge, Boulton, DePaolis, Little & Salmivalli, 2013). However, longitudinal and experimental research on risk and protective factors regarding cyberbullying and cyber-victimization is rare (Badaly, Kelly, Schwartz, & Dabney-Lieras, 2012; Fanti, Demetriou, & Hawa, 2012; Gradinger, Strohmeier, Schiller, Stefanek, & Spiel, 2012; Hemphill et al., 2012; Schiller, Gradinger, & Strohmeier, 2014; Sticca et al., 2013). This lack of knowledge makes it difficult to develop specific etiological models for cyberbullying and cyber-victimization, and consequently to develop specific cyberbullying programs.

Based on the socio-ecological model of development (Bronfenbrenner, 1979; Swearer & Espelage, 2004), risk and protective factors for (cyber) bullying and victimization are located on several systemic levels. A recent meta-analysis revealed that on the individual level cyber-victimization, traditional bullying and victimization, age, and internet usage were important cross-sectional risk factors for cyberbullying (Kowalski, Giumetti, Schroeder, & Lattanner, 2014), although gender differences are still inconclusive (Tokunaga, 2010). On the class level, good class climate was a protective factor for cyberbullying based on cross-sectional data. Some studies also identified ethnic diversity as a protective factor for traditional bullying (Juvonen, Nishina, & Graham, 2006), although there is a lack of evidence on cyberbullying and cyber-victimization.

Thus, these variables are important correlates of cyberbullying and cyber-victimization and should, therefore, be included when investigating program effectiveness. Potentially, program effects could disappear when controlling for these correlates. It is possible that changes in cyberbullying and cyber-victimization are not caused by the intervention, for example, the program, but by co-varying individual and class level characteristics. This information is important for developmental research, which examines mechanisms of change of cyberbullying and cyber-victimization.

Moreover, meta-analyses also investigated the characteristics of general anti-bullying programs associated with reduced traditional bullying and victimization (Farrington & Ttofi, 2009; Ttofi & Farrington, 2011). It was shown that the research designs, several implementation features, and program components were differentially associated with program effectiveness (Fox, Farrington, & Ttofi, 2012). More specifically, program effects were smallest in randomized control studies than other designs. Furthermore, programs with longer duration and more components for teachers or students were more effective than programs with shorter duration and fewer components. Programs containing teacher or parent trainings were more effective than programs without these elements (Fox, Farrington, & Ttofi, 2012; Ttofi & Farrington, 2011). Identifying the most promising program characteristics for cyberbullying and cyber-victimization requires further study.

To date, only few individual level characteristics, such as gender and age, have been controlled for in the analysis of program effectiveness to prevent cyberbullying and cybervictimization (e.g., Menesini et al., 2012; Ortega-Ruiz et al., 2012; Williford et al., 2013). Menesini et al. (2012) found program effects for the reduction of cyberbullying only in male peer educators. In contrast, in the studies conducted by Ortega-Ruiz et al. (2012) and Williford et al. (2013) gender was not a moderator of program effectiveness. Nevertheless, age moderated program effects. The KiVA program was effective for younger students ($M = 11.3$ years), but not for older ones (Williford et al., 2013). No existing study has investigated class climate and ethnic diversity as class level moderator variables. It is conceivable that prevention programs work better in classes with better class climate (e.g., because the program content can be more easily implemented), or in classes with lower ethnic diversity (e.g., because the program content is similarly comprehensible for all students). To better understand whether program effects can be generalized the investigation of potential moderator variables on the individual and the class level is important. Whether a program has a long-term effect is especially important for practitioners, who want to select the most sustainable program for their school.

THE ViSC SOCIAL COMPETENCE PROGRAM

The ViSC program has been developed, implemented, and evaluated as one component of the Austrian national strategy plan (Spiel & Strohmeier, 2011, 2012). ViSC is a primary preventive program including secondary preventive elements (i) to reduce aggressive behavior and bullying and (ii) to foster social and intercultural competencies in schools. The ViSC Program engages a systemic perspective and is designed for secondary schools (grades 5–8). It consists of an initial 1-year implementation phase and follows a cascaded train-the-trainer model within which scientists train multipliers, multipliers train teachers, and teachers train their students. During the program implementation, teachers are trained in (i) how to recognize bullying cases; (ii) how to tackle acute bullying cases; and (iii) how to implement preventive measures on the school and the class levels (class project). The class project aims to empower students to take the responsibility for what happens in their class. Within student centered instruction of the teacher, the students actively work together to find ways to prevent aggressive behavior in their class. At the end, the students design a small project and thus work together to achieve a positive, common goal (for details see Atria & Spiel, 2007; Strohmeier, Hoffmann et al., 2012) and practice their social skills. Regarding the most effective program components (Fox, Farrington & Ttofi, 2012; Ttofi & Farrington, 2011) the ViSC program includes teacher trainings and parent meetings, is implemented over 1 year and includes several components for teachers and students. Accordingly, it is expected that the program also prevents cyberbullying and cyber-victimization.

THE PRESENT STUDY

Considering the limited evidence regarding effective cyberbullying prevention, there is a need for high-quality studies to determine the effectiveness and the sustainability of effects. Unfortunately, empirical knowledge on longitudinal risk and protective factors for cyberbullying and cyber-victimization is rather sparse, and specific etiological models for cyberbullying and cyber-victimization necessary to design evidence-based prevention programs are still lacking. Therefore, building on the existing knowledge regarding traditional bullying is a promising strategy. Assuming that mechanisms for traditional bullying and cyberbullying are similar, it is plausible to predict that general anti-bullying programs are short- and long-term effective regarding the prevention of cyberbullying and cyber-victimization. However, because traditional and cyber forms of harassment co-occur (Gradinger, Strohmeier, & Spiel, 2009) and because the two forms share individual and contextual risk factors (Kowalski et al., 2014), it is necessary to control these variables so as not to misinterpret the results.

For this reason, the present study investigates (i) the effectiveness and (ii) the sustainability of the ViSC program within a randomized control study. The first hypothesis is that cyberbullying and -victimization has a more advantageous change over time in the intervention group than in the control group (Model 1). The second hypothesis is that such changes over time occur even when controlling for baseline levels of class climate and ethnic diversity at the class level, as well as of traditional and cyberbullying/victimization, age, gender, and internet usage on the individual level (Model 2). The third hypothesis is that class climate and ethnic diversity as class-level variables moderate program effectiveness and sustainability (Model 3). We also predicted that individual level variables moderate program effectiveness and sustainability (Model 4). To generalize program effectiveness and also for practitioners, who want to select the best program for their school, the questions of program sustainability and program moderators are of high importance.

METHOD

Design and Procedure

In December 2008, all secondary schools located in the capital city of Austria were invited to participate in the ViSC program. Out of all 155 secondary schools located in Vienna, 34 schools applied for participation from which 26 schools fulfilled the necessary requirements (e.g., the willingness to participate in the evaluation study). Applying a cluster randomization, 13 schools were assigned to the intervention group and five out of the 13 remaining schools agreed to serve as control schools. The program was implemented during the 2009/10 academic year (between September 2009 and June 2010). As shown in Table I, data were gathered at three time points: May/June 2009 (pretest), May/June 2010 (posttest), and November/December 2010 (follow-up test). Due to limited resources, the follow-up test was only collected from a sub-sample of three intervention and three control schools (i.e., planned missing data design). After the local school council and the school principals accepted the study, active parental consent was obtained. At pretest, 71% of students were present at the day of data collection and had parental consent to participate in the study. Data were collected through internet-based questionnaires that were

TABLE I. Study Design

	Pretest (May/June 2009)	Posttest (May/June 2010)	Follow-Up Test (November/December 2010)
Intervention group	10 schools	10 schools	Planned missigness
	3 schools	3 schools	3 schools
Control group	2 schools	2 schools	Planned missigness
	3 schools	3 schools	3 schools

completed during one regular school hour in the school's computer lab under the supervision of one or two trained research assistants. The order of the items within scales was counterbalanced to avoid any systematic order effect. Prior to data collection students were assured that their answers would be kept confidential.

Participants

In the present study, two different samples were used to investigate program effectiveness and program sustainability. The pretest–posttest sample for investigating program effectiveness comprised 18 schools and the posttest–follow-up test sample for investigating program sustainability comprised 6 schools.

Pretest–posttest sample. In total, 2,042 students (1,377 in intervention group, 665 in control group) located in 18 schools participated in at least one occasion of measurement and were included in the current study. At pretest, the sample comprised 1,639 students (47.6% girls) from 103 classrooms (50 fifth-grade classes, 51 sixth-grade classes, and 2 seventh-grade classes) with a mean age of 11.7 years ($SD = 0.9$, Min = 10, Max = 15), 37.5% stated that they used the Internet several times a day. According to a commonly used classification system (see Stefanek et al., 2011), 46.4% of the students were native Austrians, 20.2% from former Yugoslavia, 14.3% from Turkey, and 19.1% from other countries.

Posttest–follow-up test sample. In total, 659 students (319 in intervention group, 340 in control group) located in 6 schools participated in at least one occasion of measurement and were included in the current study. At posttest, the sample comprised 522 students (47.9% girls) from 35 classrooms (18 sixth-grade classes and 17 seventh-grade classes) with a mean age of 12.7 years ($SD = 0.8$, Min = 11, Max = 15), 53.3% stated that they used the Internet several times a day, 43.9% of the students were native Austrians, 20.6% from former Yugoslavia, 16.1% from Turkey, and 19.4% from other countries.

Table II provides a description of the sample for pretest–posttest and posttest–follow-up test and for intervention and control group separately.

Missing Data

Pattern of missing data across pre-, post-, and follow-up test are shown in Table SI of the Supplementary Material.

Pretest–posttest sample. In the pretest–posttest data, 974 records (46.2%) were incomplete resulting from two main missing data pattern: students who participated at pretest only ($n = 515$) and students who participated at posttest only ($n = 403$). The remaining 56 students had a general missing data pattern with missing values in single scales. The percentage of missing values across the 87 study variables varied between 19.7% and 28.6%. Analyses of wave nonresponse revealed that participants who missed the posttest had higher level of cyber-victimization ($d = 0.109$), traditional aggression ($d = 0.133$), and traditional victimization ($d = 0.145$) than participants with complete data (Table SII in the Supplementary Material). These variables are included in the imputation model of the multiple imputation process.

Posttest–follow-up test sample. In the posttest–follow-up test data, 328 records (49.8%) were

TABLE II. Demographic Characteristics of the Posttest–Pretest Sample at Pretest and Follow-Up Test–Posttest Sample at Posttest by Intervention and Control Groups

	Posttest–Pretest		Follow-Up Test–Posttest	
	Intervention ($n = 1{,}192$)	Control ($n = 447$)	Intervention ($n = 256$)	Control ($n = 266$)
Gender (% female)	48.5	45.2	53.5	42.5
Age in years, M (SD)	11.7 (0.9)	11.6 (0.8)	12.6 (0.9)	12.7 (0.8)
Internet usage, Mdn (IQR)	4 (3)	4 (2)	5 (2)	5 (2)

Note. Mdn, median; IQR, interquartile range. Internet usage is coded as follows: 0 = never, 1 = less often than once a week, 2 = once a week, 3 = every 2 or 3 days, 4 = once a day, 5 = several times a day.

incomplete resulting from two main missing data pattern: Students who participated at posttest only ($n = 160$) and students who participated at follow-up only ($n = 76$). The remaining 92 students had a general missing data pattern with missing values in single scales. The percentage of missing values across the 87 variables varied between 20.8% and 24.6%. Analyses of wave nonresponse showed no differences between participants with complete data and participants missing the follow-up test (Table SIII in the Supplementary Material).

Multiple imputation. Multiple imputation (Rubin, 1987) under the missing at random (MAR) assumption was used to deal with missing data. Incomplete variables were imputed under fully conditional specification (van Buuren, Brand, Groothuis-Oudshoorn & Rubin, 2006) based on an inclusive analysis strategy incorporating all variables used in the analyses of the present study, and numerous auxiliary variables into the missing data handling procedure (Collins, Schafer, & Kam, 2001). In order to account for the hierarchical data structure, 34 scale cluster means and scale item cluster means were included in the imputation model (Graham, 2012). Each variable was imputed with the predictive mean matching algorithm (van Buuren, 2012) using Tukey's tricube weighting function (Harrell, 2006). A total of 50 imputed data sets were extracted during the imputation process. In order to preserve interactions between the grouping variable and other variables, the imputation process was conducted for intervention and control group separately (Little & Rubin, 2002). Calculations were computed in R (R Core Team, 2014) using mice package (van Buuren & Groothuis-Oudshoorn, 2011) and miceadds package (Robitzsch, 2014).

Measures

Cyberbullying and cyber-victimization. Self-reported cyberbullying and cyber-victimization were measured with two scales, each containing seven specific items related to different electronic means based on Smith et al. (2008), and covering a time span of 2 months, for example, "How often have you insulted or hurt other students by mean calls during the last 2 months?" (cyberbullying calls) or "How often have you been insulted or hurt by receiving mean calls in the last two months from other students?" (cyber victimization calls). The different electronic means were calls, text messages, e-mails, chat contributions, discussion board, instant messages, and video or photos. Cronbach's α coefficients for the cyberbullying scale were .95/.96 (pretest/posttest) and .97/.94 (posttest/follow-up test). Cronbach's α coefficients for the cyber-victimization scale were .92/.95 (pretest/posttest) and .97/.94 (posttest/follow-up test).

Traditional aggression and traditional victimization. Traditional aggression and victimization were measured with three scales (i) bullying perpetration and bullying victimization; (ii) physical aggression and physical victimization; and (iii) relational aggression and relational victimization. All items covered a time span of 2 months.

Bullying perpetration and bullying victimization. Self-reported bullying and victimization were each measured by a scale consisting of a global item and three specific items covering different forms of bullying (Strohmeier, Gradinger, Schabmann, & Spiel, 2012). In the global item, students were asked "How often have you insulted or hurt other students during the last two months?" (global bullying perpetration) and "How often have others insulted or hurt you in the last two months?" (global bullying victimization). Cronbach's α coefficients for the bullying perpetration scale were .82/.83 (pretest/posttest) for and .80/.72 (posttest/follow-up test). Cronbach's α coefficients for the bullying victimization scale were 81/.82 (pretest/posttest) and .82/.79 (posttest/follow-up test).

Physical aggression and physical victimization. The peer nomination measure developed by Crick and Grotpeter (1995) was modified into a self-report questionnaire and each consisted of three items, for example, "How often have you hit one or more classmates during the last 2 months?" (physical aggression) or "How often have you been hit by one or more classmates during the last 2 months?" (physical victimization). Cronbach's α coefficients for the physical aggression scale were .79/.79 (pretest/posttest) and .79/.75 (posttest/follow-up test). Cronbach's α coefficients for the physical victimization scale were .74/.76 (pretest/posttest) and .75/.73 (posttest/follow-up test).

Relational aggression and relational victimization. These five items were also adapted from the peer nomination measure originally developed by Crick and Grotpeter (1995), for example, "Some kids leave other kids out on purpose when it's time to play or do an activity. How often have you done that during the last 2 months?" (relational aggression) or "How often during the last 2 months have you been excluded from play or another activity by one or more classmates?" (relational victimization). Cronbach's α coefficients for the relational aggression scale were .83/.87 (pretest/posttest) and .85/.81 (posttest/follow-up test). Cronbach's α coefficients for the relational victimization scale scale were .82/.81 (pretest/posttest) and .82/.78 (posttest/follow-up test).

The answering format of all scales mentioned above were given on a five-point response scale ranging 0 (*not at all*), 1 (*once or twice*), 2 (*two or three times a month*), 3 (*once a week*), and 4 (*nearly every day*).

Internet usage. Internet usage was measured with the item "How often do you use the internet? (e-mails, chat, discussion board, instant messages, . . .)" using a six-point response scale ranging 0 (*never*), 1 (*less often than once a week*), 2 (*once a week*), 3 (*every 2 or 3 days*), 4 (*once a day*), and 5 (*several times a day*).

Class climate. Class climate was measured with three items developed by Eder and Mayr (2000), for example, "In our class all students work together well and help each other." All items were answered using a four-point Likert scale ranging from 0 (*not at all true*), 1 (*somehow true*), 2 (*true*), and 3 (*certainly true*). Cronbach's α coefficients for the class climate scale were .85/.86 (pretest/posttest) and .90/.86 (posttest/follow-up test).

Ethnic diversity. Ethnic diversity in the class was measured using a formula developed by Simpson (1949, in Juvonen, Nishina, & Graham, 2006, p. 394).

$$D_c = 1 - \sum_{i=1}^{g} p_i^2 \tag{1}$$

D_c represents the ethnic diversity of a given class c and p_i is the proportion of students in the class who belong to ethnic group i. The p_i^2 is summed across g groups in a class. The possible range of this index is between 0 (i.e., all students are from the same cultural group) and 1 (i.e., every student in the class stems from a different cultural group). We calculated the ethnic diversity index based on seven groups: Austria, Turkey, former Yugoslavia, Eastern Europe, other Western Countries, Africa, and Asia (for more details see Stefanek et al., 2011).

Measurement Models

Measurement models for cyberbullying, cyber-victimization, traditional aggression, and victimization are each based on a one factor model with ordered-categorical indicators (see Bovaird & Koziol, 2012), because items measuring the frequency of incidents are not continuous. Furthermore, the highly positive skewed nature of the item response distribution makes a statistical approach based on normal-theory inappropriate (Muthén & Kaplan, 1985). For these scales, model specification and identification were based on Millsap and Yun-Tein (2004) using theta parameterization and a robust weighted least squares estimator (WLSMV).

The measurement model for class climate is based on a one factor model with continuous indicators, because items were answered on a four-point Likert scale. Multilevel confirmatory factor analysis was used to model perception of class climate on individual level and class level measured on the basis of student answers on class level.

Cyberbullying and cyber-victimization. The measurement models for cyberbullying and cyber-victimization are both based on one-factor models each comprising seven ordered-categorical indicators. CFA of the measurement models under longitudinal and between-group (control vs. intervention) invariance yield very good model fit for pretest–posttest and posttest–follow-up test (see Table SIV in the Supplementary Material) indicating sound measurement properties of both scales. Factor scores were extracted to compute difference scores *posttest minus pretest* and *follow-up test minus posttest* for cyberbullying and cyber-victimization representing change between two measurement occasions. A positive sign indicates an increase, while a negative sign indicates a decrease over time. These factor difference scores were subsequently used as dependent variables in the main analyses.

Traditional aggression and traditional victimization. The measurement models for traditional aggression and traditional victimization are based on a second-order factor model representing the hierarchical relations among the constructs measured by bullying perpetration/victimization scale, physical aggression/victimization scale, and relational aggression/victimization scale. CFA of the measurement models under strong longitudinal and between group (control vs. intervention) invariance yield very good model fit for pretest–posttest and posttest–follow-up test (see Table SIV in the Supplementary Material) indicating sound measurement properties of both scales. Factor scores for the second-order factor (i.e., traditional aggression and traditional victimization) were extracted and subsequently used in the main analysis.

Class climate. The measurement model for class climate is based on a one-factor multilevel model comprising three continuous indicators. Multilevel CFA of the measurement model under strong longitudinal and between group (control vs. intervention) within and between factor invariance yield very good model fit for pretest–posttest and posttest–follow-up test (see Table SIV in the Supplementary Material) indicating sound measurement properties. Factor scores for the between level factor (i.e., class climate) were extracted and subsequently used in the main analyses.

Analytic Strategies

Multilevel modeling (Hox, 2010) was used to investigate program effectiveness (pretest–posttest) and sustainability (posttest–follow-up test) taking class and individual level moderators and the nested data structure into account. A series of models were specified to sequentially test the hypotheses. First, we specified a Null Model to examine the proportion of the variance of the dependent variables at the class level (Model 0). Next, we included the predictor *intervention* to test for program effectiveness and sustainability (Model 1, Hypothesis 1). In the third step, we included covariates at the individual and class level to test for program effectiveness and sustainability controlling for covariates (Model 2, Hypothesis 2). In the fourth step, we included the interaction effects *intervention* × *class climate* and *intervention* × *ethnic diversity* to test for moderators at a class level (Model, 3, Hypothesis 3). In order to test for individual level moderators, we first tested for random slope effects of all covariates at an individual level using deviance tests (see Snijders & Bosker, 2011). Lastly, we specified cross-level interactions for only those covariates with a statistically significant random slope effect testing for individual level moderators (Model 4, Hypothesis 4). All models included the dependent variables change of cyberbullying and change of cyber-victimization simultaneously accounting for the covariance among both variables.

All models were analyzed in Mplus 7 (Muthén & Muthén, 1998–2012) using maximum likelihood estimation with robust standard errors (MLR).

RESULTS

Descriptive Statistics

In the first step, we inspected the means and standard deviations of cyberbullying and cyber-victimization at pre-, post-, and follow-up tests separately for intervention and control group (see Table SV in the Supplementary Material) as well as the change scores of cyberbullying and cyber-victimization between posttest–pretest and follow-up test–posttest separately for intervention and control group (see Table III). Between pre- and posttest, the control group had an increase in cyberbullying and cyber-victimization while the intervention group was rather stable. Between posttest and follow-up test, the intervention group had a decrease in cyberbullying and cyber-victimization, whereas the control group increased in cyberbullying and cyber-victimization.

Percentages of occurrence of cyberbullying and cyber-victimization vary between 4.4 and 21.5 (see Table SVI in the Supplementary Material).

Intraclass Correlation

Next, we examined the proportion of the variance of the dependent variables at the class level. The intraclass correlation (ICC) for the change score of cyberbullying and cyber-victimization for posttest–pretest and follow-up test–posttest was computed separately based on the Null Model of the multilevel model. Results indicate that between 0.3% and 7.3% of the variance laid between classes (see Table SVII in the Supplementary Material).

TABLE III. Mean and Standard Deviation of Cyberbullying Change and Cyber-Victimization Change

	Posttest–Pretest ($n = 2{,}042$)		Follow-Up Test–Posttest ($n = 659$)	
	ΔCyberbullying	ΔCyber-Victimization	ΔCyberbullying	ΔCyber-Victimization
Control				
M	0.29	0.17	0.20	0.03
SD	1.51	1.14	1.53	1.43
Intervention				
M	−0.08	0.07	−0.04	−0.34
SD	2.16	1.32	1.11	1.04

Note. Imputed data.

Despite the rather low ICCs, multilevel analysis is the appropriate analytic strategy for multilevel data, to account for design effects (see Snijders & Bosker, 2012), to examine random slope effects and to investigate moderator effects on individual and class level.

Program Effectiveness on Cyberbullying and Cyber-Victimization

In order to investigate program effectiveness, we conducted a multilevel analysis with change of cyberbullying and change of cyber-victimization as dependent variables and intervention (0 = control group, 1 = intervention group) as predictor on the class level (Model 1). Results revealed statistically significant *intercepts* for cyberbullying ($b = 0.280$, $P < .05$) and cyber-victimization ($b = 0.168$, $P < .05$), indicating that the control group increased in cyberbullying and cyber-victimization between pre- and posttest. The predictor *intervention* was also statistically significant for cyberbullying ($b = -0.358$, $P < .05$), but not statistically significant for cyber-victimization ($b = -0.095$, $P = .527$). That is, there was a decrease between pre- and posttest in the intervention group in cyberbullying. These results indicate program effectiveness for cyberbullying, but not for cyber-victimization.

Next, we examined program effectiveness controlling for several covariates at pretest on the individual and class level (Model 2, see Table IV). More specifically, on the individual level traditional aggression, traditional victimization, age, gender (0 = girls, 1 = boys), internet usage, and cyberbullying and cyber-victimization at pretest were included. All metric covariates were centered at the grand mean. On the class level, class climate and ethnic diversity were included as covariates, which were both centered at the mean. As for the change of cyberbullying, no covariate was significant. Regarding the change of cyber-victimization, the covariate

TABLE IV. Multilevel Modeling Results: Effectiveness (Posttest–Pretest) for Cyberbullying and Cyber-Victimization

	Posttest–Pretest											
	Model 2				Model 3				Model 4			
	ΔCyberbullying		ΔCyber-Victimization		ΔCyberbullying		ΔCyber-Victimization		ΔCyberbullying		ΔCyber-Victimization	
Coefficient	*b*	SE	*b*	SE	*b*	SE	*b*	SE	*b*	SE	*b*	SE
Level 1—Individual												
Intercept t1	**0.529**	0.116	**0.287**	0.082	**0.536**	0.114	**0.293**	0.083	**0.448**	0.105	**0.251**	0.079
Cyberbullying t1	−0.289	0.204	0.132	0.116	−0.287	0.204	0.133	0.116	−0.199	0.202	0.188	0.112
Cyber-victimization t1	−0.243	0.308	**−0.668**	0.169	−0.246	0.309	**−0.670**	0.169	−0.213	0.263	**−0.664**	0.156
Traditional aggression t1	0.179	0.073	0.088	0.056	0.179	0.093	0.088	0.056	0.163	0.097	0.072	0.059
Traditional victimization t1	−0.048	0.073	0.018	0.043	−0.046	0.072	0.019	0.043	−0.131	0.082	0.031	0.045
Age t1	0.075	0.052	0.037	0.033	0.076	0.052	0.038	0.033	0.078	0.061	0.063	0.049
Gender t1	0.034	0.086	0.007	0.049	0.034	0.086	0.007	0.049	0.040	0.086	0.007	0.049
Internet usage t1	−0.011	0.093	−0.017	0.016	−0.010	0.025	−0.016	0.016	−0.010	0.024	−0.015	0.016
Level 2—Class												
Intervention	**−0.749**	0.182	**−0.274**	0.121	**−0.754**	0.180	**−0.279**	0.122	**−0.670**	0.197	**−0.233**	0.130
Class climate t1	−0.189	0.167	−0.036	0.171	−0.460	0.248	−0.184	0.199	−0.203	0.167	−0.043	0.107
Ethnic diversity t1	0.355	0.204	0.149	0.138	**0.741**	0.289	0.291	0.280	0.338	0.201	0.151	0.135
Intervention x class climate t1					0.357	0.315	0.203	0.228				
Intervention x ethnic diversity t1					−0.458	0.386	−0.155	0.320				
Intervention x cyber-victimization t1									−0.201	0.159	−0.664	0.156
Intervention x traditional victimization t1									**0.129**	0.060		
Intervention x age t1									−0.018	0.091	0.063	0.049
Variance components												
Level 1—individual	3.287		1.264		3.286		1.264		3.248		1.258	
Level 2—class	0.019		0.018		0.017		0.018		0.016		0.015	
Slope cyber-victimization t1									0.004		0.001	
Slope traditional victimization t1									0.008			
Slope age t1									0.006		0.004	
Model summary												
Deviance	11,488.002				11,485.242				11,455.884			
AIC	11,544.002				11,549.242				11,531.884			

Note. Unstandardized coefficients. Intervention was tested one-tailed, all other predictors were tested two-tailed. Statistically significant coefficient at $\alpha = .05$ are shown in boldface. Gender is coded as 0 = females and 1 = males. Intervention is coded as 0 = control and 1 = intervention group.

cyber-victimization at pretest was statistically significant ($b = -0.668$, $P < .05$) indicating the higher cyber-victimization at pretest, the stronger the decrease in cyber-victimization controlling for all other covariates in the model. All other covariates were not statistically significant.

The *intercept* for cyberbullying ($b = 0.529$, $P < .05$) and cyber-victimization ($b = 0.287$, $P < .05$) were both statistically significant. The *intervention* effect controlling for the covariates was still present for cyberbullying ($b = -0.749$, $P < .05$) indicating a stabilization in cyberbullying in the intervention group between pre- and posttest. For cyber-victimization, *intervention* became statistically significant ($b = -0.274$, $P < .05$) indicating a stabilization in cyber-victimization in the intervention group between pre- and posttest. In sum, the results demonstrate the effectiveness of the intervention in cyberbullying and cyber-victimization when controlling for several covariates at individual and class level.

Program Sustainability on Cyberbullying and Cyber-Victimization

The *intercept* for the cyberbullying change score was statistically significant ($b = 0.197$, $P < .05$), although that for the change in cyber-victimization was not ($b = 0.034$, $P = .722$), indicating an increase in cyberbullying between posttest and follow-up test, but no change for cyber-victimization in the control group (Model 1). *Intervention* was not statistically significant for the change of cyberbullying ($b = -0.233$, $P = .218$) indicating a similar trend in both groups after posttest, which shows sustainability of program effects. However, *intervention* was statistically significant for the change of cyber-victimization ($b = -0.376$, $P < .05$) indicating a reduction in cyber-victimization after posttest in the intervention group (sleeper effect).

Furthermore, program sustainability was investigated controlling for the same covariates at the

TABLE V. Multilevel Modeling Results: Sustainability (Follow-up Test - Posttest) for Cyberbullying and Cyber-victimization

	Follow-Up Test–Posttest							
	Model 2				Model 3			
	ΔCyberbullying		ΔCyber-Victimization		ΔCyberbullying		ΔCyber-Victimization	
	b	SE	*b*	SE	*b*	SE	*b*	SE
Level 1—Individual								
Intercept t2	**0.281**	0.137	−0.044	0.110	**0.381**	0.144	0.018	0.117
Cyberbullying t2	**−0.489**	0.088	**0.308**	0.104	**−0.498**	0.093	**0.302**	0.120
Cyber-victimization t2	−0.038	0.104	**−0.879**	0.097	−0.031	0.109	**−0.873**	0.113
Traditional aggression t2	0.118	0.072	0.125	0.081	0.115	0.074	0.121	0.083
Traditional victimization t2	0.040	0.052	0.030	0.055	0.043	0.054	0.033	0.061
Age t2	0.063	0.063	0.054	0.059	0.065	0.069	0.058	0.094
Gender t2	0.159	0.142	0.088	0.116	0.168	0.146	0.096	0.128
Internet usage t2	0.001	0.039	−0.017	0.043	0.003	0.044	−0.015	0.066
Level 2—Class								
Intervention	**−0.590**	0.217	**−0.327**	0.196	**−0.595**	0.216	**−0.316**	0.191
Class climate t2	0.049	0.199	0.049	0.199	0.327	0.328	0.328	0.386
Ethnic diversity t2	0.272	0.395	0.444	0.361	−0.633	0.810	−0.047	1.092
Intervention x class climate t2					−0.674	0.481	−0.538	0.622
Intervention x ethnic diversity t2					1.206	0.963	0.624	1.237
Variance components								
Level 1—individual	1.374		1.091		1.373		1.091	
Level 2—class	0.017		0.013		0.010		0.008	
Model summary								
Deviance	3,259.662				3,255.644			
AIC	3,315.662				3,319.643			

Note. Unstandardized coefficients. Intervention was tested one-tailed, all other predictors were tested two-tailed. Statistically significant coefficient at $\alpha = .05$ are shown in boldface. Gender is coded as 0 = females and 1 = males. Intervention is coded as 0 = control and 1 = intervention group.

individual and class level (Model 2, see Table V). For the change in cyberbullying, *cyberbullying at posttest* was statistically significant ($b = -0.489$, $P < .05$) indicating that the higher cyberbullying at posttest, the stronger the decrease in cyberbullying. For the change in cyber-victimization, *cyberbullying at posttest* ($b = 0.308$, $P < .05$) and *cyber-victimization at posttest* ($b = -0.879$, $P < .05$) were statistically significant. The higher cyberbullying was at posttest, the stronger the increase in cyber-victimization, whereas the higher cyber-victimization was at posttest, the stronger the decrease in cyber-victimization. All other covariates were not statistically significant. The *intercept* for cyberbullying ($b = 0.281$, $P < .05$) was statistically significant, indicating an increase in cyberbullying in the control group after posttest controlling for all covariates. The *intercept* for cyber-victimization ($b = -0.044$, $P = .690$) was not statistically significant. Controlling for all covariates, *intervention* was statistically significant for the change in cyberbullying ($b = -0.590$, $P < .05$) and cyber-victimization ($b = -0.327$, $P < .05$). This result indicates that there was a decrease in cyberbullying and cyber-victimization in the intervention group after posttest (sleeper effect). In sum, the results demonstrate sustainability of the intervention in cyberbullying and cyber-victimization when controlling for several covariates at individual and class level.

The model equation for Model 2 is shown in the Appendix.

Class Level Moderators on Effectiveness

In order to investigate class level moderators on program effectiveness, we estimated a model including interaction effects *intervention × class climate* and *intervention × ethnic diversity* on class level. Because no interaction effects were found (see Table IV, Model 3), neither class climate nor ethnic diversity moderated the intervention effects. Therefore, these interaction terms were excluded in all subsequent models (see Table IV, Model 4).

Class Level Moderators on Sustainability

In order to investigate class level moderators on program sustainability we estimated a model including interaction effects *intervention × class climate* and *intervention × ethnic diversity* on class level. Because no interaction effects were found (see Table V, Model 3), neither class climate nor ethnic diversity moderated the intervention effects. Therefore, these interaction terms were excluded in all subsequent models.

Individual Level Moderators on Effectiveness

Individual level moderators on program effectiveness were investigated in two steps.

In the first, we tested the variability of slope parameters between classes of all covariates at an individual level with a series of deviance tests (i.e., random slope effects; see Table SVIII in the Supplementary Material).

For the change of cyberbullying, there was a random slope effect for *cyber-victimization*, *traditional victimization*, and *age*. For the change of cyber-victimization, there was a random slope effect for *cyber-victimization* and *age*. In the second step, we predicted the variability of slope parameters of covariates found in step one between classes using the predictor *intervention* (i.e., cross-level interaction). The cross-level interaction *intervention* × *covariate* represents the moderating effect of a covariate on program effectiveness.

As shown in Table IV, Model 4 (including all cross-level interactions) showed that only *intervention* × *traditional victimization* was statistically significant ($b = 0.129$, $P < .05$) indicating the higher the traditional victimization the smaller the decrease in cyberbullying in the intervention group (i.e., smaller intervention effects). All other cross-level interactions for the change of cyberbullying or cyber-victimization were not statistically significant.

The model equations for Model 4 are shown in the Appendix.

Individual Level Moderators on Sustainability

In order to investigate individual-level moderators of program sustainability, we tested random effects of slope parameters for all covariates at an individual level (see Table SVIII in the Supplementary Material). Deviance tests indicated no random slope effect of any covariate on cyberbullying or cyber-victimization. Thus, none of the investigated covariates were moderators of program sustainability for cyberbullying or cyber-victimization.

DISCUSSION

The present study examined the effectiveness and sustainability of program effects of a general anti-bullying program for cyberbullying and cyber-victimization. By using an advanced methodology, the study is both informative for prevention science and basic research. Because several possible moderators at the individual and class level have been included in the analyses, the study provides important knowledge regarding the prediction of change of cyberbullying and cyber-victimization above the participation in an intervention which is important for developmental psychology.

Program Effectiveness and Sustainability

The ViSC program effectively and sustainably prevented cyberbullying and cyber-victimization. Controlling for baseline levels of cyberbullying, cyber-victimization, traditional aggression, traditional victimization, age, gender, and Internet usage at the individual level and class climate and ethnic diversity at the class level, the intervention group decreased in cyberbullying and increased lesser in cyber-victimization, whereas the control group increased in cyberbullying and cyber-victimization, during the program implementation of 1 year. During the follow up phase comprising another 6 months and controlling for the same covariates at the posttest, the intervention group decreased in cyberbullying and cyber-victimization, whereas the control group increased in cyberbullying and was stable in cyber-victimization. This effectiveness and sustainability is remarkable, because the ViSC program does not include any specific elements to prevent cyberbullying and cyber-victimization. Thus, it is likely that the ViSC program indirectly tackled mechanisms of cyberbullying and cyber-victimization which are presumably similar to those of traditional bullying and victimization. The ViSC program induces a complex school developmental process and covers both indicated actions and preventive measures. Therefore, it is impossible to determine the exact mechanisms of change in the present study. What can be concluded is that the ViSC program needs no specific cyber element to effectively and sustainably prevent youth's negative behavior in cyberspace. Until now, the few other evaluated general antibullying programs contained specific cyber elements (e.g., Menesini et al., 2012; Williford et al., 2013), and some even exclusively targeted cyberbullying (e.g., Ortega-Ruiz et al., 2012; Pieschl & Porsch, 2013; Schultze-Krumbholz et al., 2014). Nevertheless, it is conceivable that effect sizes might be even stronger if elements to prevent cyberbullying and cyber-victimization were included in the program.

Individual Level Moderators of Effectiveness and Sustainability

Unexpectedly, most individual level variables were neither moderators of program effectiveness nor sustainability. This indicates that the intervention is effective independently of student characteristics such as gender, age, internet usage, or involvement in traditional bullying. For gender, this was consistent with some other studies (Ortega-Ruiz et al., 2012; Williford et al., 2013), whereas younger age was an important moderator in the KiVa program (Williford et al., 2013). In the present study, traditional victimization was the only important moderator. The higher traditional victimization at the pretest, the smaller was the decrease in cyber-bullying after the first year of program implementation. This smaller program effectiveness for highly involved traditional victims is interesting and might indicate that a helpless status in real life might immunize against stopping to take revenge in cyberspace.

Baseline levels of cyber-victimization and cyberbullying were related to changes of cyber-victimization and cyberbullying. The higher the levels of cyber-victimization at pretest, the stronger was the decrease in cyber-victimization between pretest and posttest, and between posttest and follow-up test. Moreover, the higher cyber bullying at posttest, the stronger was the decrease in cyber bullying over time between posttest and follow-up test. This might show a normative developmental trend in this age group. Students who are highly involved in cyber behavior reduce their negative behavior over time.

Class Level Moderators of Effectiveness and Sustainability

Contrary to our hypotheses, the variability in the change scores of cyberbullying and cyber-victimization on the class level was rather small, indicating negligible effects of classroom characteristics on the change. Despite the very low ICCs, multilevel analysis was applied to handle the multilevel data structure and to investigate predictors at a class level. In the present study, class climate and class room ethnic diversity moderated neither program effectiveness nor sustainability. Thus, independent of class climate and ethnic diversity, the ViSC program is effective and shows sustainable effects.

Strengths and Limitations

The present study has several strengths. To begin with, the ViSC program was implemented within a national strategy (Spiel & Strohmeier, 2011, 2012), so that it was possible to investigate a large sample of schools and to realize a cluster randomization at a school level. Longitudinal data were collected at three time points to determine the effectiveness and the sustainability of effects. As a limitation, it was only possible to collect the follow-up data in a subsample of six schools due to lack of resources. Data were collected via self-assessments which could be considered also a limitation; however, all constructs were measured with multiple items and scales were rigorously tested. Although we had missing data due to the longitudinal character of the study, they were adequately handled with the best possible method and Multilevel Modeling was applied to test the hypotheses. Although several possible moderators were examined, there could be others (e.g., parent's participation rate in program meetings) which were not measured but might influence the results.

To summarize, the present study indirectly demonstrated that traditional bullying and cyberbullying might share similar mechanisms, as cyberbullying and cyber-victimization were also changed by a general antibullying prevention program. Specific cyberbullying prevention programs are certainly valuable; however, general antibullying programs including specific cyber elements might be most effective in the long run, as they use long-established knowledge about traditional bullying and also tackle cyberbullying.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's web-site.

APPENDIX: MODEL EQUATION

In the present study, the final model for investigating program effectiveness is Model 4, whereas the final model investigating program sustainability is Model 2 because we did not find any moderator effects on the individual or class level. Based on the notation by Raudenbush and Bryk (2002) the model equation for the final model investigating program effectiveness for the change of cyberbullying is given by $Y_{ij} = \beta_{0j} + \beta_{1j}$ (cyber bullying) $+ \beta_{2j}$ (cyber-victimization) $+ \beta_{3j}$ (traditional aggression) $+ \beta_{4j}$ (traditional victimization) $+ \beta_{5j}$ (age) $+ \beta_{6j}$ (sex) $+ \beta_{7j}$ (internet usage) $+ r_{ij}$ on the individual level and by $\beta_{0j} = \gamma_{00} + \gamma_{01}$ (intervention) $+ \gamma_{02}$ (class climate) $+ \gamma_{03}$ (ethnic diversity) $+ u_{0j}$, $\beta_{2j} = \gamma_{10} + \gamma_{11}$ (intervention) $+ u_{1j}$, $\beta_{4j} = \gamma_{30} + \gamma_{31}$ (intervention) $+ u_{3j}$, $\beta_{5j} = \gamma_{40} + \gamma_{41}$ (intervention) $+ u_{4j}$ on the class level. The model equation for the change of cyber-victimization is given by $Y_{ij} = \beta_{0j} + \beta_{1j}$ (cyberbullying) $+ \beta_{2j}$ (cyber-victimization) $+ \beta_{3j}$ (traditional aggression) $+ \beta_{4j}$ (traditional victimization) $+ \beta_{5j}$ (age) $+ \beta_{6j}$ (sex) $+ \beta_{7j}$ (internet usage) $+ r_{ij}$ on the individual level and by $\beta_{0j} = \gamma_{00} + \gamma_{01}$ (intervention) $+ \gamma_{02}$ (class climate) $+ \gamma_{03}$ (ethnic diversity) $+ u_{0j}$, $\beta_{2j} = \gamma_{10} + \gamma_{11}$ (intervention) $+ u_{1j}$, and $\beta_{5\mathrm{j}} = \gamma_{40} + \gamma_{41}$(intervention) $+ u_{4j}$ on the class level.

The model equation for the final model investigating program sustainability for the change of cyberbullying is given by $Y_{ij} = \beta_{0j} + \beta_{1j}$ (cyberbullying) $+ \beta_{2j}$ (cyber-victimization) $+ \beta_{3j}$ (traditional aggression) $+ \beta_{4j}$ (traditional victimization) $+ \beta_{5j}$ (age) $+ \beta_{6j}$ (sex) $+ \beta_{7j}$ (internet usage) $+ r_{ij}$ on the individual level and by $\beta_{0j} = \gamma_{00} + \gamma_{01}$ (intervention) $+ \gamma_{02}$ (class climate) $+ \gamma_{03}$(ethnic diversity) $+ u_{0j}$ on the class level. The model equation for the change of cyber-victimization is given by $Y_{ij} = \beta_{0j} + \beta_{1j}$ (cyberbullying) $+ \beta_{2j}$ (cyber-victimization) $+ \beta_{3j}$ (traditional aggression) $+ \beta_{4j}$ (traditional victimization) $+ \beta_{5j}$ (age) $+ \beta_{6j}$ (sex) $+ \beta_{7j}$ (internet usage) $+ r_{ij}$ on the individual level and by $\beta_{0j} = \gamma_{00} + \gamma_{01}$ (intervention) $+ \gamma_{02}$ (class climate) $+ \gamma_{03}$ (ethnic diversity) $+ u_{0j}$ on the class level.