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Investigating Students' Academic Self-Concepts and Persistence in STEM: How Do Gender Differences Relate to Female Representation?

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ABSTRACT

The research literature often treats STEM subjects as a homogeneous group despite considerable differences in gender composition. This article examines gender differences in students' academic self-concepts across STEM fields with different shares of female students, and how students' academic self-concepts affect their graduation likelihood. This paper argues that gender disparities in STEM students' academic self-concepts favour male students and systematically relate to gender composition in the respective subject. Using student-cohort data from the German National Educational Panel Study (NEPS), I performed regression analyses to predict students' academic self-concepts and their likelihood of graduating. The study revealed that female students exhibit weaker academic self-concepts only in fields with either low (< 30%) or high (> 50%) female representation, with the latter presenting the larger gender gap. Moreover, students' academic self-concepts relate to their graduation likelihood in STEM fields with low female presentation. The research underscores the necessity of distinguishing between STEM fields when examining gender disparities in academic self-concepts, challenging the prevalent view of treating STEM as a uniform group.

KEYWORDS

Gender; academic self-concept; higher education; STEM; persistence; gender composition

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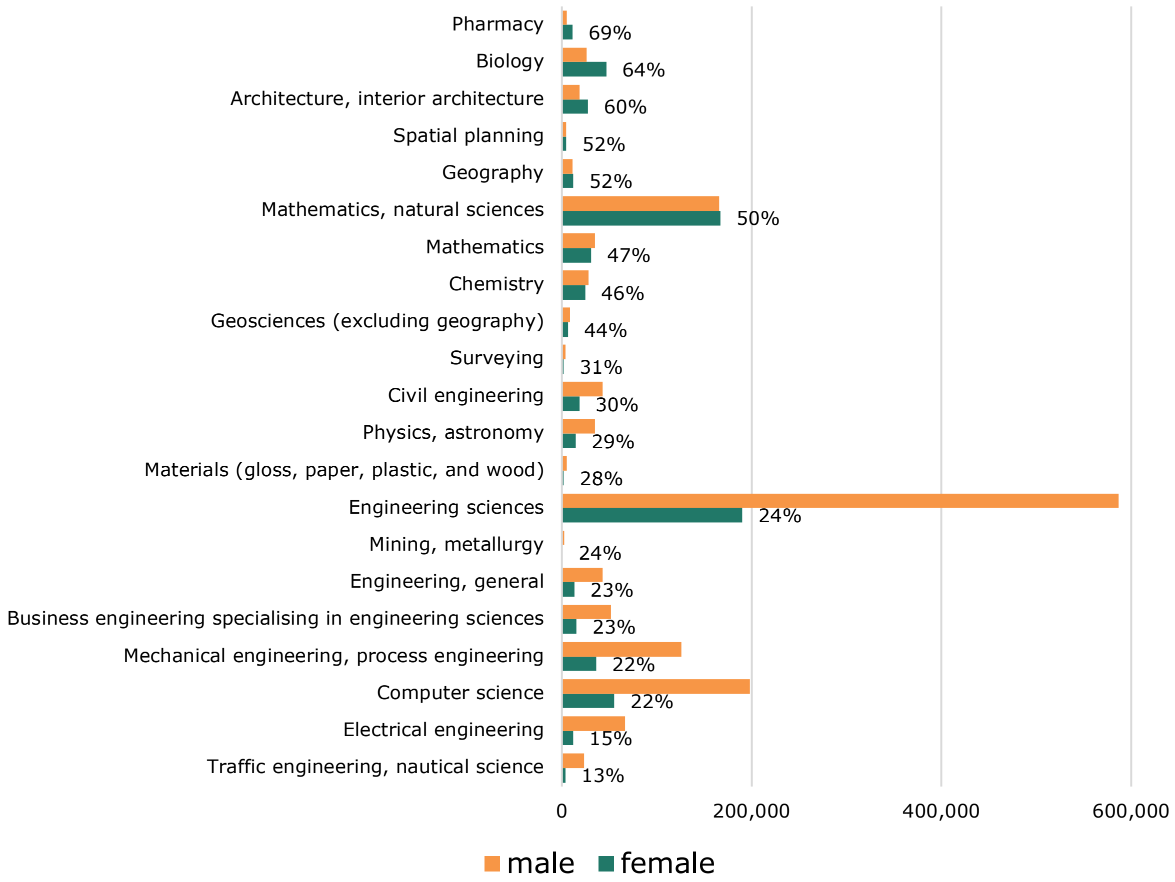
INTRODUCTION

There is an urgent need for specialists in the fields of science, technology, engineering, and mathematics (STEM). Yet, the number of higher education graduates in these fields is comparatively low (OECD, 2022). Consequently, improving the recruitment, retention, and training of STEM professionals remains a political priority and an area of concern. Of particular interest is the persistent underrepresentation of women in STEM at different stages of education. The fewer number of women enrolling in and completing STEM degrees (e.g., Buchmann, 2009; Isphording & Qendrai, 2019; Key & Sass, 2019), resulting in their continued minority status in STEM occupations (e.g., Lažetić, 2020), highlights this issue. International comparative data underscores this gender gap. Less than 40% of STEM graduates are female, with Germany showing a concerning 30% average (World Bank, 2018).

Research examining women's participation in STEM education has provided a variety of explanations for the ongoing gender segregation. Related studies highlight factors shaping educational and career choices, including the influence of gender-stereotypical perceptions, individual aptitude promotion, and the culture of STEM fields (e.g., Nosek et al., 2002; Thébaud & Charles, 2018). The (actual or perceived) culture of STEM fields and deeply held beliefs about the "natural" dispositions of men and women correspondingly influence aspirations to work in STEM fields (Thébaud & Charles, 2018). Moreover, women perceive their abilities as poorer and often underestimate themselves in STEM, even if they perform just as well as men (e.g., Nagy et al., 2010). This more critical self-assessment of their abilities is a key factor in women's underrepresentation in STEM at different stages of education (OECD, 2015). Yet, even those women who pursue STEM studies in the face of these barriers often show weaker academic self-concepts, meaning they often perceive their academic abilities on a lower level than men do (e.g., Ackerman et al., 2013; Moschner & Dickhäuser, 2018; Sikora & Pokropek, 2012; Turnbull et al., 2020; van Soom & Donche, 2014).

But does this hold true across all STEM fields? Studies seldom consider exactly which subjects "STEM" includes and often neglect diversity within this category. For example, although women are underrepresented in STEM overall, they were the majority among pharmacy, architecture, and biology first-year students in 2021–2022 in Germany (German Federal Statistical Office, 2022). However, those fields register only a small proportion of all students (see Figure 1). Keeping this variation in mind, analysing gender differences using STEM as an aggregate category may oversimplify the perception (Cheryan et al., 2017). Therefore, the present study assumes that STEM fields differ in their gender composition and aims to uncover variations across fields whose proportions of female students differ. The primary objective is to examine gender differences in academic self-concepts and their relation to graduation rates within STEM in light of different gender distributions. By recognising the heterogeneity within the STEM category, this study sheds light on variations across fields and their implications for gender disparities in STEM education and workforce participation.

Figure 1
Enrolment rates in STEM higher education in winter term 2021–2022



Note. Female share in %. Source: German Federal Statistical Office (2022); own illustration.

The persisting gender gap in STEM

Numerous publications highlight women's underrepresentation in STEM in higher education (e.g., Buchmann, 2009; Eccles & Wang, 2015; Shapiro & Sax, 2011). A meta-analysis by Cheryan et al. (2017) indicates that such factors as (negative) stereotypes, perceived bias, insufficient early experiences, peer support, math ability, and gender gaps in self-efficacy contribute to this underrepresentation. Additionally, structural barriers, such as formal discrimination, absence of role models, and institutional forces also pose challenges (Cheryan et al., 2017; Kanny et al., 2014). Although these factors affect female representation, they do not necessarily contribute to gender disparities *within* the STEM domain. Research shows that female STEM students have weaker academic self-concepts than male STEM students – hence, they perceive their own STEM abilities as worse than male students perceive theirs (e.g., Ackerman et al., 2013; Moschner & Dickhäuser, 2018; Sikora & Pokropek, 2012; Turnbull et al., 2020; van Soom & Donche, 2014). Most gender disparity research in STEM focuses on specific subjects or encompasses all related fields. Fewer studies compare STEM fields to one another or consider variation within one STEM domain (e.g., Cohoon, 2002; Deemer et al., 2014; Leslie et al., 2015; Su & Rounds, 2015). Fields that men particularly dominate, such as engineering, physics, and computer science receive increased attention (e.g., Cheryan et al., 2015; Förtsch & Schmid, 2018; Luttenberger et al., 2019). Certain studies indicate that female students in these male-dominated courses are more confident of their academic abilities than in other STEM fields (Förtsch & Schmid, 2018; Luttenberger et al., 2019). However, reliable case numbers and comparisons of male *and* female students across *all* STEM subjects are lacking.

Women's underrepresentation in STEM is attributable not only to recruitment barriers, but also to challenges in maintaining their persistence in these fields. STEM fields register higher numbers of student dropouts than other fields, with women being at particular risk (e.g., Isphording & Qendrai, 2019; Key & Sass, 2019). Research on STEM student dropout in Germany leans on Tinto's (1975, 1987) student integration model, suggesting academic and social integration are key to graduation (e.g., Klein, 2019; Meyer & Strauß, 2019; Müller & Klein, 2022). Yet, individual psychological resources also influence the likelihood of dropping out in certain fields. Compared to non-STEM students, the tendency among STEM students to drop out is more strongly associated with academic self-concept (e.g., Fellenberg & Hannover, 2006). A study by Meyer and Strauß (2019) on student dropout in gender-atypical fields found that in male-dominated subjects, women's higher dropout risk seems to come from a more negative self-perception. Severiens and ten Dam (2012) compared students in male- and female-dominated majors, without focusing on STEM, and observed that male students' lower-level perception of their own skills does not contribute to their leaving fields with a high proportion of women. However, they also found that their perceived ability affects female students in all subjects less, and other noncognitive traits, such as diligence, ambition, and motivation affect them more (e.g., Severiens & ten Dam, 2012).

Though not aiming to fully explain student persistence, the present study contributes to the existing literature by investigating the role of male and female STEM students' academic self-concepts and considering variance across STEM fields.

Theoretical framework

The academic self-concept represents individuals' subjective perceptions of their own abilities in academic contexts (Shavelson et al., 1976). It can be further differentiated into subareas that relate to specific domains, i.e., mathematics, English, or science (Shavelson et al., 1976). Research suggests that domain-specific self-concepts may then be further separated into different components such as competence and affect (Arens et al., 2011). According to the internal/external frame-of-reference model (Marsh, 1986), academic achievements in one domain strongly influence the domain-specific academic self-concept. To assess their own academic abilities, individuals process information they receive from significant others through social comparisons (external frame) as well as dimensional and temporal comparisons (internal frame) (Marsh, 1986; Wolff et al., 2018). Various empirical studies have found evidence that the academic self-concept influences one's learning behaviour and individual skill development (e.g., Dulay, 2017; Guay et al., 2003) impacting education-related decision-making processes (e.g., Dickhäuser et al., 2005; Henderson et al., 2017). Accordingly, individuals' academic self-concepts play a formative role in their educational and employment trajectories. In higher education research, the academic self-concept is a suitable predictor for successful completion of studies, retention in the chosen subject, higher motivation, and better academic performance (e.g., Fellenberg & Hannover, 2006; van Soom & Donche, 2014).

Empirical evidence suggests a reciprocal relationship between individuals' academic performance and their academic self-concepts (e.g., Guay et al., 2003; Marsh, 1986). However, observed disparities between girls' and boys' academic self-concepts often align with prevalent gender stereotypes rather than actual performance differences (e.g., Eccles et al., 1989; Eccles et al. 1993; Möller & Trautwein, 2015; Schilling et al., 2006). Girls typically express a weaker self-concept in mathematics and demonstrate self-criticism in male-associated fields such as science (OECD, 2015; Schilling et al., 2006). Boys often display a weaker verbal academic self-concept (Schilling et al., 2006; Skaalvik & Skaalvik, 2004). Societal experiences, particularly among school-aged students, largely shape these tendencies. Gender-related stereotypes that teachers and parents frequently hold regarding innate abilities in various fields are often internalised and play a key role in shaping the socialisation of both girls and boys (e.g., Marsh, 1986; Schilling et al., 2006; Tiedemann, 2000; Wolter et al., 2011; Wolter & Hannover, 2016). This internalisation corrupts individuals' perceptions of themselves and their abilities, irrespective of their actual abilities. In addition, students who perceive their abilities in STEM subjects to be inadequate may be discouraged from pursuing further studies in these areas, regardless of their actual potential (e.g., Ellis et al., 2016).

Kanter's (1977) tokenism theory provides a crucial framework for understanding the dynamics of gender representation in STEM fields. This theory distinguishes between "tokens", members of underrepresented groups, and "dominants", the majority group members. In gender-skewed environments such as male-dominated STEM fields, women face specific challenges due to their minority status. These challenges include (1) increased visibility due to limited numbers, (2) being defined in contrast to the dominant group, and (3) being subject to stereotyping. Consequently, despite their visibility due to their distinctiveness from the dominant male group, women are often not recognised for their individual traits. Instead, they are predominantly identified by stereotypical characteristics (Kanter, 1977). These stereotypes, which often depict women as less competent than men in STEM fields, can adversely affect women's academic self-concepts (e.g., Ertl et al., 2017; Marsh, 1986; Schilling et al., 2006; Wolter & Hannover, 2016). Kanter further proposes that in more gender-balanced environments, the minority group can create alliances and influence cultural norms, potentially reducing these dynamics (Main, 2018). Therefore, the challenges of being a female student in STEM might be less prevalent in those fields with higher proportions of female students.

Moreover, the cues hypothesis posits that situational cues such as features of an academic setting or underrepresentation can trigger a social identity threat in potentially targeted individuals (Murphy et al., 2007). A social identity threat is a type of psychological stress that individuals experience when they perceive potential negative treatment or devaluation in a setting due to a social identity that they hold (Murphy et al., 2007). This threat often occurs in environments where the individual's identity is underrepresented or negatively stereotyped, creating discomfort and potentially influencing behaviour and performance (Murphy et al., 2007). When female students are strongly underrepresented in a STEM field of study, they may perceive situational cues that reinforce their minority status, thereby inciting a social identity threat. Such an environment could amplify female students' feelings of not belonging or being out of place, increasing the likelihood of self-doubt and undermining their confidence in their academic abilities (Inzlicht & Good, 2006). This can lead to decreased engagement, lower academic performance, and potentially a decision to leave the field altogether.

The present study

Two main research questions guide this study: (1) To what extent do gender differences in academic self-concepts vary across STEM fields with different proportions of women? (2) How do academic self-concepts of male and female STEM students relate to their degree completion, and how do STEM fields vary in that regard?

Consistent with earlier research, female STEM students are expected to have lower-level academic self-concepts than their male fellows (e.g., Ackerman et al., 2013; Moschner & Dickhäuser, 2018; Sikora & Pokropek, 2012; Turnbull et al., 2020; van Soom & Donche, 2014). However, the tokenism theory (Kanter, 1977) and the cues hypothesis (Murphy et al., 2007) suggest that these differences may be more pronounced in male-dominated STEM fields. Here, female students are more likely to face the described challenges of visibility, contrast, and stereotyping (Kanter, 1977), and to encounter situational cues that underscore their minority status (Murphy et al., 2007). These dynamics should negatively impact their academic self-concepts, as experiences within the social environment influence them. Consequently, in STEM fields with higher female proportions, the gender differences should be less pronounced (Kanter, 1977; Main, 2018; Robnett, 2016). An opposing assumption would be that women in extremely male-dominated STEM fields may be less affected, having already overcome previous obstacles (Ertl et al., 2017; Luttenberger et al., 2019), potentially resulting in less pronounced academic self-concept differences in these fields.

In line with previous findings, having a strong STEM-related academic self-concept should favour degree completion in all STEM fields for both men and women (Ellis et al., 2016). However, this effect is assumed to be less pronounced for female than for male students (e.g., Denissen et al., 2007; Severiens & ten Dam, 2012). This difference is partly attributable to the effects of stereotype threat, which suggests that women in STEM often face and must counteract negative stereotypes about their abilities (Ertl et al., 2017). While dealing with these stereotypes can induce stress and negatively impact female students' persistence, it can also lead to the development of coping mechanisms and resilience (Wilkins-Yel et al., 2019). Consequently, female students might not solely depend on their academic self-concepts as a predictor of success. Instead, other factors might influence them more, such as intrinsic motivation, social integration, or peer support, which can play crucial roles in their academic achievements and persistence in STEM fields (e.g., Luttenberger et al., 2019; Meyer & Strauß, 2019; Robnett, 2016).

METHODS

Participants and procedure

This study uses data from the fifth starting cohort of the German National Educational Panel Study (NEPS Network, 2022). Participants in this starting cohort were first-year students from Germany's public or state-approved higher education institutions in the winter term of 2010–2011. The longitudinal NEPS study asks respondents annually about their educational paths using computer-assisted telephone interviews and additional online surveys every one to two years. Currently, data from 18 panel waves up to 2021 is available.

The analyses of the present study restricted the sample to students aiming at a bachelor's degree or first state examination and enrolled in a STEM field of study (n = 3,600). They excluded student teachers (n = 933) who considerably differ from other STEM students in their study-choice motives and occupational opportunities

(Neugebauer, 2013), which influence their likelihood of graduating (Heublein et al., 2017; Isleib et al., 2019). Furthermore, students in teacher education are more frequently female (Neugebauer, 2013). Hence, they are a pre-selected group in terms of the variables of interest in this study.

The listwise deletion approach was used to manage missing data. This method ensures that the analyses include only cases with complete information on all variables of interest. This reduces the risk of bias or distortion that missing data could cause and provides the most efficient use of available data (Allison, 2009). After excluding the respective cases (n = 318), 2,349 STEM students, 34% of whom were female, were analysed. Sample characteristics appear in Appendix Table A1.

Measures

Respondents provided their demographic information in the first panel wave during winter term 2010–2011. They self-reported their gender, which was categorised into a binary variable, 0 for male and 1 for female students.

Students openly reported their field of study upon enrolment in the first panel wave. The NEPS coded this data based on the Federal Statistical Office's classification (destatis) for the winter term 2010–2011 (German Federal Statistical Office, 2011). I assessed gender distribution by merging the NEPS data with administrative data on the male-female student ratio in various STEM fields. STEM fields were categorized by high (HPF, > 50%, n = 433, 72% women), moderate (MPF, 30%-50%, n = 300, 44% women), or low (LPF, < 30%, n = 1,616, 22% women) proportions of female students. Following Buchmann et al. (2002), I used a 30% threshold to distinguish typically male and more integrated fields. However, due to the skewed gender distribution in STEM, the threshold for high female proportions was set at 50%. Appendix Table A2 provides the included STEM fields, their categories, and the female student share according to official statistics.

The second panel wave, conducted as an online survey in winter 2011, measured academic self-concept. The measurement utilised a shortened instrument that Dickhäuser et al. (2006) developed. This instrument featured four items with a seven-point response scale. Two items captured students' perceptions of their talents and skills ("I think my talent for studying is" and "My study-related skills are" low = 1 to high = 7). The other two items captured students' assessments of their learning behaviours and task management skills ("Learning new things during my studies is" and "Tasks within the scope of my studies fall to me" difficult = 1 to easy = 7). In the present study, I combined these items into one factor representing students' academic self-concepts (α = 0.83).

The binary variable denoting STEM degree completion assigns 0 to study dropouts (n = 425, 31% women) and 1 to graduates (n = 1,606, 34% women). Graduates were students who reported they obtained their degree in STEM. In the analysis sample, 81% of the female students and 78% of the male students graduated. Study dropouts were students who, at the end of their STEM studies, reported having no degree. Based on the winter 2010–2011 cohort, the average bachelor's degree takes 7–8 semesters and the first state examination 11–12 semesters (Autor:innengruppe Bildungsberichterstattung, 2020, Tab. F4-3web). I classified students not graduating within these timelines and then leaving the panel (n = 106) as dropouts. It was not possible to determine for 318 respondents whether they graduated or dropped out because they exited the panel during their initial 8

(12) semesters; hence, I coded these cases as missing. Switchers within STEM subjects who graduated (n = 96) were still considered successful. The present study strictly defined dropout as STEM study termination.

To control for achievement bias, students' final school grades were included in the analyses, reported by respondents retrospectively in the first panel wave. Final school grades influence students' perceptions of their abilities (Ellis et al., 2016) and have been empirically shown to predict academic success (Trapmann et al., 2007). In Germany, grades range from 1 (excellent) to 6 (insufficient). However, I inverted the grades to intuitively interpret the coefficients. Hence, higher values of the inverted variable meant better grades. Additionally, in the models predicting degree completion, I controlled for subject changes, which risk increased dropout rates (Wolter et al., 2014). Subject changes were dummy coded to indicate if students have switched their subject before their academic self-concept measurement. Age, migration background, and parents' educational level served as demographic control variables in all models because they relate to the variables of interest in the present study (e.g., Heublein, 2014; Heublein et al., 2017). Age was included as a continuous variable in years. Migration background was dummy coded with 0 for non-migrants and 1 for migrants of the first, second, or third generation. Parents' educational level was dummy coded to indicate an academic background when at least one parent had obtained an academic degree.

Data analyses

I performed all empirical analyses using the Stata 17 software (StataCorp., 2021). The first part of the analyses used linear regression models to investigate STEM students' academic self-concepts. The models were built stepwise. The first model only included students' gender and demographic covariates (i.e., age, migration background, academic background). The second model additionally considered students' final school grades to control for differences in achievement. To assess variation across STEM fields, the last model also included the share of female students as a categorical variable and its interaction with gender. Non-collinearity and homoscedasticity tests confirmed validity of the models (Chen et al., 2003).

The second part used logistic regression models to analyse STEM students' likelihood of graduating. I estimated separate regression models for male and female students to capture gender-specific effects of academic self-concept. Therefore, the models only included academic self-concept and the covariates (i.e., final school grade, subject change, age, migration background, academic background) in a first step. In a second step, they considered the categorical variable for female student share. To statistically examine variation across STEM fields and between male and female students, a fully engaged model was calculated in which gender was included as a variable. This model introduced a threefold interaction encompassing gender, academic self-concept, and female student share. As robustness checks for predicting STEM degree completion, I calculated multinomial logit models in which uncertain cases were not coded as missing, but as a third outcome, "panel dropout", providing comparable results.

I assessed the academic self-concept structure through confirmatory factor analysis, revealing a two-factor model of academic self-concept to be statistically preferable (RMSEA = 0.030; CFI = 0.999; SRMR = 0.004) to a single-factor model (RMSEA = 0.168; CFI = 0.962; SRMR = 0.036) in the analytical sample (Chen, 2007). The two factors were "talent", signifying students' perceptions of their talents and skills (α = 0.79), and "effort", depicting students' evaluations of their learning behaviours and task-management skills (α = 0.73). Appendices B and C detail the results of robustness analyses based on this model.

RESULTS

Gender differences in STEM students' academic self-concepts

Table 1 presents the results of the linear regression models. Model 1, which only included gender and the demographic covariates, revealed no significant gender difference in STEM students' academic self-concepts. However, when I included students' prior academic achievement, a significant gender effect occurred, with female students reporting lower-level perceptions of their academic abilities than male students (Model 2). As expected, the final school grade was positively related to students' academic self-concepts. Model 3 assessed variation across the STEM fields by including the interaction between gender and the share of female students in the field of study. The gender effect persisted, as did the effect of students' final school grades. Students in HPF-STEM fields showed significantly higher-level perceptions of their academic abilities than did students in LPF-STEM fields. Figure 2 displays the corresponding linear prediction of students' academic self-concepts by gender. Overlapping confidence intervals suggested no significant difference between male and female students in MPF-STEM fields. Although the difference was statistically significant in LPF-STEM fields, it was minimally distinct. The most pronounced gender gap appeared in HPF-STEM fields. The interaction effect of gender and female share revealed that the difference in gender disparities between LPF- and HPF-STEM fields was statistically significant (Table 1, Model 3).

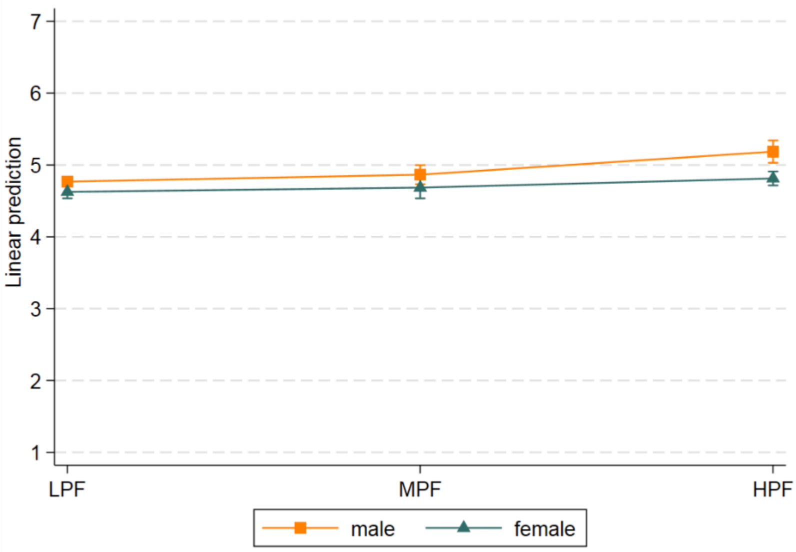
Results of the robustness analyses investigating two factors for students' academic self-concepts suggested that female students perceived their study-related talents as significantly lower than male students in *all* STEM fields (see Appendix Table B1 and Figure B1). The significant interaction between gender and female share was only evident for the factor "effort" (see Appendix Table B2) and indicated significant gender disparities only in HPF-STEM fields (see Appendix Figure B2).

Table 1
Gender differences in STEM students' academic self-concepts

	Model 1		Model 2		Model 3	
	B	*SE*	*B*	*SE*	*B*	*SE*
Gender (ref. male)	-0.062	0.039	-0.104 **	0.039	-0.143 **	0.053
Final school grade			0.312 ***	0.030	0.318 ***	0.030
Female share						
LPF					(ref.)	
MPF					0.097	0.073
HPF					0.418 ***	0.083
Gender*female share						
Female*LPF					(ref.)	
Female*MPF					-0.038	0.114
Female*HPF					-0.231 *	0.107
Age	-0.032 ***	0.007	-0.019 ***	0.007	-0.017 *	0.007
Migration background	-0.155 ***	0.045	-0.113 **	0.044	-0.105 *	0.044
Academic background	0.107 **	0.038	0.069	0.037	0.064	0.037
Constant	5.470 ***	0.152	3.724 ***	0.223	3.616 ***	0.223
Adjusted R^2	0.019 ***		0.062 ***		0.074 ***	
N	2,349		2,349		2,349	

Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students. *B* = unstandardised coefficients, *SE* = standard errors. Results of linear regression analysis. ***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$.

Figure 2
Gender differences in STEM students' academic self-concepts



Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students; Source: NEPS SC5. Linear prediction with 95% confidence intervals. Results of linear regression analysis with interaction terms. This model controls for students' final school grades, age, migration background, and academic background.

Degree completion in STEM

The second part of the analyses addressed the relationship between STEM students' academic self-concepts and their graduation likelihood. Table 2 shows the results of two logistic regression models, each calculated separately for male and female STEM students. Models 4 and 5 show that students' academic self-concepts were significantly positively related to their probability of graduating. The effect was slightly smaller among female students. Model 5 indicated that being enrolled in an MPF- or HPF-STEM field compared to an LPF-STEM field was not significantly associated with a higher graduation likelihood. The fully engaged model-including a threefold interaction between gender, academic self-concept, and female student ratio critically examined variations between male and female students and across STEM disciplines. Figure 3 graphically illustrates the results of this model, depicting the associated conditional average marginal effects. Appendix D displays the respective odds ratios of the interacted model. Academic self-concepts significantly influenced the graduation probability for both male and female students exclusively in LPF-STEM fields, and there was a slightly more substantial effect among female students. Yet, the interaction effect was statistically not significant (Model D1).

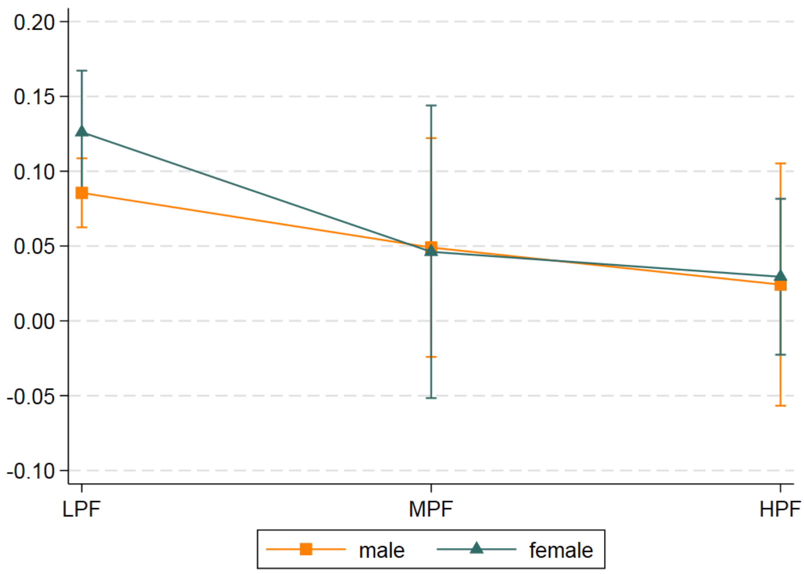
Results of the robustness analyses showed that for female students only their perceptions of their talents were related to their graduation likelihood; for male students, both factors had significant effects (see Appendix Table C1). The interacted model provided robust results only for students' perceptions of their talents and skills (see Appendix Figure C1), but not for their assessments of their task-management skills (see Appendix Figure C2).

Table 2
Male and female students' likelihood of graduating in STEM

	Model 4				Model 5			
	Men		Women		Men		Women	
	AME	*SE*	*AME*	*SE*	*AME*	*SE*	*AME*	*SE*
Academic self-concept	0.081 ***	0.011	0.076 ***	0.016	0.082 ***	0.011	0.073 ***	0.016
Final school grade	0.138 ***	0.018	0.157 ***	0.023	0.136 ***	0.018	0.162 ***	0.023
Subject changes	-0.096 *	0.043	-0.116 *	0.047	-0.095 *	0.043	-0.116 *	0.046
Female share								
LPF					(ref.)		(ref.)	
MPF					0.018	0.036	-0.046	0.044
HPF					-0.022	0.040	0.045	0.030
Age	-0.001	0.004	0.003	0.005	-0.001	0.004	0.003	0.005
Migration background	-0.028	0.030	-0.088 *	0.036	-0.029	0.026	-0.077 *	0.035
Academic background	0.001	0.022	-0.004	0.028	0.001	0.022	-0.005	0.028
Pseudo R^2	0.105 ***		0.152 ***		0.105 ***		0.159 ***	
N	1,348		683		1,348		683	

Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students. *AME* = Average marginal effects, *SE* = Standard errors. Results of logistic regression analysis. ***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$.

Figure 3
Average marginal effects of students' academic self-concepts on their likelihood of graduating in STEM



Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students; Source: NEPS SC5. Average marginal effects derived from a threefold interaction model, with 95% confidence intervals. This model controls for students' final school grades, field changes, age, migration background and academic background.

DISCUSSION

The complex issues of women's underrepresentation in STEM occupies both policy and research. Overall, female students constitute less than one third of STEM first-year students and graduates in Germany (World Bank, 2018). However, the different STEM fields vary considerably in their respective female share (German Federal Statistical Office, 2022). This paper investigated how the numerical representation of women in a STEM field of study relates to gender differences in students' academic self-concepts and how students' academic self-concepts relate to their likelihood of graduating in STEM.

The empirical analyses revealed that female students reported significantly weaker academic self-concepts than male students only in STEM fields with either low or high proportions of female students. Against the assumptions based on the tokenism theory (Kanter, 1977) and the cues hypothesis (Murphy et al., 2007), the gender difference in students' academic self-concepts is most evident in STEM fields with high proportions of women. In fields with low female representation, female students' academic self-concepts were almost on par with those of male students. This may result from selection processes prior to higher education. Females with a strong STEM-related academic self-concept are more likely to pursue and maintain a career in a STEM field with low female representation in the first place because their strong academic self-concepts helped them navigate numerous challenges such as stereotypes and lack of peer or family support at earlier stages (e.g., Wang et al., 2015). Conversely, one could argue that in fields with a higher female share, there might be fewer barriers or stereotypes discouraging women from entering (Robnett, 2016). As a result, the population in these fields may be more diverse in terms of the strength of their academic self-concepts leading to more pronounced gender differences. Yet, the data of the present study does not support this assumption, as standard deviations of academic self-concepts in LPF- and HPF-STEM fields were quite similar. The analyses suggested that students in HPF-STEM fields generally had higher academic self-concepts than those in LPF-STEM fields. This could link to the distinct disciplinary cultures of the subjects that belong to these fields. Rapid course paces, intensive workloads, and competitive grading environments, for example, characterise LPF-STEM fields such as engineering (Riley, 2017). Such a culture may prompt students to reevaluate and moderate their perceptions of their abilities. Why this disparity is more marked among male students compared to female students remains unclear. The results of the present study suggested that in these LPF-STEM fields, having higher-level perceptions of academic abilities was associated with a higher graduation likelihood, with no significant differences between male and female students. Hence, high-level perceptions of abilities contribute to students persisting in these fields, irrespective of their gender.

Limitations and strengths

This study has some limitations. First, it relied on administrative data to assess gender composition in STEM fields, potentially overlooking institution-specific variations or the impact of institutional culture or resources (Meyer & Strauß, 2019). Future research could benefit from university-level data analysis. It is also crucial to consider that multiple factors, such as collective beliefs (Leslie et al., 2015), math-intensiveness, gender-specific interests (Diekman et al., 2017), and male culture (Cheryan et al., 2017) influence female participation in STEM. These aspects can also serve as potential criteria for distinguishing different STEM fields. However, differentiating fields based on the proportion of female students provides a starting point for understanding gender dynamics in the different STEM fields.

Furthermore, the data did not capture gender stereotypes in the respective fields. It is a stretch to infer from the theory of tokenism (Kanter, 1977) and the cues hypothesis (Murphy et al., 2007) that minority representation relates to stereotyping. Research including data on stereotypes, such as that by Ertl and colleagues (2017), could further enhance our understanding. Another limitation was the inability to include early dropouts due to the timing of data collection despite their prevalence (Heublein, 2014). Furthermore, I could not consider academic achievement in higher education, which potentially impacts both students' study-related academic self-concepts and degree completion. However, I used previous academic achievement as a control, as it also predicts academic success in higher education (e.g., Trapmann et al., 2007). The study also utilised a shortened instrument to measure academic self-concepts. Replicating this study with a more comprehensive measure of different components of the academic self-concept is recommended (Arens et al., 2011). The robustness analyses of the present study suggested a potential distinction between talent and effort-related aspects of academic self-concept. However, lacking theoretical backing, the respective results should be interpreted cautiously. Nevertheless, they highlight the evolving nature of academic self-concepts (e.g., Guay et al., 2003; Nagy et al., 2010), which should be considered when analysing young adults such as students. Finally, the difference between the initial sample and the analysed sample is quite large, mainly due to the exclusion of teacher education students. I based this decision on selection issues. However, especially considering the current debate about not only skills shortages but also teacher shortages in Germany, the group of teacher education students demands extensive attention (Franz & Paetsch, 2023). Nonetheless, a substantial number of cases were analysed, which can be considered a strength of the present study.

Conclusion and implications

Approaching STEM fields as differentiated groups rather than an aggregate has yielded new insights, particularly regarding students' perceptions of their academic abilities in STEM fields with high female representation compared to those with low female representation. The study's findings support the conclusion that fostering a robust STEM-related academic self-concept early on is crucial, as we know from previous research that the academic self-concept forms already in childhood and stabilises over time (e.g., Nagy et al., 2010). The present study also highlighted its role for persistence in higher education for both female and male students. Regarding STEM degree completion, such factors as individual resilience, institutional support, and pedagogical strategies may have a greater influence on degree completion than gender representation (see Cheryan et al., 2017). Yet, variation across STEM fields should always be considered.

AUTHOR NOTE

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I have no conflicts of interest to disclose. Please direct all correspondence to Isabelle Fiedler: fiedler@dzhw.de.

DATA AVAILABILITY

This paper uses data from the National Educational Panel Study (NEPS; see Blossfeld & Roßbach, 2019). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network.

REFERENCES

Ackerman, P. L., Kanfer, R., & Beier, M. E. (2013). Trait complex, cognitive ability, and domain knowledge predictors of baccalaureate success, STEM persistence, and gender differences*. Journal of Educational Psychology, 105*(3), 911–927. https://doi.org/10.1037/a0032338

Allison, P. D. (2009). Missing data. In R. E. Millsap & A. Maydeu-Olivares (Eds.), *The Sage handbook of quantitative methods in psychology* (pp. 72–89). Sage Publications Ltd. https://doi.org/10.4135/9780857020994.n4

Arens, A. K., Yeung, A. S., Craven, R. G., & Hasselhorn, M. (2011). The twofold multidimensionality of academic self-concept: Domain specificity and separation between competence and affect components. *Journal of Educational Psychology, 103*(4), 970–981. https://doi.org/10.1037/a0025047

Autor:innengruppe Bildungsberichterstattung. (2020). *Bildung in Deutschland 2020: Ein indikatorengestützter Bericht mit einer Analyse zu Bildung in einer digitalisierten Welt* [Education in Germany 2020: An indicator-based report with an analysis of education in a digitalized world]. wbv. https://doi.org/10.3278/6001820gw

Blossfeld, H.-P., & Roßbach, H.-G. (Eds.). (2019). *Education as a lifelong process: The German National Educational Panel Study (NEPS)* (Edition ZfE, 2nd Rev. ed.). Springer.

Buchmann, C. (2009). Gender inequalities in the transition to college. *Teachers College Record: The Voice of Scholarship in Education, 111*(10), 2320–2346. https://doi.org/10.1177/016146810911101002

Buchmann, M., Kriesi, I., Pfeifer, A., and Sacchi, S. (2002). *Halb drinnen — halb draussen. Analysen zur Arbeitsmarktintegration von Frauen in der Schweiz* [Half inside — half outside. Analyses on the integration of women into the labor market in Switzerland]. Rüegger.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Chen, X., Ender, P. B., Mitchell, M., & Wells, C. (2003). *Regression with Stata*. Retrieved August 1, 2023, from https://stats.idre.ucla.edu/stat/stata/webbooks/reg/default.htm

Cheryan, S., Master, A., & Meltzoff, A. N. (2015). Cultural stereotypes as gatekeepers: Increasing girls' interest in computer science and engineering by diversifying stereotypes. *Frontiers in Psychology*, *6*, Article 49. https://doi.org/10.3389/fpsyg.2015.00049

Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin*, *143*(1), 1–35. https://doi.org/10.1037/bul0000052

Cohoon, J. M. (2002). Women in CS and biology. *Proceedings of the 33rd SIGCSE Technical Symposium on Computer Science Education*, 82–86. https://doi.org/10.1145/563340.563370

Deemer, E. D., Thoman, D. B., Chase, J. P., & Smith, J. L. (2014). Feeling the threat: Stereotype threat as a contextual barrier to women's science career choice intentions. *Journal of Career Development*, *41*(2), 141–158. https://doi.org/10.1177/0894845313483003

Denissen, J. J. A., Zarrett, N. R., & Eccles, J. S. (2007). I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child Development, 78*(2), 430–447. https://doi.org/10.1111/j.1467-8624.2007.01007.x

Dickhäuser, O., Reuter, M., & Hilling, C. (2005). Coursework selection: A frame of reference approach using structural equation modelling. *British Journal of Educational Psychology, 75*(4), 673–688. https://doi.org/10.1348/000709905X37181

Dickhäuser, O., Schöne, C., Spinath, B., & Stiensmeier-Pelster, J. (2006). Die Skalen zum akademischen Selbstkonzept: Konstruktion und Überprüfung eines neuen Instrumentes [The academic self concept scales: Construction and evaluation of a new instrument]. *Zeitschrift für Differentielle und Diagnostische Psychologie, 23*(4), 393–405. https://doi.org/10.1024//0170-1789.23.4.393

Diekman, A. B., Steinberg, M., Brown, E. R., Belanger, A. L., & Clark, E. K. (2017). A goal congruity model of role entry, engagement, and exit: Understanding communal goal processes in STEM gender gaps. *Personality and Social Psychology Review, 21*(2), 142–175. https://doi.org/10.1177/1088868316642141

Dulay, S. (2017). The effect of self-concept on student achievement. In E. Karadağ (Ed.), *The factors effecting student achievement: Meta-analysis of empirical studies* (pp. 117–132). Springer. https://doi.org/10.1007/978-3-319-56083-0_7

Eccles, J. S., & Wang, M.-T. (2015). What motivates females and males to pursue careers in mathematics and science? *International Journal of Behavioral Development*, *40*(2), 100–106. https://doi.org/10.1177/0165025415616201

Eccles, J. S., Wigfield, A., Flanagan, C. A., Miller, C., Reuman, D. A., & Yee, D. (1989). Self-concepts, domain values, and self-esteem: Relations and changes at early adolescence. *Journal of Personality*, *57*(2), 283–310. https://doi.org/10.1111/j.1467-6494.1989.tb00484.x

Eccles, J. S., Wigfield, A., Harold, R. D., & Blumenfeld, P. (1993). Age and gender differences in children's self- and task perceptions during elementary school. *Child Development*, *64*(3), 830–847. https://doi.org/10.2307/1131221

Ellis, J., Fosdick, B. K., & Rasmussen, C. (2016). Women 1.5 times more likely to leave STEM pipeline after calculus compared to men: Lack of mathematical confidence a potential culprit. *PLoS ONE*, *11*(7), Article e0157447. https://doi.org/10.1371/journal.pone.0157447

Ertl, B., Luttenberger, S., & Paechter, M. (2017). The impact of gender stereotypes on the self-concept of female students in STEM subjects with an under-representation of females. *Frontiers in Psychology*, *8*, Article 703. https://doi.org/10.3389/fpsyg.2017.00703

Fellenberg, F., & Hannover, B. (2006). Kaum begonnen, schon zerronnen? Psychologische Ursachfaktoren für die Neigung von Studienanfängern das Studium abzubrechen oder das Fach zu wechseln [Easy come, easy go? Psychological causes of students' drop out of university or changing the subject at the beginning of their study]. *Empirische Pädagogik*, *20*(4), 381–399.

Förtsch, S., & Schmid, U. (2018). The influence of academic self-concept on the study program choice of computer scientists. In A. Zamfira, C. de Montlibert, & D. Radu (Eds.), *Gender in focus: Identities, codes, stereotypes and politics* (pp. 275–292). Barbara Budrich Publishers. https://doi.org/10.2307/j.ctvddzn5f.16

Franz, S., & Paetsch, J. (2023). Academic and social integration and their relation to dropping out of teacher education: A comparison to other study programs. *Frontiers in Education, 8*, Article 1179264. https://doi.org/10.3389/feduc.2023.1179264

German Federal Statistical Office (Ed.). (2011). *Bildung und Kultur. Studierende an Hochschulen — Wintersemester 2010/2011* [Education and culture. Students at higher education institutions — winter semester 2010/2011]. German Federal Statistical Office. https://www.statistischebibliothek.de/mir/receive/DEHeft_mods_00005831

German Federal Statistical Office. (2022). *Students enrolled in STEM courses*. Retrieved February 15, 2023, from https://www.destatis.de/EN/Themes/Society-Environment/Education-Research-Culture/Institutions-Higher-Education/Tables/students-in-stem-courses.html

Guay, F., Marsh, H. W., & Boivin, M. (2003). Academic self-concept and academic achievement: Developmental perspectives on their causal ordering. *Journal of Educational Psychology, 95*(1), 124–136. https://doi.org/10.1037/0022-0663.95.1.124

Henderson, M., Hansen, K., & Shure, N. (2017). *Does academic self-concept predict further and higher education participation?* Centre for Global Higher Education. Retrieved October 13, 2022, from https://www.researchcghe.org/perch/resources/publications/wp262.pdf

Heublein, U. (2014). Student drop-out from German higher education institutions. *European Journal of Education, 49*(4), 497–513. https://doi.org/10.1111/ejed.12097

Heublein, U., Ebert, J., Hutzsch, C., Isleib, S., König, R., Richter, J., & Woisch, A. (2017). *Zwischen Studienerwartungen und Studienwirklichkeit. Ursachen des Studienabbruchs, beruflicher Verbleib der Studienabbrecherinnen und Studienabbrecher und Entwicklung der Studienabbruchquote an deutschen Hochschulen* [Between study expectations and the reality of studies: Causes of study dropout, career paths of dropouts and the development of the drop-out rate at German universities]. German Centre for Higher Education Research and Science Studies (DZHW).

Inzlicht, M., & Good, C. (2006). How environments can threaten academic performance, self-knowledge, and sense of belonging. In S. Levin & C. van Laar (Eds.), *Stigma and group inequality: Social psychological perspectives* (pp. 129–150). Lawrence Erlbaum Associates, Inc.

Isleib, S., Woisch, A., & Heublein, U. (2019). Ursachen des Studienabbruchs: Theoretische Basis und empirische Faktoren [Causes of higher education dropout: Theoretical basis and empirical factors]. *Zeitschrift für Erziehungswissenschaft, 22*(5), 1047–1076. https://doi.org/10.1007/s11618-019-00908-x

Isphording, I. E., & Qendrai, P. (2019). Gender differences in student dropout in STEM. *IZA Research Reports, 87*. Retrieved February 28, 2023, from

https://ftp.iza.org/report_pdfs/iza_report_87.pdf
Kanny, M. A., Sax, L. J., & Riggers-Piehl, T. A. (2014). Investigating forty years of STEM research: How explanations for the gender gap have evolved over time. *Journal of Women and Minorities in Science and Engineering, 20*(2), 127–148. https://doi.org/10.1615/JWomenMinorScienEng.2014007246
Kanter, R. M. (1977). *Men and women of the corporation*. Basic Books.
Key, K. A., & Sass, T. R. (2019). *Explaining the gender gap in STEM attainment: Factors from primary school to STEM degree completion* (EdWorkingPaper No. 19–42). https://doi.org/10.26300/4DT9-HN79
Klein, D. (2019). Das Zusammenspiel zwischen akademischer und sozialer Integration bei der Erklärung von Studienabbruchintentionen. Eine empirische Anwendung von Tintos Integrationsmodell im deutschen Kontext [The interplay between academic and social integration in explaining higher education dropout intentions. An empirical application of Tinto's integration model in the German context]. *Zeitschrift für Erziehungswissenschaft, 22*(2), 301–323. https://doi.org/10.1007/s11618-018-0852-9
Lažetić, P. (2020). The gender gap in graduate job quality in Europe — A comparative analysis across economic sectors and countries. *Oxford Review of Education, 46*(1), 129–151. https://doi.org/10.1080/03054985.2019.1687439
Leslie, S.-J., Cimpian, A., Meyer, M., & Freeland, E. (2015). Expectations of brilliance underlie gender distributions across academic disciplines. *Science, 347*(6219), 262–265. https://doi.org/10.1126/science.1261375
Luttenberger, S., Paechter, M., & Ertl, B. (2019). Self-concept and support experienced in school as key variables for the motivation of women enrolled in STEM subjects with a low and moderate proportion of females. *Frontiers in Psychology, 10*, Article 1242. https://doi.org/10.3389/fpsyg.2019.01242
Main, J. B. (2018). Kanter's theory of proportions: Organizational demography and PhD completion in science and engineering departments. *Research in Higher Education, 59*(8), 1059–1073. https://doi.org/10.1007/s11162-018-9499-x
Marsh, H. W. (1986). Verbal and math self-concepts: An internal/external frame of reference model. *American Educational Research Journal, 23*(1), 129–149. https://doi.org/10.3102/00028312023001129
Meyer, J., & Strauß, S. (2019). The influence of gender composition in a field of study on students' drop-out of higher education. *European Journal of Education, 54*(3), 443–456. https://doi.org/10.1111/ejed.12357
Möller, J., & Trautwein, U. (2015). Selbstkonzept [Self-concept]. In E. Wild & J. Möller (Eds.), *Pädagogische Psychologie* [Educational psychology] (2nd ed., pp. 177–199). Springer. https://doi.org/10.1007/978-3-642-41291-2
Moschner, B., & Dickhäuser, O. (2018). Selbstkonzept [Self-concept]. In D. H. Rost, J. R. Sparfeldt, & S. Buch (Eds.), *Handwörterbuch pädagogische Psychologie* [Handbook of educational psychology] (5th ed., pp. 750–756). Beltz.
Müller, L., & Klein, D. (2022). Social inequality in dropout from higher education in Germany. Towards combining the student integration model and rational choice theory. *Research in Higher Education, 64,* 300–330. https://doi.org/10.1007/s11162-022-09703-w
Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How

situational cues affect women in math, science, and engineering settings. *Psychological Science, 18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01995.x

Nagy, G., Watt, H. M. G., Eccles, J. S., Trautwein, U., Lüdtke, O., & Baumert, J. (2010). The development of students' mathematics self-concept in relation to gender: Different countries, different trajectories? *Journal of Research on Adolescence, 20*(2), 482–506. https://doi.org/10.1111/j.1532-7795.2010.00644.x

NEPS Network. (2022). *National Educational Panel Study. Scientific use file of starting cohort first-year students.* Leibniz Institute for Educational Trajectories (LIfBi). https://doi.org/10.5157/NEPS:SC5:17.0.0

Neugebauer, M. (2013). Wer entscheidet sich für ein Lehramtsstudium — und warum? Eine empirische Überprüfung der These von der Negativselektion in den Lehrerberuf [Who chooses to study education — and why? An empirical examination of the thesis of negative selection into the teaching profession]. *Zeitschrift für Erziehungswissenschaft, 16*(1)*,* 157–184. https://doi.org/10.25656/01:10587

Nosek, B. A., Banaji, M. R., & Greenwald, A. G. (2002). Math = male, me = female, therefore math ≠ me. *Journal of Personality and Social Psychology, 83*(1)*,* 44–59. https://doi.org/10.1037/0022-3514.83.1.44

OECD. (2015). *The ABC of gender equality in education: Aptitude, behaviour, confidence.* OECD Publishing. https://doi.org/10.1787/9789264229945-en

OECD. (2022). *Education at a glance 2022: OECD indicators*. OECD Publishing. https://doi.org/10.1787/3197152b-en

Riley, D. (2017). Rigor/Us: Building boundaries and disciplining diversity with standards of merit. *Engineering Studies, 9*(3), 249–265. https://doi.org/10.1080/19378629.2017.1408631

Robnett, R. D. (2016). Gender bias in STEM fields: Variation in prevalence and links to STEM self-concept. *Psychology of Women Quarterly, 40*(1), 65–79. https://doi.org/10.1177/0361684315596162

Schilling, S. R., Sparfeldt, J. R., & Rost, D. H. (2006). Facetten schulischen Selbstkonzepts: Welchen Unterschied macht das Geschlecht? [Gender differences in subject-specific academic self-concepts]. *Zeitschrift für Pädagogische Psychologie, 20*(1/2), 9–18. https://doi.org/10.1024/1010-0652.20.12.9

Severiens, S., & ten Dam, G. (2012). Leaving college: A gender comparison in male and female-dominated programs. *Research in Higher Education, 53*(4), 453–470. https://doi.org/10.1007/s11162-011-9237-0

Shapiro, C. A., & Sax, L. J. (2011). Major selection and persistence for women in STEM. *New Directions for Institutional Research, 2011*(152), 5–18. https://doi.org/10.1002/ir.404

Shavelson, R. J., Hubner, J. J., & Stanton, G. C. (1976). Self-concept: Validation of construct interpretations. *Review of Educational Research, 46*(3), 407–441. https://doi.org/10.3102/00346543046003407

Sikora, J., & Pokropek, A. (2012). Gender segregation of adolescent science career plans in 50 countries. *Science Education, 96*(2), 234–264. https://doi.org/10.1002/sce.20479

Skaalvik, S., & Skaalvik, E. M. (2004). Gender differences in math and verbal self-concept, performance expectations, and motivation. *Sex Roles: A Journal of Research, 50*(3–4), 241–252. https://doi.org/10.1023/B:SERS.0000015555.40976.e6

StataCorp. (2021). Stata statistical software: Release 17 [computer software]. StataCorp LLC.

Su, R., & Rounds, J. (2015). All STEM fields are not created equal: People and things interests explain gender disparities across STEM fields. *Frontiers in Psychology, 6*, Article 189. https://doi.org/10.3389/fpsyg.2015.00189

Tiedemann, J. (2000). Parents' gender stereotypes and teachers' beliefs as predictors of children's concept of their mathematical ability in elementary school. *Journal of Educational Psychology, 92*(1), 144–151. https://doi.org/10.1037/0022-0663.92.1.144

Thébaud, S., & Charles, M. (2018). Segregation, stereotypes, and STEM. *Social Sciences, 7*(7), 111. https://doi.org/10.3390/socsci7070111

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*(1), 89–125. https://doi.org/10.3102/00346543045001089

Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition*. University of Chicago Press.

Trapmann, S., Hell, B., Weigand, S., & Schuler, H. (2007). Die Validität von Schulnoten zur Vorhersage des Studienerfolgs — Eine Metaanalyse [The validity of school grades for academic achievement — A meta-analysis]. *Zeitschrift für Pädagogische Psychologie, 21*(1), 11–27. https://doi.org/10.1024/1010-0652.21.1.11

Turnbull, S. M., Meissel, K., Locke, K., & O'Neale, D. R. J. (2020). The impact of science capital on self-concept in science: A study of university students in New Zealand. *Frontiers in Education, 5,* Article 27. https://doi.org/10.3389/feduc.2020.00027

van Soom, C., & Donche, V. (2014). Profiling first-year students in STEM programs based on autonomous motivation and academic self-concept and relationship with academic achievement. *PloS ONE, 9*(11), Article e112489. https://doi.org/10.1371/journal.pone.0112489

Wang, M.-T., Degol, J., & Ye, F. (2015). Math achievement is important, but task values are critical, too: Examining the intellectual and motivational factors leading to gender disparities in STEM careers. *Frontiers in Psychology,* 6, Article 36. https://doi.org/10.3389/fpsyg.2015.00036

Wilkins-Yel, K. G., Simpson, A., & Sparks, P. D. (2019). Persisting despite the odds: Resilience and coping among women in engineering. *Journal of Women and Minorities in Science and Engineering, 25*(4), 353–368. https://doi.org/10.1615/JWomenMinorScienEng.2019026945

Wolff, F., Helm, F., Zimmermann, F., Nagy, G., & Möller, J. (2018). On the effects of social, temporal, and dimensional comparisons on academic self-concept. *Journal of Educational Psychology, 110*(7), 1005–1025. https://doi.org/10.1037/edu0000248

Wolter, I., & Hannover, B. (2016). Gender role self-concept at school start and its impact on academic self-concept and performance in mathematics and reading. *European Journal of Developmental Psychology, 13*(6), 681–703. https://doi.org/10.1080/17405629.2016.1175343

Wolter, I., Kessels, U., & Hannover, B. (2011). Geschlechtsspezifische Unterschiede in der Selbstkonzeptentwicklung [Gender-specific differences in self-concept development]. In F. Hellmich (Ed.), *Selbstkonzepte im Grundschulalter: Modelle, empirische Ergebnisse, pädagogische Konsequenzen* [Self-concepts in primary school: Models, empirical results, educational implications] (pp. 119–132). Kohlhammer.

Wolter, S. C., Diem, A., & Messer, D. (2014). Drop-outs from Swiss universities: An empirical analysis of data on all students between 1975 and 2008. *European Journal of Education, 49*(4), 471–483. https://doi.org/10.1111/ejed.12096

World Bank (2018). *Female share of graduates from Science, Technology, Engineering and Mathematics (STEM) programs, tertiary (%)* [data file]. Retrieved October 13, 2022, from https://databank.worldbank.org/source/gender-statistics

APPENDIX

Appendix A

Table A1
Demographic characteristics of the sample analysed

		Total	Female	Male
Academic self-concept	*Ø (SD)*	4.78 (0.91)	4.75 (0.87)	4.79 (0.92)
Final school grade	*Ø (SD)*	4.78 (0.63)	4.89 (0.68)	4.73 (0.64)
Age in years	*Ø (SD)*	21.79 (2.89)	21.30 (2.48)	22.05 (3.01)
Migration background	*N*	516	181	335
Academic background	*N*	1085	390	695
	N	2,349	802	1,547

Note. SD = Standard deviation. Academic background indicates that at least one parent has an academic degree.

Table A2
Gender distribution in the different STEM fields of study in the analysis sample

Female share	STEM field of study	Total	Female	Male
Low proportion of female students:		1,616	357	1,259
8.78%	Electrical engineering and information technology	164	17	147
11.04%	Traffic engineering, nautical engineering	64	18	46
14.49%	Mining, metallurgy	1	0	1
17.72%	Engineering in general	162	31	131
17.81%	Mechanical engineering, process engineering	511	117	394
18.13%	Computer science	342	72	270
18.56%	Physics, astronomy	128	28	100
19.19%	Industrial engineering with engineering focus	123	27	96
26.98%	Civil engineering	121	47	74
Moderate proportion of female students:		300	133	167
30.32%	Surveying and mapping	10	5	5
40.40%	Earth sciences (without geography)	37	17	20
42.15%	Mathematics	122	48	74
44.96%	Chemistry	131	63	68
High proportion of female students:		433	312	121
50.21%	Spatial planning	18	10	8
50.66%	Geography	83	47	36
53.79%	Mathematics, natural sciences in general	10	4	6
61.84%	Architecture, interior design	58	44	14
63.37%	Biology	195	144	51
73.82%	Pharmacy	69	63	6
Total		2,349	802	1,547

Note. Female share according to the official statistics in winter term 2010–2011 in Germany in %.

Appendix B

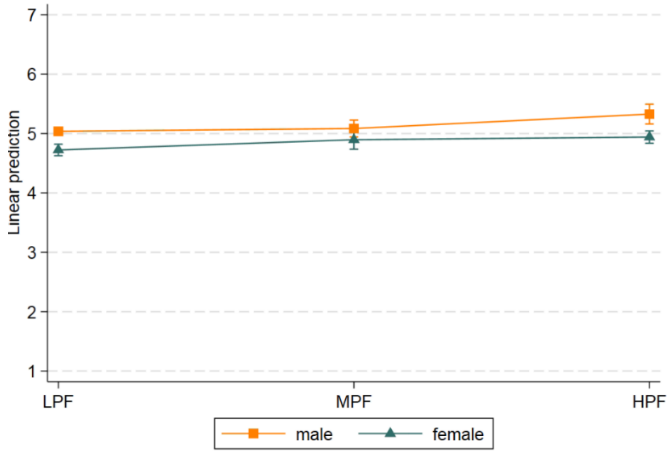
Table B1
Gender differences in STEM students' subjective perceptions of their study-related talents and skills ("talent")

	Model B1		Model B2		Model B3	
	B	*SE*	*B*	*SE*	*B*	*SE*
Gender (ref. male)	-0.183 ***	0.042	-0.230 ***	0.041	-0.314 ***	0.056
Final school grade			0.349 ***	0.032	0.350 ***	0.032
Female share						
LPF					(ref.)	
MPF					0.047	0.078
HPF					0.290 ***	0.089
Gender*female share						
Female*LPF					(ref.)	
Female*MPF					0.126	0.122
Female*HPF					-0.073	0.115
Age	-0.028 ***	0.007	-0.014	0.007	-0.012	0.007
Migration background	-0.141 **	0.048	-0.094 *	0.047	-0.089	0.047
Academic background	0.132 ***	0.040	0.089 *	0.039	0.085 *	0.039
Constant	5.622 ***	0.162	3.667 ***	0.237	3.613 ***	0.238
Adjusted R^2	0.020 ***		0.069 ***		0.075 ***	
N	2,349		2,349		2,349	

Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students. *B* = unstandardised coefficients, *SE* = standard error. Results of linear regression analysis. ***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$.

Figure B1

Gender differences in STEM students' subjective perceptions of their study-related talents and skills ("talent")



Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students; Source: NEPS SC5. Linear prediction with 95% confidence intervals. Results of linear regression analysis with interaction terms. This model controls for students' final school grades, age, migration background and academic background

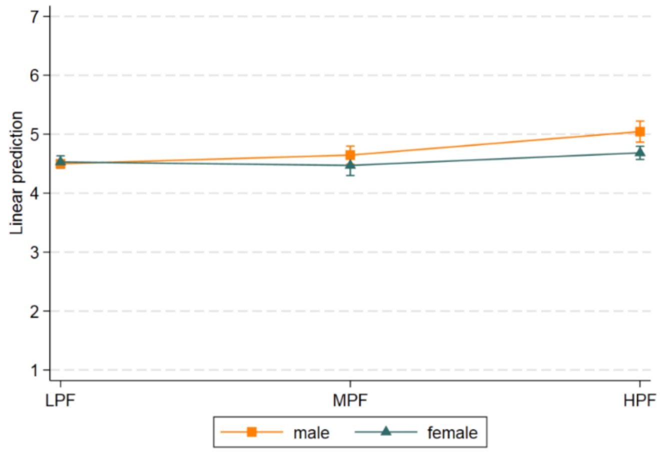
Table B2
Gender differences in STEM students' subjective assessments of their learning behaviours and task-management skills ("effort")

	Model B4		Model B5		Model B6	
	B	*SE*	*B*	*SE*	*B*	*SE*
Gender (ref. male)	-0.059	0.045	0.022	0.045	0.030	0.060
Final school grade			0.275 ***	0.034	0.285 ***	0.034
Female share						
LPF					(ref.)	
MPF					0.147	0.083
HPF					0.545 ***	0.096
Gender*female share						
Female*LPF					(ref.)	
Female*MPF					-0.204	0.131
Female*HPF					-0.390 **	0.123
Age	-0.036 ***	0.008	-0.025 ***	0.008	-0.022 **	0.008
Migration background	-0.167 ***	0.051	-0.130 **	0.051	-0.118 *	0.050
Academic background	0.082	0.043	0.049	0.043	0.043	0.042
Constant	5.322 ***	0.173	3.788 ***	0.256	3.628 ***	0.256
Adjusted R^2	0.017 ***		0.042 ***		0.057 ***	
N	2,348		2,349		2,349	

Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students. *B* = unstandardised coefficients, *SE* = standard error. Results of linear regression analysis. n=1 case provided no answer on this factor. ***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$.

Figure B2

Gender differences in STEM students' subjective assessments of their learning behaviours and task-management skills ("effort")



Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students; Source: NEPS SC5. Linear prediction with 95% confidence intervals. Results of linear regression analysis with interaction terms. This model controls for students' final school grades, age, migration background and academic background.

Appendix C

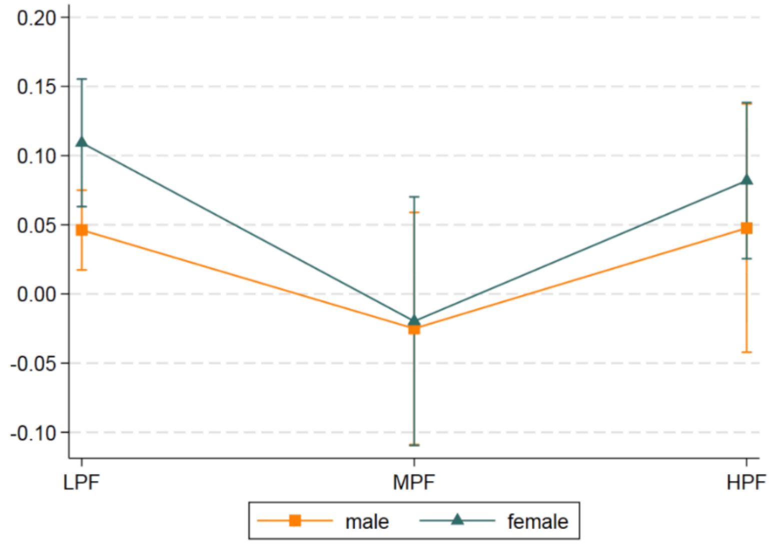
Table C1
Male and female students' likelihood of graduating in STEM

	Model C1				Model C2			
	Men		Women		Men		Women	
	AME	*SE*	*AME*	*SE*	*AME*	*SE*	*AME*	*SE*
Talent	0.042 **	0.014	0.070 ***	0.018	0.043 **	0.014	0.069 ***	0.018
Effort	0.039 **	0.013	0.003	0.019	0.039 ***	0.013	0.001	0.019
Final school grade	0.138 ***	0.018	0.153 ***	0.023	0.136 ***	0.018	0.158 ***	0.023
Subject changes	-0.096 *	0.043	-0.121 **	0.046	-0.095 *	0.043	-0.122 **	0.046
Female share								
LPF					(ref.)		(ref.)	
MPF					0.018	0.036	-0.052	0.044
HPF					-0.022	0.040	0.042	0.030
Age	-0.001	0.004	0.002	0.005	-0.001	0.004	0.002	0.005
Migration background	-0.024	0.026	-0.084 **	0.036	-0.029	0.026	-0.073 *	0.035
Academic background	0.001	0.022	-0.009	0.028	0.001	0.022	-0.011	0.028
Pseudo R^2	0.105 ***		0.155 ***		0.105 ***		0.164 ***	
N	1,348		682		1,348		682	

Note. "Talent" represents students' perceptions of their study-related talents and skills. "Effort" represents students' assessments of their learning behaviours and task-management skills. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students. *AME* = Average marginal effects, *SE* = Standard errors. Results of logistic regression analysis. n = 1 case provided no answer on the factor effort. ***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$.

Figure C1

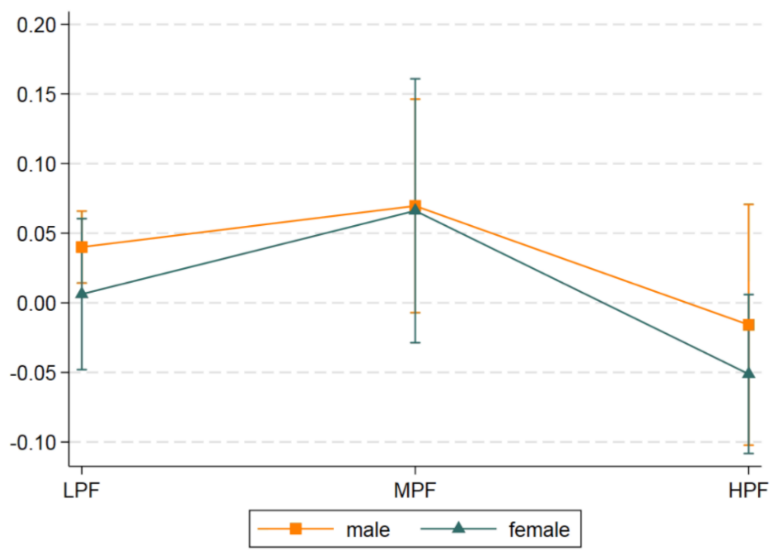
Average Marginal Effects of students' subjective perceptions their study-related talents and skills ("talent") on their likelihood of graduating in STEM



Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students; Source: NEPS SC5. Average marginal effects derived from a threefold interaction model, with 95% confidence intervals. This model controls for students' final school grades, field changes, age, migration background and academic background.

Figure C2

Average Marginal Effects of students' subjective assessments of their learning behaviours and task-management skills ("effort") on their likelihood of graduating in STEM



Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students; Source: NEPS SC5. Average marginal effects derived from a threefold interaction model, with 95% confidence intervals. This model controls for students' final school grades, field changes, age, migration background and academic background.

Appendix D

Table D1
Students' likelihood of graduating in STEM

	Model D1	
	OR	*SE*
Gender (ref. male)	0.220	0.203
Academic self-concept	1.811 ***	0.158
Final school grade	2.793 ***	0.294
Subject changes	0.491 **	0.110
Female share		
LPF	(ref.)	
MPF	3.026	4.565
HPF	4.484	10.665
Gender*ASC	1.400	0.293
ASC*female share		
ASC*LPF	(ref.)	
ASC*MPF	0.783	0.221
ASC*HPF	0.650	0.185
Gender*female share		
Female*LPF	(ref.)	
Female*MPF	4.263	8.917
Female*HPF	4.438	8.636
ASC*gender*female share		
ASC*female*LPF	(ref.)	
ASC*female*MPF	0.658	0.296
ASC*female*HPF	0.768	0.309
Age	1.003	0.020
Migration background	0.758 *	0.102
Academic background	0.991	0.120
Pseudo R^2	0.125 ***	
N	2,031	

Note. LPF = low proportion of female students, MPF = moderate proportion of female students, HPF = high proportion of female students. ASC = academic self-concept. *OR* = Odds ratios. *SE* = Standard error. Results of logistic regression analysis. ***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$.