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Online mentoring for girls in secondary education to increase participation rates of women in STEM: A long-term follow-up study on later university major and career choices

Heidrun Stoeger[1] | Tobias Debatin[1] | Michael Heilemann[1] | Sigrun Schirner[1] | Albert Ziegler[2]

[1]Department of Educational Sciences, University of Regensburg, Regensburg, Germany

[2]Department of Educational Psychology, University of Erlangen-Nuremberg, Nuremberg, Germany

Correspondence
Heidrun Stoeger, Department of Educational Sciences, University of Regensburg, Universitätsstraße 31, 93053 Regensburg, Germany.
Email: heidrun.stoeger@ur.de

Abstract

An important first step in talent development in science, technology, engineering, and mathematics (STEM) is getting individuals excited about STEM. Females, in particular, are underrepresented in many STEM fields. Since girls' interest in STEM declines in adolescence, interventions should begin in secondary education at the latest. One appropriate intervention is (online) mentoring. Although its short-term effectiveness has been demonstrated for proximal outcomes during secondary education (e.g., positive changes in elective intentions in STEM), studies of the long-term effectiveness of STEM mentoring provided during secondary education—especially for real-life choices of university STEM majors and professions—are lacking. In our study, we examine females' real-life decisions about university majors and entering professions made years after they had participated in an online mentoring program (CyberMentor) during secondary education. The program's proximal positive influence on girls' elective intentions in STEM and certainty about career plans during secondary education had previously been demonstrated in several studies with pre–post-test waitlist control group designs. Specifically, we compared the choices that former mentees (n = 410) made about university majors and entering professions several years after program participation with (1) females of their age cohort and (2) females of a group of girls comparably interested in STEM who had signed up for the program but then not participated (n = 71). Further, we examined the explanatory contribution to these later career-path-relevant, real-life choices based on (1) mentees' baseline conditions prior to entering the program (e.g., elective intentions in STEM), (2) successful 1-year program participation, and (3) multiyear program participation. Findings indicate positive long-term effects of the program in all areas investigated.

KEYWORDS
gender studies, online mentoring, participation rates in STEM, science, talent development

INTRODUCTION

To meet the challenges of our time—the COVID-19 pandemic or climate change, for example—and realize positive visions for a common future, outstanding scientists are crucial. Talent development toward eminence and innovation has been the subject of research for decades. Bloom's seminal interview study of 120 individuals who had achieved world-class levels of performance in various domains has made an important contribution to a better understanding of what eminence and innovation entail.[1] He identified three stages of talent development. Stage 1 is about interest development. Individuals fall in love with a subject, an idea, or a discipline. Stage 2 is about skill acquisition. Individuals develop technical mastery through deliberate practice. Stage 3, finally, is about style formation. Individuals who have typically dedicated their lives to a domain may eventually form a unique style and transform a field by solving significant problems in original ways. Although Bloom's stages have been adapted and expanded by various giftedness and talent development researchers (e.g., Ref. 2), they continue to play an important role in practice.[3]

In science, technology, engineering, and mathematics (STEM), the first stage of talent development poses a particular problem. This can, for example, be seen in the chronic shortages of skilled professionals.[4] Attracting talented girls and women to STEM has proven particularly challenging. Although the situation at this initial stage of talent development has improved in recent years, women are still less likely to opt for STEM majors and professions in many countries, especially in disciplines such as computer science and engineering.[5–7] For this reason, extensive efforts have been made in recent decades to improve the situation. In this context, it has proven important to start interventions as early as possible, at the latest early on in secondary education, as girls' interest in STEM subjects declines substantially during adolescence,[8] and decisions related to future career choices are made during this period.[9,10]

As crucial as it is that interventions to attract talented girls to STEM careers start early, it is difficult to verify the long-term effectiveness of such measures. Definitive real-life choices for or against long-term engagement with STEM domains—in the sense of decisions about university majors and about careers—often take place years after an intervention targeting girls. Research studies often rely on self-reports completed after early interventions, for example, about girls' elective intentions or certainty about future career plans, and assume that any such proximal improvements in STEM-related outlooks or preferences presage definitive later choices about university majors and about careers. In more rigorous studies, researchers specify developmental trajectories based on participants' self-reports made before, during, and after an intervention and compare these with responses provided by suitable control groups (i.e., groups of individuals with similar initial characteristics but who did not receive the intervention).[11] However, follow-up studies on later real-life choices are hard to find.[12,13]

The aim of our study was, therefore, to investigate whether a measure that has proven effective for getting girls interested in STEM subjects early on—namely, online mentoring being offered to girls enrolled in secondary education—also increases the rates at which participants make STEM career choices after high school (i.e., majoring in a STEM subject at university and/or entering a STEM profession). We examined this for CyberMentor, a Germany-wide online mentoring program for girls enrolled in university-track secondary education. CyberMentor has been scientifically evaluated and extensively studied for nearly two decades in terms of its short-term effectiveness and determinants of success.[14–16]

Attracting girls in secondary education to STEM via mentoring

Mentoring is a relatively stable dyadic relationship between one or more experienced individuals (mentors) and one or more less experienced individuals (mentees) characterized by mutual trust, goodwill, and the shared goal of mentees' advancement and growth.[17] Mentoring is important for youth career guidance[13] and for Bloom's Stage 1 of talent development[1] in three ways. First, it provides mentees with a connection to adults who probe and cultivate mentees' interests and help them achieve their goals. Second, mentors serve as role models who share their own experiences in identifying (career) interests and their career paths with their mentees. For career guidance and the promotion of girls' STEM interests, female role models who are themselves studying a STEM subject or working professionally in a STEM field are particularly effective.[18] Third, mentors act as advocates for their mentees, giving them access to other individuals and institutions to explore and deepen their career interests.[19]

Online mentoring is a specific form of mentoring in which interaction occurs primarily or exclusively through digital technologies.[20] Communication can be both synchronous and asynchronous. While synchronous communication requires the simultaneous presence of both communication partners, asynchronous communication is characterized by a temporal succession. Examples of synchronous communication tools include video conferencing, instant messaging, and chat. Asynchronous communication can take place via email, newsgroups, or forums.[21]

In the context of STEM promotion for girls, online mentoring has proven to be particularly successful for at least four reasons. First, online mentoring makes it easier to find suitable female role models as mentors. The rationale is that while women who are themselves studying a STEM subject or working in a STEM field act as particularly suitable role models (e.g., Ref. 18), it is often difficult to find them in the mentees' immediate vicinity due to the low participation rates of women in STEM. Online mentoring facilitates matching mentees with suitable mentors due to its spatial and temporal flexibility. Moreover, the online format makes frequent communication (ideally on a weekly basis) easier, which is essential for successful mentoring.[22]

Second, by using an appropriate platform, online mentoring enables mentees to network with other females interested in STEM. Networking with other mentors prevents counterproductive subtyping processes,[23] that is, girls recognize that their individual mentors are not an exception (i.e., a subtype), but that their mentors are among many women successful in STEM. This can help to reduce the stereotype that STEM is a typically male domain.[24–26] In addition, by networking with other female mentors, mentees learn about different STEM career paths and discuss a wide variety of STEM-related topics, thereby deepening their interests. Networking with other mentees in an online mentoring program can make mentees aware that many other girls are also interested in STEM, which is usually not the case in their immediate social environments.[15] Moreover, the other mentees in a program provide same-age role models. Same-age role models have been shown to be particularly effective for changing girls' perceptions of STEM subjects as unfeminine.[27] Furthermore, studies indicate that peer support plays an important role in girls' willingness to stay in STEM fields.[28]

Third, online mentoring enables the establishment of an optimal learning environment for girls in STEM.[17] For example, it is possible to host topic chats on STEM or provide low-threshold access to STEM lectures, discussions, and Q-and-A sessions. Mentees and mentors can use collaboration tools to work jointly on STEM projects or manuscripts, or, with proper facilitation, to organize their own symposia.[3]

Finally, some aspects that predict successful mentoring[29] are particularly well realized in online mentoring. For example, it is more feasible for employed mentors to participate in training sessions essential to mentoring success before and during a mentoring program[22] if these are offered via instructional videos or online.[30] The continuous support of participants by trained program staff (e.g., regular check-ins with mentees and mentors) is an important criterion for successful mentoring[31] and easier to implement online.

Research on mentoring during secondary education and females' later STEM-related choices

There is evidence that mentors have an influence on mentees' career choices in STEM (i.e., majoring in a STEM subject at university or entering a STEM profession). For example, in a retrospective survey of 1425 female graduates of selective science, high schools in the United States[32] found that having a teacher as a mentor during high school correlated with university STEM major choices and degrees in STEM. However, studies examining associations between participation in formal STEM mentoring programs during secondary education and later career choices are lacking.[13,33] To date, evaluation studies of such programs have mainly examined more proximal program effects on precursors of later choices of STEM majors or careers (e.g., elective intentions in STEM, certainty about career plans, or career interests; for an overview, see Ref. 13). In the following, we describe the results of two evaluation studies reporting proximal beneficial effects of STEM mentoring programs offered during secondary education.

In their evaluation study of the Spanish Inspira STEAM program, which aims to increase girls' participation in STEM,[34] researchers found positive effects on professional aspirations. One hundred and ninety-six students attending the same secondary school participated in an in-school mentoring program in which female STEM professionals acted as mentors during six class periods. One hundred and seven students from the same school constituted the control group. In an open-ended question about what occupation the study participants could imagine for themselves later in life, the preference for STEM occupations of girls in the intervention group increased, while the preference for STEM occupations of girls in the control group decreased somewhat from the presurvey to the postsurvey questionnaire.

Evaluation studies of the Germany-wide online mentoring program, CyberMentor, also reported, among other things, positive effects on girls' elective intentions and certainty about career plans. In an initial evaluation study[14] with 312 students in secondary education, 208 girls were selected by random assignment to participate in the program without delay. The remaining 104 students acted as a waitlist control group of comparably interested girls who were only admitted to the program 1 year later. In questionnaires completed by both groups before starting the program, 6 months after starting, and at the end of the mentoring year, girls who had participated in the mentoring program reported a greater increase in elective intentions in STEM than girls in the waitlist control group. In a follow-up study,[15] 789 of 1237 girls who applied to the program were randomly selected to participate. Their developmental trajectories were compared with those of 448 girls who had been randomly assigned to a waitlist control group and with those of a random sample of 663 girls and 841 boys. Across the three measurements, participating girls exhibited more positive trajectories with respect to certainty about career plans. Furthermore, ongoing program research has investigated conditions for successful mentoring in the CyberMentor program. For example, it was shown that the more mentees talked about STEM on the platform, the more they networked with other mentees and mentors on the platform; and the more positive they were in assessing their relationships with their mentors, the more positive the girls' developmental trajectories of elective intentions in STEM were and the more certain they were about career plans.[15,16,35] Together, these findings support the assumptions noted above about the benefits of online mentoring for supporting girls in STEM.

The results of these studies are encouraging. However, they focus on the early prerequisites of later career choices. Whether these promising changes in elective intentions in STEM, in certainty about career plans, and for other relevant constructs—observed while girls were in secondary education and participating in online and in-person mentoring programs—actually lead to real-life decisions, often made years later, to major in a STEM subject at university and/or to choose a STEM career has not yet been investigated.[13,33]

Although studies with adults suggest that online and in-person mentoring do indeed influence career-path-relevant, real-life choices,[36,37] in these studies, the career choices occurred immediately or very shortly after participation. In the case of online and in-person mentoring programs for girls in secondary education, real-life choices about university courses of study and entering professions often do not occur until years after program participation. Findings on the effects from mentoring programs with adults thus cannot be generalized to programs with youths. To fill this research gap, studies are needed to examine whether youth mentoring programs that have been shown to have positive effects on elective intentions in STEM and other related constructs during secondary education lead in the longer term to career choices in STEM (i.e., decisions about university majors and entering professions).

Research questions

In our study, we, therefore, investigated whether girls who participated in the online mentoring program CyberMentor for at least 1 year during secondary education were more likely to make a STEM career choice (majoring in a STEM subject or entering a STEM profession) later on. To do this, we compared the STEM career choices of former mentees with different control groups. We formulated three research questions. In the following, we state each research question and provide additional rationale for Research Questions 2 and 3.

Research Question 1: A few years after participating in the program, are former CyberMentor participants significantly more likely to make a career choice in STEM than women of the same age cohort?

Girls who enroll in longer-term STEM programs, such as CyberMentor, differ from girls who do not enroll in such programs on several characteristics.[15,38] For example, they exhibit significantly greater interest in STEM and have better grades in STEM subjects. Therefore, to determine whether subsequent career choices can actually be attributed to program participation, it is not sufficient to compare the proportion of participants' career choices to those of the same age cohort. Rather, it is important to compare the proportion of participants' career choices with those of comparable nonparticipating females of the same age who were similarly interested in STEM at the time of program participation. Only in this way can it be determined whether participation in the mentoring program is (partly) responsible for subsequent career choices in STEM, or whether the above-average interest would have led such girls to make these choices even without having participated in such a mentoring program.

Research Question 2: A few years after participating in the program, are former CyberMentor participants significantly more likely to make a STEM career choice than females who had also originally enrolled in the program (i.e., girls of the same age who were similarly interested in STEM at the time) but then did not participate?

Not only does STEM interest differ among girls who enroll in long-term STEM programs. Often, these girls are characterized by greater elective intentions in STEM and less certainty about career plans before program participation.[15] Therefore, it is important to clarify whether successful program participation makes an additional explanatory contribution to later career choices beyond the elective intentions for STEM and certainty about career plans girls were reporting before they started the program. Further, it is of interest to determine whether multiyear participation in CyberMentor has added value for subsequent career choices in comparison to 1 year of successful participation.

Research Question 3: What is the explanatory contribution for later career choices made by (1) students' baseline conditions (i.e., elective intentions in STEM and certainty about career plans) prior to entering the program, (2) 1 year of successful participation in CyberMentor (operationalized via gains in elective intentions in STEM and certainty about career plans), and (3) several years of participation in the program?

METHODS

CyberMentor as a research setting

CyberMentor is a Germany-wide online mentoring program founded in 2005. Its goal is to inspire girls for STEM and to contribute to an increased participation of women in STEM in the long term. The program takes place on a members-only online platform that was planned and programmed by the project team based on the mentoring goals and the underlying mentoring concept. Mentees are enrolled in grades 5–13 of university-track secondary education in Germany.[a] Each mentee is mentored for at least 1 year by a mentor, a woman who is majoring in a STEM subject or working in a STEM field. Up to 800 mentees and up to 800 mentors participate in the program annually. The mentees and mentors communicate with one another on a weekly basis for at least half an hour via emails, instant messages, and forum posts. The program is free of charge for the students, and the mentors volunteer their time.

In CyberMentor, dyads are matched based on the mentees' STEM interests and the mentors' STEM fields, as well as shared personal interests. Mentors act as successful STEM role models, provide insight into their careers and everyday work, discuss STEM-related topics as well as personal issues, and provide support for mentees' STEM projects. To prevent subtyping processes and to provide both role models that are professionally successful in STEM (mentors) and same-age role models who are also interested in STEM (mentees), the platform offers extensive networking opportunities with other mentors and mentees.

The mentoring year is divided into four phases of equal length. In the first quarter, the focus is on getting to know one another and learning more about STEM majors and professions. In addition, mentees and mentors jointly investigate where STEM plays a role in everyday life. The results of these discussions are made available to the entire online mentoring community in STEM wikis written to stimulate platform-wide discussions about STEM in everyday contexts and illustrate that STEM plays a role in diverse everyday settings that are often not apparent at first glance. In the second quarter, two mentoring dyads with similar STEM interests (e.g., computer science) collaborate on a project in their STEM field (e.g., programming an app). In the third quarter, several mentoring dyads from different STEM fields work together on an interdisciplinary project (e.g., researching and writing a plan for surviving on Mars). The last quarter is dedicated to a review of and reflection on the first three quarters of the mentoring year. For example, participants write articles for the monthly program magazine, *CyberNews*, and present their most interesting projects from the mentoring year.

[a] In most German federal states, secondary education starts in fifth grade and runs through twelfth and in some federal states the thirteenth grade.

Sample and procedure

For our follow-up study, in 2017, we contacted 2158 women from three mentoring cohorts (cohort 1: 2009–2010; cohort 2: 2010–2011; and cohort 3: 2011–2012). Five hundred and seventy-nine individuals responded (26.8%) and participated in our study.[b] For our analysis, we excluded all participants who were not yet working or studying at the time of the survey ($n = 20$) or provided information we could not code concerning STEM-relatedness because of a lack of detail ($n = 78$; e.g., "trainee"). Of the remaining 481 women, 410 were former mentees (mean age when applying for participation: $M = 14.58$ years, $SD = 2.02$) and 71 were women who had applied for the program and been randomly assigned to a waitlist control group with an option to join the program 1 year later but who never participated in the mentoring program (mean age when applying for participation: $M = 13.87$ years, $SD = 1.72$).

For Research Question 1, we compared the percentage of STEM career choices of the 410 former mentees with the percentages of STEM career choices of females in their German age cohort in the year 2014. More precisely, we compared our percentages from the follow-up against the rates of first-year university students reported by the German Federal Statistical Office.[c,45] We chose 2014 as the year of comparison for the following reasons: The average age of participants in the follow-up sample when applying for the program years earlier (in 2009, 2010, or 2011) was 14.58 years. In Germany, most students in university-track secondary education as in our sample go to school for 12 years, starting school at about the age of 6 years. Accordingly, our former mentees should have decided what to study when they were between 18 and 19 years old, an age most of our sample should have reached in 2014, making that age an approximate mean starting year for university studies for our sample.

For Research Question 2, we compared the percentage of the 410 former mentees who had later made a STEM career choice with the percentage of STEM career choices in the group of the 71 women who had applied for the program during secondary school but never participated. As the two groups were not comparable concerning age and STEM interest when entering the program, propensity score matching was used to make the groups as comparable as possible (described in detail in the section on data analysis), which resulted in a matched sample of 265 former mentees who were then compared to the 71 women who had not participated in the program but had originally applied for participation.

For Research Question 3, we analyzed within the sample of the 410 former mentees the explanatory contribution for STEM career choices made by (1) students' elective intentions in STEM and certainty about career plans as expressed at the beginning of the program (i.e., their baseline conditions), (2) successful program participation (operationalized by increases in elective intentions in STEM and certainty about career plans during their first mentoring year), and (3) multiyear participation in the program.

All participants of the follow-up study filled out an online questionnaire reporting their university major or, if they already had completed their university studies, their profession as well as several other questions not used for the analyses in this article (e.g., an evaluation of the program). Years earlier, all participants had already filled out a short questionnaire for their application for CyberMentor (i.e., prior to participating in the program during secondary education or prior to being shunted into a waitlist control group), which included questions about their STEM interests at the time. Most of the participants had additionally filled out an online questionnaire at three time points over the course of 1 year, either during their time in a waitlist control group or while they were mentees in the CyberMentor program. The time points were based on the mentoring year of the participating mentees, but also used for those in the respective waitlist control group. The first time point was before the beginning of the mentoring year, the second time point was after the first half of the mentoring year, and the third time point was at the end of the mentoring year. Of these 481 participants, 432 (89.8%) had filled out the questionnaire at Time Point 1; 327 (68.0%) had done so at Time Point 2; and 283 (58.8%) had done so at Time Point 3. These online questionnaires were implemented during the 2009–2010 (cohort 1), 2010–2011 (cohort 2), or 2011–2012 (cohort 3) mentoring years.

Measures

All measures were administered via questionnaires, except the length of program participation. As described in more detail in the previous section, all participants completed a short application questionnaire for CyberMentor between 2009 and 2012. Additionally, they completed three questionnaires during the respective mentoring years or, for the waitlist control groups, during the respective 1-year waiting periods. The follow-up questionnaire was administered in 2017.

Application questionnaire

STEM interests

Participants indicated with "yes" or "no" whether they were interested in each of the following six areas: mathematics, computer science, biology, chemistry, physics, and technology. It was possible to select "yes" or "no" more than once.

[b] Although our response rate is appropriate for our sample size,[53] selection bias could still be a problem. Therefore, we analyzed differences between respondents and nonrespondents for age, elective intentions in STEM, and certainty about career plans at the beginning of the mentoring period. While there were significant differences, the differences were small. Cohen's *d*s were 0.13 for both age (respondents were slightly older) and certainty about career plans (lower values for respondents) and 0.27 for elective intentions in STEM (higher values for respondents), which indicates low selection bias.

[c] While some of our former mentees reported only their recent job in the follow-up, it is often possible to deduce what they studied at university. When analyzing a reduced sample of former mentees who were still studying, the differences compared to the age cohort were even slightly larger.

Questionnaires during the mentoring year

Elective intentions in STEM

We assessed participants' elective intentions in STEM with a five-item scale by Ref. 14. Respondents indicated on a 6-point Likert-type scale ranging from 1 (*completely disagree*) to 6 (*completely agree*) on how well they could picture themselves making choices about STEM activities. A sample item reads, "I can picture myself studying a STEM subject at university." Cronbach's alpha was 0.82, 0.84, and 0.88 for the three time points.

Certainty about career plans

We assessed participants' certainty about career plans with a 10-item scale by Ref. 14. Respondents indicated how certain they were about their future career plans on a 6-point Likert-type scale ranging from 1 (*completely disagree*) to 6 (*completely agree*). A sample item reads, "I know quite well for which careers I am best suited." Cronbach's alpha was 0.91, 0.92, and 0.93 for the three time points.

Program data

Length of program participation

We counted the number of years the mentees participated in the program.

Follow-up questionnaire

STEM career choice

Depending on which applied to them, participants either indicated which major they were currently studying at university, or they indicated their current profession via an open-response item. Using the classification of the National Pact for Women in STEM Professions,[39] we coded whether their major or profession was in a STEM field (1) or not (0).

STEMM career choice

We additionally coded a broader STEM variable, called STEMM. It refers to science, technology, engineering, mathematics, and also medical sciences.

Computer science and engineering career choice

As the participation of women in STEM and STEMM in Germany is not generally low in all domains but is especially low in computer science and engineering, we also coded choices in these fields separately.

Data analysis

For answering Research Question 1, simple descriptive statistics were used. For properly assessing the treatment effect for Research Question 2, we first had to check the balance of our two groups concerning relevant pretreatment covariates. We considered age, the CyberMentor cohort (cohort 1, 2, or 3), and the pretreatment STEM interests from the application questionnaire described in the methods section (i.e., in mathematics, computer science, biology, chemistry, physics, and technology) as relevant variables. Information about these variables was available for all participants as the corresponding questions were part of the program application.

There was a significant age difference as well as marginally significant differences concerning interest in chemistry and interest in technology. However, even nonsignificant differences should be reduced as much as possible.[40] Therefore, we used propensity score matching based on all noted pretreatment variables using the program PS Matching 3.0.4 to achieve balance concerning these variables.[41] More specifically, we used nearest-neighbor matching without replacement and a ratio of 1:4. The 1:4 ratio means that we found four matches for each person in our control group, drawing from the larger treatment group. There are many possible procedures for matching, but as the goal of each matching procedure is to achieve balance, a procedure that achieves balance can be deemed suitable.[40]

Our analyses for Research Question 3 are based on the latent growth-curve approach. In the latent growth-curve approach—which is situated in the framework of structural equation modeling[42]—a growth process of a variable repeatedly assessed at consecutive time points is modeled by two latent variables, the intercept factor and the slope factor. The intercept factor represents the initial level of the variable of interest, while the slope factor represents the change of this variable over the assessed time points. Variances of these factors represent individual differences in initial level and in the amount of change, respectively. In extended growth models, the two factors can be regressed on other variables, or several growth processes can be modeled simultaneously (i.e., as parallel-process latent growth-curve models) to investigate relationships with the individual growth trajectories.

The dependent variable in Research Question 3 was the variable STEMM career choice. Elective intentions and certainty about career plans were both modeled as growth curves with intercepts and slopes, respectively. In step 1 of the analysis, only the intercepts predicted STEMM career choice. In step 2, both the intercepts and slopes predicted STEMM career choice. Finally, in step 3, we tested whether the length of program participation explained additional variance beyond the intercepts and slopes of elective intentions and certainty about career plans.

Estimation of the models

The analyses were conducted with M*plus* 8.[43] A robust weighted least-squares estimator (WLSMV of M*plus*) was used for the models in

TABLE 1 Career choices by STEM/M area in 2014 for former CyberMentor mentees ($N = 410$) and their age cohort ($N = 252{,}737$).

	German age cohort	Former CyberMentor mentees
STEM career choice	23.9%	51.2%
STEMM career choice	31.1%	61.7%
Computer science and engineering career choice	10.6%	24.9%

Abbreviations: STEM, science, technology, engineering, and mathematics; STEMM, science, technology, engineering, mathematics, and medical sciences.
Source: Ref. 45 and data collected for this study.

Research Question 3, as our main dependent variable, STEMM career choice, was dichotomous, resulting in probit regressions for its prediction. Model fit was assessed following the criteria of Ref. 44. Therefore, a value close to 0.95 for the Comparative Fit Index, a value close to 0.06 for the root mean squared error of approximation, and a value close to 0.08 for the standardized root mean squared residual were the cutoff criteria for assuming good model fit. Missing values were handled using the default four-step procedure in M*plus* for the robust weighted least squares estimator we applied.

RESULTS

Research Question 1

As can be seen in Table 1, compared to their German age cohort who made a career choice in 2014,[45] the sample of former mentees (who also made their choice on average in 2014) showed clearly higher percentages of choices in the areas of STEM and STEMM as well as in computer science and engineering, which has the lowest female participation rate in Germany.

Research Question 2

As can be seen in Table 2, in the treatment and the control groups, similar means and standard deviations concerning age and STEM interests were achieved using the nearest-neighbor propensity score matching procedure described in the prior section on data analyses. The matching procedure also resulted in a similar composition of the different cohorts in the control group (cohort 1: 29.6%, cohort 2: 26.8%, cohort 3: 43.7%) and the matched treatment group (cohort 1: 29.8%, cohort 2: 29.4%, cohort 3: 40.8%). The matched treatment sample was used for our comparisons regarding the effect of treatment. Descriptive statistics of all pretreatment covariates as well as a career choice are presented in Table 2 for the control group, the matched treatment group, and the full treatment group separately.

The matched treatment group showed significantly higher percentages than the control group for STEMM career choice (58.1%, 95% CI [52.4%, 64.4%] vs. 43.7%, 95% CI [31.5%, 55.2%], $p = 0.030$) and for

TABLE 2 Descriptive statistics for pretreatment covariates and for the career choices for the control group ($N = 71$), the matched treatment group ($N = 265$), and the full treatment group ($N = 410$).

	Control group	Matched treatment group	Full treatment group
Mean age	13.87 ($SD = 1.72$)	13.95 ($SD = 1.70$)	14.58 ($SD = 2.02$)
Mathematics interest	56.3%	58.9%	60.7%
Informatics interest	40.8%	41.9%	44.9%
Biology interest	60.6%	59.2%	54.6%
Chemistry interest	40.8%	44.5%	51.7%
Physics interest	39.4%	41.5%	44.1%
Engineering interest	19.7%	21.9%	31.2%
STEM career choice	26.8%	46.8%	51.2%
STEMM career choice	43.7%	58.1%	61.7%
Computer science and engineering career choice	18.3%	21.1%	24.9%

Abbreviations: STEM, science, technology, engineering, and mathematics; STEMM, science, technology, engineering, mathematics, and medical sciences.

TABLE 3 Model fit for all growth models.

Model	χ^2	*df*	*p*	CFI	RMSEA	SRMR
1	8.68	12	0.730	1.00	0.00	0.02
2	8.68	12	0.730	1.00	0.00	0.02
3	16.60	17	0.482	1.00	0.00	0.02

Note. Model 1 and Model 2 have the same fit as two correlations were simply changed to regressions.
Abbreviations: CFI, Comparative Fit Index; RMSEA, root mean squared error of approximation; SRMR, standardized root mean squared residual.

STEM career choice (46.8%, 95% CI [41.3%, 53.3%] vs. 26.8%, 95% CI [16.7%, 37.7%], $p = 0.001$). For computer science and engineering career choice, the matched treatment group showed no significantly higher percentages than the control group (21.1%, 95% CI [16.4%, 26.4%] vs. 18.3%, 95% CI [9.5%, 27.8%], $p = 0.602$).

Research Question 3

Next, we tested within our sample of former mentees which variables predict later STEMM career choices. The structural equation models showed very good model fit according to every index we examined (see Table 3).

In step 1 (Model 1), we examined how well the baseline values (i.e., the intercepts, which are the values at the beginning of the first mentoring year) in elective intentions in STEM and certainty about career plans predicted the future STEMM career choice (controlling for age).

TABLE 4 Results of the probit regressions predicting STEMM career choice ($N = 410$).

Predictors	beta	*SE*	95% CI [LL, UL]	*p* value	R^2
			Step 1		
Age	0.07	0.07	[−0.05, 0.20]	0.255	
Elective intentions in STEM (intercept)	0.39	0.06	[0.27, 0.51]	<0.001	
Certainty about career plans (intercept)	−0.13	0.07	[−0.26, −0.00]	0.043	16.4%
			Step 2		
Age	0.09	0.07	[−0.05, 0.22]	0.203	
Elective intentions in STEM (intercept)	0.33	0.07	[0.20, 0.46]	<0.001	
Certainty about career plans (intercept)	0.04	0.08	[−0.12, 0.19]	0.649	
Elective intentions in STEM (slope)	0.25	0.09	[0.08, 0.43]	0.005	
Certainty about career plans (slope)	0.32	0.09	[0.14, 0.50]	0.001	31.0%
			Step 3		
Age	0.11	0.07	[−0.03, 0.25]	0.110	
Elective intentions in STEM (intercept)	0.31	0.06	[0.19, 0.43]	<0.001	
Certainty about career plans (intercept)	0.05	0.08	[−0.10, 0.21]	0.488	
Elective intentions in STEM (slope)	0.23	0.09	[0.04, 0.41]	0.015	
Certainty about career plans (slope)	0.33	0.09	[0.15, 0.51]	<0.001	
Length of program participation	0.14	0.07	[0.00, 0.27]	0.049	32.6%

Note. Beta indicates the standardized probit regression weights. LL and UL indicate the lower and upper limits of the 95% confidence interval, respectively.

The predictors explained 16.4% of the variance in the outcome, and the baseline value of elective intentions in STEM was clearly the best predictor (see Table 4, step 1).

In step 2 (Model 2), we examined how much the prediction improved when adding the changes (slopes) in elective intentions in STEM and certainty about career plans during the first mentoring year as further predictors. The explained variance almost doubled to 31.0%, and both slope variables significantly contributed to this increase (see Table 4, step 2).

In the next step, we went beyond predictors from the first mentoring year and added the overall length of program participation (the overall number of years the mentees participated in the program) as another predictor. While the overall length of program participation was a significant predictor, it only improved the explained amount of variance to 32.6% (Model 3, see Table 4, step 3).

DISCUSSION

Talent development in STEM is essential for realizing solutions to the epochal challenges faced by our world and fulfilling positive dreams for our shared future. However, many countries around the world are already failing at Stage 1 of talent development, namely, getting enough individuals interested in these subjects. This is demonstrated, among other things, by a shortage of specialists in STEM. It is particularly difficult to attract females to talent development in STEM fields. Although choices about university majors and careers are now approaching gender parity in some fields, such as medicine, females remain underrepresented in these fields at higher levels of talent development and in senior leadership positions.[46,47] In other fields, such as computer science and engineering, things are even worse. Women's overall participation rates—at all stages of talent development and all levels of seniority—are significantly lower than men's.[5–7]

This situation has led to extensive attempts in recent decades to inspire females to pursue STEM and to increase females' participation in STEM majors and careers. Because girls' interest in STEM declines markedly during adolescence[8] and initial decisions about STEM are made during secondary education,[9,10] interventions should begin when girls enter secondary education at the latest. Many of these interventions lead to positive changes in relevant outcomes during secondary education. Evaluation studies have shown that mentoring during secondary education can help girls to improve the STEM affinity of their interests, elective intentions, or certainty about career plans, for example (for an overview, see Ref. 13).[14,15,48–50] However, studies are lacking that examine whether positive changes in these outcomes achieved while girls are still enrolled in secondary education have an impact on real-life choices of STEM majors and careers made later on.[12,13]

With our study, we endeavored to make a contribution to addressing this research gap. Specifically, we investigated the real-life choices of STEM majors and careers made by women who had—years before while enrolled in secondary education—participated in the Germany-wide online mentoring program CyberMentor. We chose this program because online mentoring is a particularly promising intervention for engaging girls in STEM.[14–16] Furthermore, the short-term effectiveness of CyberMentor has been demonstrated in numerous evaluation studies that meet quality standards.[33] Girls who participated in the program had more positive developmental trajectories in terms of elective intentions in STEM and certainty about career plans than did girls in waitlist control groups who were comparably interested in STEM.[15] Thus, the program was particularly well suited to investigating the significance of successful STEM promotion provided to girls during secondary education for their later real-life STEM choices.

In a first step, we investigated whether years after program participation of former CyberMentor participants were more likely to choose STEM majors and professions than females of the same age cohort. The results of these analyses were encouraging. Former female CyberMentor participants were more than twice as likely to choose STEM majors (51.2% vs. 23.9%). When medical science—a STEM field in which women are actually overrepresented in many countries—was included in the analysis, former mentees were still almost twice as likely to choose STEM majors as females in their age cohort (61.7% vs. 31.1%). Interestingly, however, this means the ratio between the groups became somewhat smaller when medical science was included. The real-life choices for computer science and engineering, that is, the two STEM fields that are by far the least likely to be chosen by females in Germany,[45] confirm this tendency of higher ratios in fields with fewer women. While only 10.6% of females in the age cohort chose these fields, more than twice as many of CyberMentor's former mentees did, namely, 24.9%. Thus, these findings suggest that there was an even stronger increase in percentages in STEM fields in which there are few females. One reason for this could be that a disproportionately high number of mentors in the CyberMentor program came from these fields.[51] As CyberMentor not only offers one-on-one mentoring, but also facilitates networking with numerous other mentors and mentees on the platform, it is conceivable that the particularly large number of role models from the computer science and engineering fields were partly responsible for the frequent choices of these STEM fields that former participants went on to make after high school.

Comparing the real-life STEM choices of former mentees with those of females in the age cohort is an important step in examining the long-term effectiveness of CyberMentor. However, because girls who enroll in programs such as CyberMentor already differ positively from girls of the same age at program enrollment with respect to several characteristics—such as their STEM interests and elective intentions in STEM[15],[38]—a comparison with the age cohort is not a very stringent criterion for success. In other words, our analyses provide evidence that CyberMentor influenced later real-life STEM choices, but they do not allow us to draw firm conclusions about whether comparably interested girls were not similarly likely as former CyberMentor mentees to go on to make later real-life pro-STEM choices about university majors and about professions (see also Ref. 49). For this reason, in a second step, we compared the real-life choices of former participants of CyberMentor with those of females who had also signed up for the program in the same year but later did not participate. Thus, the comparison is with a group of females who were similarly interested in STEM and of the same age cohort. Applying this even more stringent criterion also revealed clear effects. Former CyberMentor participants were significantly more likely to select STEM fields (46.8% vs. 26.8%). When Medical Sciences was included, differences in favor of former mentees were still evident, but smaller (58.1% vs. 43.1%). These results suggest that the disproportionately large percentage of real-life STEM choices made by former mentees are not due to the fact that they are a particularly interested group of girls who would have chosen a STEM major or career anyway—even without having participated in CyberMentor—but that CyberMentor at least made a significant contribution to these choices.

To further support this assumption empirically, in a third step, we examined the explanatory contribution to the real-life STEM choices of former mentees of (1) their baseline conditions prior to program participation, specifically their elective intentions in STEM and certainty about career plans, (2) successful 1-year participation in the program (operationalized by increases in elective intentions in STEM and certainty about career plans during program participation), and (3) multiyear participation in the program. Again, the results were favorable. Successful participation in the program for 1 year had a comparable explanatory contribution to later real-life STEM choices as did mentees' baseline conditions. In contrast, several years of participation in CyberMentor played a minor role. Specifically, elective intentions in STEM and certainty about career plans reported by mentees before entering the program explained 16.4% of the variance in later real-life choices of STEM majors or professions. Successful participation in CyberMentor for 1 year explained another 14.6% of the variance, while multiyear participation made a small explanatory contribution of 1.6%. The finding on multiyear participation in CyberMentor should be interpreted with caution, however, as it did not measure successful participation (i.e., changes in elective intentions in STEM and certainty about career plans due to multiyear participation), but only how many years females had participated in the program.

Our study shows that online mentoring can make an important contribution to Stage 1 talent development according to Bloom[1,2]—especially when it comes to inspiring females to enter a STEM field and motivate them to stay in the STEM talent development pipeline. To our knowledge, this is the first study to systematically examine whether successful participation in a mentoring program offered to girls enrolled in secondary education can positively influence real-life STEM choices made years after participation. While studies have examined the impact of (online) mentoring on real-life choices of STEM majors and careers,[32] they were either retrospective surveys that did not address formal (online) mentoring programs or were studies with adults.[36,37] Studies with students in secondary education have so far primarily examined the short-term effectiveness of formal (online) mentoring programs (e.g., influences on STEM interests and elective intentions in STEM).[13] Moreover, many of these studies evince methodological shortcomings (e.g., inappropriate or wholly lacking control groups, reliance on postprogram satisfaction surveys), making even conclusions about the short-term effectiveness of the programs difficult in some cases.[13] Our evaluation study, which included appropriately designed randomized waitlist control groups and followed up with former participants years later, provides preliminary evidence that a formal online mentoring program that had been demonstrated to be effective in the short term did indeed also contribute to females' later real-life STEM choices and, therefore, also possesses long-term effectiveness. However, our study also has its own limitations. These should be considered when interpreting our findings and can inform future research.

Limitations and future research directions

A first limitation is the generalizability of our results. CyberMentor is a Germany-wide online mentoring program that has been continuously optimized and adapted to the needs of participants via an extensive program of accompanying research.[52] How well the short-term and long-term effects can be generalized to other (online) mentoring programs, cultures, and age groups would have to be examined in future research. When doing so, it would be important to specify as precisely as possible which similarities and differences these programs and samples have in comparison to CyberMentor. Only in this way can it be clarified, in the event of divergent results, which aspects may have an influence on later real-life choices in STEM.

A second limitation is a certain degree of selection bias in our follow-up sample. Although our response rate is appropriate for our sample size,[53] selection bias could still be a problem. Therefore, we analyzed differences between respondents and nonrespondents for age, elective intentions in STEM, and certainty about career plans at the beginning of the mentoring period. While there were significant differences, the differences were small. Cohen's *d*s were 0.13 for both age (respondents were slightly older) and certainty about career plans (lower values of respondents) and 0.27 for elective intentions in STEM (higher values of respondents), which indicates low selection bias.

A third limitation is the choice of the comparison group to answer Research Question 2. Although females in the comparison group had originally registered for CyberMentor, it is not clear why they ultimately did not participate in the program. Comparisons of the initial STEM interests of the two groups showed differences although participants were randomly selected. While these were accounted for in the analyses using propensity score matching, it still cannot be assumed with certainty that the groups are truly comparable. However, because program-goal-relevant, long-term, real-life choices do not occur until years after participation in STEM-promotion programs, such as CyberMentor targeting girls in secondary education, it is difficult to create more appropriate comparison groups. For example, waitlist control groups cannot be implemented over such long periods of time, and longitudinal examination of the developmental trajectories of statistical twins is also difficult to implement in practical terms. One possibility might be to select as a comparison group of girls enrolled in secondary education who enroll in and attend other long-term STEM programs. While this would not allow for an absolute test of effectiveness, it could provide insight into how effective online mentoring (or CyberMentor) is compared to other long-term extracurricular STEM programs. Finally, it would be interesting to examine different combinations of in-school and out-of-school STEM opportunities and their impact on later real-life STEM choices.

A fourth limitation is that we operationalized multiyear participation in CyberMentor only by the number of years. Future research should examine the impact of multiple years of successful participation in the program and whether it makes a greater contribution to explaining former participants' later real-life STEM choices. However, this would require surveys (e.g., of elective intentions and certainty about career plans) at multiple time points. In addition, it would be desirable to include in future studies the quality of mentoring for each year of program participation. For example, it could be examined how the relationship quality between mentee and mentor, the extent of STEM communication, or the networking of mentees on the platform affect short-term and long-term effectiveness.

CONCLUSION

Mentoring can be one of the most promising methods of talent development,[1,2] as it enables highly individualized support for learners, tailored to their developmental stage, their levels of knowledge and competence, and their individual needs. Online mentoring in particular is suited to sustainably inspiring females to engage with STEM subjects and topics and thus makes an important contribution at Stage 1 of talent development. However, numerous studies indicate that despite the extraordinary potential of mentoring, most formal mentoring programs achieve only low or moderate effects, and in some cases, even negative effects,[22,29] a phenomenon Ref. 54 recently named the *mentoring paradox*. One reason for the mentoring paradox is that, in practice, important quality standards of mentoring programs often go unaddressed or are insufficiently attended to.[11,55,56]

In the case of mentoring programs in secondary education aiming to increase the labor-force participation rates of females and other underrepresented groups for the long term, a crucial weakness has been a lack of evaluation studies that considered the long-term effects of such programs to understand whether and, if so, to which extent such programs are effective for achieving such long-term goals. This is crucial, as much of the work on addressing gender disparities and other equity gaps in STEM education and talent development is built on a consensus about the importance of working through educational measures to make STEM talent development and the entire STEM workforce more representative of diverse societies. With our study, we provided a first-ever control-group-based evaluation of the ability of one such early-intervention mentoring program to effect long-term changes in the major STEM-relevant career choices that former participants go on to make after high school.

AUTHOR CONTRIBUTIONS

H.S., T.D., and A.Z. designed the study. H.S. and A.Z. conceptualized the questionnaires. M.H. and S.S. collected and prepared the data for analysis. T.D. carried out the data analysis. H.S. wrote the manuscript. It was reviewed and edited by all authors. All authors read and approved the final manuscript.

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COMPETING INTERESTS

The authors declare that they have no competing interests.

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