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Do student teachers experience self-worth threats in computational thinking?

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ABSTRACT

Theory: The successful implementation of computational thinking into primary schools requires that primary school teachers feel safe and confident in teaching this topic to young learners. However, many student teachers face low expectancy of success and heightened anxiety towards computational thinking. Self-worth theory suggests that this may lead to a self-worth threat and in consequence to engagement in self-protective behaviours, hampering the successful acquisition of skills needed to implement computational thinking into their future classrooms.
Aims: This study aims to investigate potential self-worth threats as amplifiers of student teachers' resistance to engage in computational thinking.
Method: 323 student teachers participated in the study. Participants filled out a questionnaire on expectancy of success and anxiety towards computational thinking, and rated how likely they were to engage in self-protective behaviours, i.e., self-handicapping, avoiding novelty, and academic cheating, when learning about computational thinking at the start of the semester.
Results: Students showed heightened levels of anxiety and low levels of expectancy towards computational thinking. Further, they reported that they would be likely to engage in self-protective behaviours. A structural equation model showed that anxiety towards computational thinking was positively related to self-protective behaviours. Moreover, expectancy had a negative indirect effect via anxiety towards computational thinking on self-protective behaviours.
Discussion: Student teachers might experience self-worth threats when learning about computational thinking and engage in self-protective behaviours that might hamper their success. Our findings caution the impact of possible self-worth threats on teaching methods, thus influencing children's learning in the 21st century.

1. Introduction

The implementation of computational thinking (CT) as a 21st century skill into primary school classrooms has been advocated for several years by various stakeholders in politics, education, and research (Fraillon et al., 2020; National Research Council, 2010; OECD, 2018; Wing, 2006). As information technology becomes increasingly integrated into today's society, even young children are using digital devices, such as smartphones, tablets, and computers (Feierabend et al., 2023; Lafton et al., 2024). Additionally, a recent forecast indicates that most jobs will involve some form of automation or artificial intelligence in the near future (Gmyrek et al., 2023). Therefore, educating future generations in CT from an early age is not only a necessary task but also an urgent one (Bers, 2018; Sengupta et al., 2018). To achieve this goal, CT needs to be incorporated into primary school teacher training programmes, ensuring that future primary school teachers are proficient in CT (Butler & Leahy, 2021; Yadav et al., 2014).

However, previous research suggests that primary school teachers, and especially female (student) teachers, often experience low expectancy of their skills and a sense of apprehension, scepticism, or fear associated with this subject (Gal-Ezer & Stephenson, 2010; Weber et al., 2022; Yadav et al., 2014; Zha et al., 2020). These negative feelings may prevent them from sincerely engaging in and effectively acquiring CT skills, potentially affecting their future willingness to implement CT into their classrooms. Thus, it is crucial to investigate how these feelings impact student teachers' learning processes of CT.

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Self-worth theory of motivation suggests that students may sabotage their learning processes to protect their self-worth, i.e., their judgment of their worthiness, when fearing failure (Covington, 2009; Lee et al., 2013). Accordingly, low expectancies of students' CT skills and high programming anxiety may pose a threat to their self-worth, especially when they have invested a lot of effort, thus evoking self-protective behaviours, such as self-handicapping, avoiding novelty, academic cheating, or defensive pessimism. These self-protective behaviours harm the learning process (Lee et al., 2013) and should be considered when teaching CT to student teachers (see Török et al., 2018). Indeed, Fairlamb (2022) even claims that simply investing in achievement might be unsuccessful, if students experience a self-worth threat and that, therefore, measures should be taken to discover these threats in students. The hypothesised relations are presented in Fig. 1. By bridging the gaps between psychology, education, and computer science, this study addresses two research gaps; (1) whether student teachers experience a self-worth threat when learning CT and (2) whether this perceived self-worth threat translates to self-protective behaviours during their learning processes.

2. Literature review

2.1. Computational thinking

CT is conceptualised as a problem-solving process during which problems and their solutions are formulated with the help of computational concepts (e.g., logical reasoning) and information-processing agents (e.g., computers). However, while CT includes skills fundamental to computer science (e.g., abstraction, algorithm design), it is not limited to the field of computer science but is understood as a thinking skill applicable for everyday activities and problems (Shute et al., 2017; Wing, 2006), such as sorting mismatched socks, taking the easiest way to work, or getting ready for work/school in the morning by following a specific order of steps (Angeli et al., 2016; Relkin & Strawhacker, 2021). Several researchers even advocate for CT as a new literacy, comparable to reading or writing, and as a universal problem-solving approach (Angeli & Georgiou, 2023; Bers, 2018; Kong et al., 2023; Tsarava et al., 2022). They underline the importance of introducing CT not only into the STEM fields (Weintrop et al., 2016) but also into fields like literature (Burke & Kafai, 2012), arts (Bequette & Bequette, 2012), and music (Edwards, 2011).

CT includes several analytical thinking processes, such as decomposition, pattern recognition, abstraction, and algorithm design, that align with reasoning (Angeli & Georgiou, 2023; Grover & Pea, 2013; Li et al., 2020). Studies by Fletcher (1984), Shute (1991), and Weber et al. (2021) found strong associations between logical reasoning, programming skills, and CT. In line with such studies, CT is often taught through programming tasks in the primary school classroom, even though it has applications beyond computer science (Kong & Wang, 2020; Román-González et al., 2017). Such programming tasks are typically taught at a basic level, aligned with the cognitive abilities of primary school children. They are characterised by low complexity, are based on students' everyday experiences, are written in block-based programming languages (e.g., Scratch, NEPO), and are easy to implement into the classroom (Kong & Lai, 2022; Weber et al., 2022). Primary school students often find learning with digital devices particularly engaging, which can boost their motivation for CT (Acosta et al., 2024).

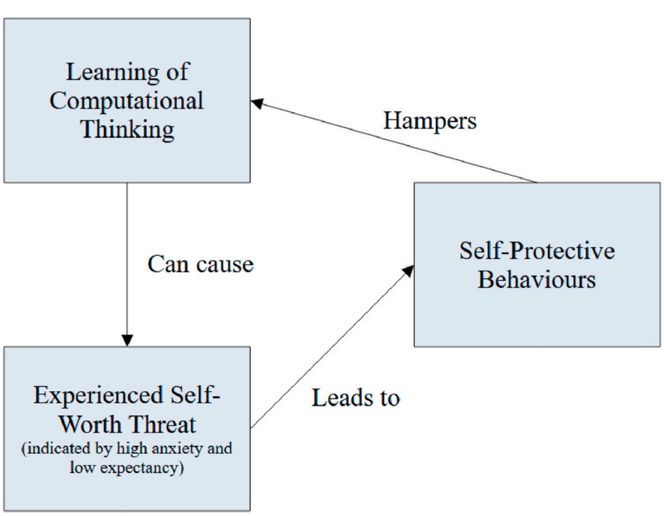

Fig. 1. Conceptual framework of the study.

Similarly, a study by Jaipal-Jamani and Angeli (2017) suggests that student teachers' confidence in their CT skills can be boosted by introducing them to simple programming tasks with engaging toy robots. Similarly, Weber et al. (2022) designed a seminar for student teachers aiming at enhancing students' expectancies and decreasing their anxiety towards CT. They found that the use of simple programming tasks set in an everyday context supported students' academic self-concept in programming and decreased their anxiety towards CT.

Although there have been studies on student teachers' motivation and perception (Guggemos, 2021; Ye et al., 2022), expectancies and values (Weber et al., 2022; Yadav et al., 2022), and self-efficacy (Jaipal-Jamani & Angeli, 2017; Tankiz & Atman Uslu, 2023) and the impact of these variables on acquiring CT skills, to our knowledge, no research has yet examined how negative feelings towards CT may affect student teachers' learning behaviours. Yet, from related fields like mathematics, we know that low expectancy and high anxiety towards a subject can lead to a self-worth threat, which may trigger unintended self-protective learning behaviours and avoidance (Casad et al., 2019; Fairlamb et al., 2022; Lee et al., 2013).

2.2. Self-worth threat

Studies suggest that students are driven by dual needs: On the one hand they thrive to be successful, on the other hand they aim to avoid failure (Fairlamb et al., 2022). Both success and failure have the potential to influence students' self-worth, especially in combination with high or low effort (Covington, 2007; Lee et al., 2013; Tuominen et al., 2020).

Many students view success in academic settings as something valuable, even if a student needs to invest effort to be successful, especially in the case of novel tasks. However, being successful without investing any or only marginal effort is (mistakenly) viewed by many as an indicator for high ability (Muenks & Miele, 2017). In consequence, success without effort has the potential to boost students' self-worth (Lee et al., 2013). Thus, if a student solves a programming task without studying CT and programming basics, it might be viewed as an indication that the student is very talented. Yet, this assumption may turn out to be a fallacy, since the student might have just been lucky, or the programming task might have been very easy.

Failure, on the other hand, is viewed as something inherently negative and has the potential to threaten students' self-worth, even more so when effort has been invested, e.g., in a task, as it seemingly implies low ability (Muenks & Miele, 2017; Song & Chung, 2020). Again, this might be a fallacy, because other reasons, such as bad luck, high task difficulty, or tiredness, could explain failure as well (Miele et al., 2020). Failure after little or no effort is often perceived as less threatening to a person's self-worth than failure after investing a lot of effort. In line with these assumptions, Jiang et al. (2020) found that self-worth threats are related to students' avoidance intentions and negatively affect achievement. Similarly, Fairlamb et al. (2022) found that striving for success was related to increased levels of anxiety in university students, while avoidance was related to higher levels of experienced self-worth threats.

Consequently, students may try to protect their self-worth through cognitive measures (Lee et al., 2013). In line with this, a study by Del Ferradás et al. (2019) found that university students with low self-esteem were most likely to engage in self-protective behaviours. Similarly, student teachers might engage in the following self-protective behaviours or thoughts that can help alleviate a self-worth threat when confronted with CT. (a) Self-handicapping describes the process of wilfully creating obstacles and investing low effort which might serve as explanations in case of failure. Typical forms of self-handicapping include procrastination, not practicing for an upcoming exam, and creating performance-debilitating circumstances (Martin et al., 2001; Schwinger et al., 2014). For example, a student might go to a party the night before an end of semester exam on CT. In case of a bad grade, the party, tiredness, and maybe even a hangover might serve as an explanation for the failure. Schwinger et al. (2014) point out that in case the self-handicapping student is successful, the success can be (falsely) attributed to a high ability, as the person must be highly intelligent or able to succeed under such performance-debilitating circumstances, e. g., received a good grade in spite of procrastination. Self-handicapping has been found to be particularly harmful for academic achievement (Török et al., 2018). In line with this, Fairlamb et al. (2022) suggest that students of psychology engage in self-handicapping in their statistics classes, a subject that is often a cause for anxiety in psychology students.

(b) Defensive pessimism refers to acknowledging the chance of failure and cognitively working through it by always expecting the worst and/or setting goals that are so low that nearly everyone can achieve them (Lim, 2009; Martin et al., 2001, 2003). For example, students might constantly think about the possibility of not passing a seminar or an exam on CT and try to not be confident in their abilities. Thus, in case of failure, they can tell themselves that they always knew they would fail. Cano et al. (2018) investigated the relations between anxiety, self-handicapping, defensive pessimism, and learning in higher education students. Their findings suggest that self-protective behaviours (self-handicapping and defensive pessimism) are related to lower achievement and higher anxiety. Moreover, Del Ferradás et al. (2017) found that students often engage in both self-handicapping and defensive pessimism, suggesting that they employ multiple self-protective strategies.

(c) Avoiding novelty characterises the attempts to avoid new things, because a person might fail at them (Lee et al., 2013). Since CT is a novel subject for many student teachers, many are likely to avoid the subject and engage in other science subjects that they are familiar with, given the choice. For example, Betoret and Artiga (2011) found that students who avoided novelty often used surface-learning strategies and had lower achievement.

(d) Academic cheating describes cheating behaviour that can be used to either avoid failure or explain failure, because only low effort would be invested into a task or a subject (Lee et al., 2013). For example, students might copy programs from their peers or download solutions to tasks from the internet. Thus, they do not engage with the subject matter and can blame their potential failure on it. Niiya et al. (2008) found that self-worth threats were associated with academic cheating behaviours in men, but not in women.

Whether students experience a self-worth threat might be dependent on a combination of factors (Del Ferradás et al., 2019). On an emotional level, students who experience heightened levels of anxiety might be more prone to self-worth threats, especially if they have low expectancies of success, e.g., a low academic self-concept. Covington (1992, 1997, 2009) suggests that four orientations towards success and failure can be defined: overstrivers, optimists, self-protectors, and failure acceptors. Moreover, Lee et al. (2013) highlight the role of expectancy for success in these orientations. Two recent studies by Jiang et al. (2020) and Fairlamb et al. (2022) suggest that self-worth threats, self-protective behaviours, and anxiety are related. Thus, we argue that task anxiety might affect self-worth, as higher levels of programming anxiety are related to lower programming performance (Weber et al., 2022, Table 1).

Table 1
Self-worth threat predicted by anxiety and expectancy, based on the model by Covington (1992, 1997, 2009).

		Expectancy	
		high	Low
Anxiety	high	Overstrivers **Low threat**	Self-protector **high threat**
	low	Optimist **no threat**	Failure acceptors **low threat**

Students who experience high levels of anxiety and have high expectancies of themselves are called *overstrivers* (Covington, 2009). While these students are afraid of failures, they are also likely to make an effort and work for their success to meet their high expectancies of success, leading to a low risk of self-worth threat (Martin et al., 2003). Therefore, they have a low likelihood of engaging in self-protective behaviours, such as academic cheating or avoiding novelty. Similarly, *optimists*, students who experience low levels of anxiety and high levels of expectancy, are at no risk of experiencing a self-worth threat (Covington, 2009). These individuals tend to invest effort and are likely to be unafraid of failures (Lee et al., 2013). Since they often handle failures well, failures are not perceived as threatening. At the highest risk of experiencing a self-worth threat are the so-called *self-protectors* (Covington, 2009). These individuals experience high anxiety and have low expectancies of success. To avoid failure, it is assumed that they are prone to engage in self-protective behaviours and in consequence often experience failures (Del Ferradás et al., 2019; Martin et al., 2001). Last, *failure acceptors*, students with low anxiety and expectancy levels, are at a low risk of experiencing a self-worth threat (Covington, 2009). These students expect to be unsuccessful and tend to be okay with that. Therefore, they are less likely to engage in self-protective behaviours than self-protectors. However, they might still engage in these behaviours to a lesser degree (Lee et al., 2013). These four profiles have recently been confirmed in a study on high school students for foreign language learning (Leis et al., 2022).

While many studies have investigated the impact of self-protective behaviours on children and adolescents, little research has addressed university students studying to be primary school teachers. For their future students' success in STEM, it will be crucial that student teachers make the active decision to implement STEM topics into their future classrooms. Previous research suggests that primary school teachers feel intimidated by CT as a potential subject (Jaipal-Jamani & Angeli, 2017; Weber et al., 2022). Therefore, investigating potential reasons, such as a perceived self-worth threat and the behaviours that follow, can help university lecturers design workshops and seminars that support student teachers' CT and at the same time alleviate fears, perceived threats, and foster enjoyment and expectancies.

2.3. Research questions

Introducing CT into primary schools can only be achieved if the primary school teachers feel safe and confident in teaching this topic to young learners. Since previous research has shown that student teachers tend to have heightened anxiety towards the subject and low expectancies of their success (Jaipal-Jamani & Angeli, 2017; Weber et al., 2022), this study will investigate potential consequences of these circumstances from an interdisciplinary perspective by integrating psychological theories (self-worth theory of motivation) with educational and computer science topics (CT) in an effort to examine potential consequences of negative emotions on student teachers' learning behaviours. By utilising self-worth theory, we identified the following research gaps: (1) do students experience a self-worth threat (i.e., high anxiety and low expectancy) when confronted with CT, and (2) does the potential self-worth threat affect their learning behaviours in terms of self-protection. We will address these research gaps by investigating the following research questions.

1. Is higher anxiety related to higher self-protective behaviours?
   a. Students who experience higher anxiety are more likely to report self-protective behaviours.
2. Is lower expectancy related to higher self-protective behaviours?
   a. Students who experience lower expectancies of success are more likely to report self-protective behaviours.
3. Does anxiety mediate the relationship between expectancy and self-protective behaviours?
   a. Anxiety mediates the relationship between expectancy and self-protective behaviours.

3. Method

3.1. Participants

A total of 323 student teachers (275 women, 44 men, 4 gave no indication) participated in the study. One participant was excluded due to missing data, leading to a total sample size of 322 (275 women, 44 men, 3 gave no indication). All participants studied primary school education in the master programme of a German university. Thus, all participants had a bachelor's degree in education from a university, and had attended mandatory lectures and seminars on teaching STEM topics in primary school during their bachelor and master studies, but had not received specific instruction on CT. Therefore, they had not received any formal education on implementing CT into their future classrooms during their university studies. On average, the students were 24 years old ($SD = 2.57$) and had studied for 1.51 ($SD = 1.30$) semesters in the master programme (Table 2). The standard study period for primary school education is 2 semesters (with 2 semesters being one academic year) at this German university. All students were informed about the goal of the study and gave written consent to participation. However, they were unaware of the exact research questions and hypotheses. The institutional review board granted approval for the study in accordance with faculty regulations.

3.2. Procedure

All participants attended a mandatory seminar on CT and how to support CT in primary school children taking place over the course of one semester. In the first week of the semester, the students were asked to fill out a questionnaire on their expectancies, values, and anxiety towards CT. Moreover, they were asked to provide information on possible self-protective behaviours as indicators for a potential self-worth threat that they might engage in during the seminar. A flowchart of our procedure can be found in Fig. 2.

3.3. Measures

The items for programming anxiety and programming self-concept were adapted from validated measurement instruments used in the Program for International Student Assessment (PISA) items in accordance with Marsh et al. (2019) and underwent rating by three independent experts, two of them from education, and one from psychology. All items were rated on a 4-point Likert scale ranging from 0 (*strongly disagree*) to 3 (*strongly agree*).

3.3.1. Anxiety

Anxiety towards CT was operationalised as programming anxiety. Programming anxiety was assessed with 6 items in line with Wigfield and Meece's (1988) definition of mathematics anxiety. Thus, programming anxiety was conceptualised as feelings of worry, stress, and helplessness, e.g., *"I get very tense when I have to solve programming tasks"*. Cronbach's α for programming anxiety was .89.

3.3.2. Expectancy

Expectancy was conceptualised as academic self-concept (Eccles, 2009). Domain-specific self-concept in CT was conceptualised as programming self-concept and assessed with 5 items focusing on student teachers' perceived programming abilities (Marsh et al., 2012), e.g., *"I believe that programming is one of my strengths"*. Cronbach's α for programming self-concept was .79.

3.3.3. Self-protective behaviours

Cognitive self-protection was measured with four scales, self-handicapping, avoiding novelty, academic cheating, and defensive pessimism.

Self-handicapping was measured with 5 items adapted from the German version of the Academic Self-Handicapping Scale (Schwinger & Stiensmeier-Pelster, 2012), e.g., *"Some students go out late the night before a programming assignment is due in the seminar. They can then cite that as a reason if they don't do well on an assignment. How much does that apply to you?"*. Cronbach's α for self-handicapping was .82.

Avoiding novelty was conceptualised as the preference for engaging in familiar tasks and topics during the seminar compared to new topics. The measure for avoiding novelty was adapted from the avoiding novelty items from the Patterns of Adaptive Learning Scale (Midgley et al., 2000), e.g., *"I would prefer to do seminar work that is familiar to me, rather than work I would have to learn how to do"*, and consisted of 5 items. Cronbach's α for avoiding novelty was .81.

Academic cheating was operationalised as the estimated likelihood that other students would cheat on the programming assignments during the seminar. As asking about whether a person was likely to cheat themselves might lead to biased responses due to socially desirable response patterns, we chose to assess the estimated likelihood of others cheating as a proxy. The measure was adapted from the Cheating Behaviour subscale of the Patterns of Adaptive Learning Scale (Midgley et al., 2000), e.g., *"Many students will probably download the solutions to the programming tasks online"*. Cronbach's α for academic cheating was .88.

Defensive pessimism was assessed with 5 items adapted from the Defensive Pessimism Questionnaire by Norem (2001) and Lim (2009). However, the shortened version of the questionnaire yielded a

Table 2
Age/gender of participants and semester participants are enrolled in.

	Age (in years)														
	21	22	23	24	25	26	27	28	29	30	31	34	35	37	40
Ntotal (%)	7 (2)	59 (19)	88 (29)	56 (18)	39 (13)	20 (6)	11 (4)	6 (2)	10 (3)	4 (1)	2 (1)	3 (1)	1 (0)	1 (0)	1 (0)
N_{women} (%)	7 (3)	58 (22)	80 (34)	48 (18)	32 (12)	15 (6)	5 (2)	4 (2)	7 (3)	2 (1)	1 (0)	1 (0)	1 (0)	–	1 (0)
N_{men} (%)	–	1 (2)	7 (16)	8 (19)	5 (12)	5 (12)	6 (14)	2 (5)	3 (7)	2 (5)	1 (2)	2 (5)	–	1 (2)	–
	Semester														
	1	2	3	4	5	6	7	8	9	10					
N_{total} (%)	221 (72)	66 (21)	9 (3)	2 (1)	–	–	3 (1)	6 (2)	–	1 (0)					
N_{women} (%)	191 (73)	54 (21)	8 (3)	–	–	–	3 (1)	6 (2)	–	1 (0)					
N_{men} (%)	29 (67)	11 (26)	1 (2)	2 (5)	–	–	–	–	–	–					

Notes. $N = 308$ students reported their age. $N = 309$ students reported their study semester.

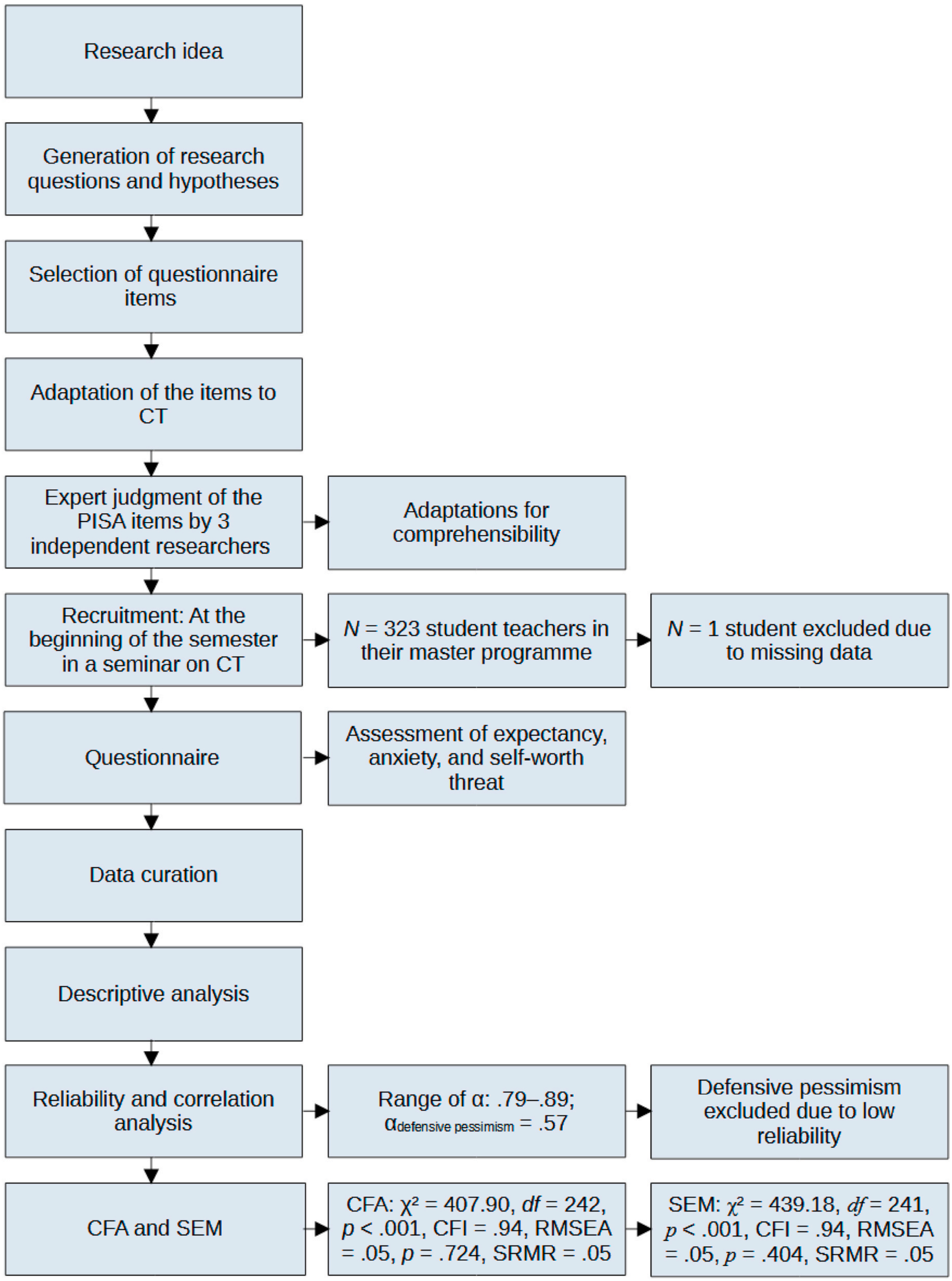

Fig. 2. Flowchart of the research procedure.

Cronbach's α of .57 and was therefore dropped from further analysis.

3.3.4. *Prior programming knowledge*

Student teachers' programming knowledge was used as a control variable and measured with two items (i.e., "*I already learned programming in school*" and "*I had already written programs before taking the seminar*").

3.4. *Data analysis*

The statistics program R, version 4.3.1 (R Core Team, 2023), was used for data analysis. The significance level was set at $p < .05$.

Descriptive statistics and correlations between variables were calculated with the R packages psych (Revelle, 2023), and car (Fox & Weisberg, 2019). To address the research questions, a structural equation model (SEM) with anxiety mediating the relation between expectancy and self-protection was calculated (see Fig. 3), using the R packages lavaan (Rosseel, 2012) and lavaanplot (Lishinski, 2021).

In the first step, we specified a confirmatory factor analysis (CFA) with full-information maximum likelihood and Yuan-Bentler correction and the latent factors *expectancy*, *anxiety*, *self-handicapping*, *avoiding novelty*, and *academic cheating* to investigate the validity of the constructs and to ensure that the latent factors can be differentiated. The CFA yielded a good fit, $\chi^2 = 407.90$, $df = 242$, $p < .001$, CFI = 0.94, RMSEA = 0.05, $p = .724$, SRMR = 0.05. Moreover, the items loaded positively and significantly (all $p < .001$) on their respective factor, lending support to the construct validity of our assessment and ensuring that the latent factors are different from each other.

Next, in order to assess whether the assumptions for SEM are met, we checked for the distribution of the variables. Specifically, we investigated univariate normality using the Shapiro-Wilk test, and multivariate normality using the Mardia's Multivariate Skewness and Kurtosis tests. Both analyses suggested that the data were not normally distributed. Thus, we used the maximum likelihood estimator and bootstrapping for standard errors (1000 draws; Brick et al., 2019).

To ensure the convergent validity of the analysis, we calculated the average variance extracted, anxiety = 0.57, expectancy = 0.30, self-handicapping = 0.32, avoiding novelty = 0.39, academic cheating = 0.67. Moreover, we calculated the composite reliability, anxiety = 0.89, expectancy = 0.68, self-handicapping = 0.69, avoiding novelty = 0.75, academic cheating = 0.86. For the average variance extracted, the minimum of 0.50 should be exceeded. This is not the case for three of our variables, i.e., expectancy, self-handicapping, and avoiding novelty. However, Fornell and Larcker (1981) suggest that if composite reliability is higher than 0.60, the convergent validity is still adequate. Therefore, convergent validity for the measurement model can be assumed.

Next, we estimated the latent correlations between constructs to ensure discriminant validity. According to Rönkkö and Cho (2022), correlations higher than .80 are a cause for concern. The correlations for our measurement model range from $r = .01$ for the correlation of expectancy with academic cheating to $r = 0.64$ for the correlation of anxiety and expectancy. Therefore, divergent validity can be assumed.

For significance testing of the indirect effects, the lavaan package, by default, reports the results from the Sobel test, which relies on the assumption that the indirect effects are normally distributed. However, since indirect effects are the product of path coefficients, they are not necessarily asymptotically normally distributed, causing the Sobel test to be underpowered. Generally, statistical procedures, such as *z*- or Wald-approximations, should not be used to test the significance of indirect effects (Ellis & Mayer, 2019). Instead, other approximation methods, such as the Monte Carlo method, are advised; thus, we used Monte Carlo confidence intervals for testing the significance of the indirect effects with the R package RMediation (Tofighi, 2023).

4. Results

4.1. Descriptive statistics and correlations

In the first step, descriptive statistics were calculated for all scales and are presented in Table 3. The mean values suggest that programming expectancy was relatively low and programming anxiety was average to slightly heightened in the sample compared to the expected mean of the scales of 1.50. Moreover, student teachers seemed to engage in at least some self-protection. Last, programming knowledge of the sample was at the low end, suggesting that most participants had little to no prior experience with CT.

The correlations of the measures are presented in Table 4. We found a negative correlation for programming expectancy with programming anxiety, $r = -.59$, $p < 0.001$, as well as a positive correlation with prior programming knowledge, $r = .32$, $p < .001$. This indicates that participants with higher expectancies of success tended to have lower levels of anxiety but were more likely to have prior experience with programming. However, programming expectancy was not correlated with any of the self-protection scales. Programming anxiety was negatively related to prior programming knowledge, indicating that participants with little to no prior knowledge tended to be more anxious about CT. Moreover, programming anxiety was positively related to avoiding novelty ($r = .24$, $p < .001$), suggesting that individuals experiencing

Table 3
Descriptive statistics.

	n	*M*	*SD*	Range
Expectancy	320	0.75	0.52	0–3
Anxiety	322	1.94	0.73	0–3
Self-handicapping	321	0.52	0.52	0–3
Avoiding novelty	320	1.34	0.58	0–3
Academic cheating	320	1.29	0.60	0–3
Prior programming knowledge	322	0.32	0.66	0–3

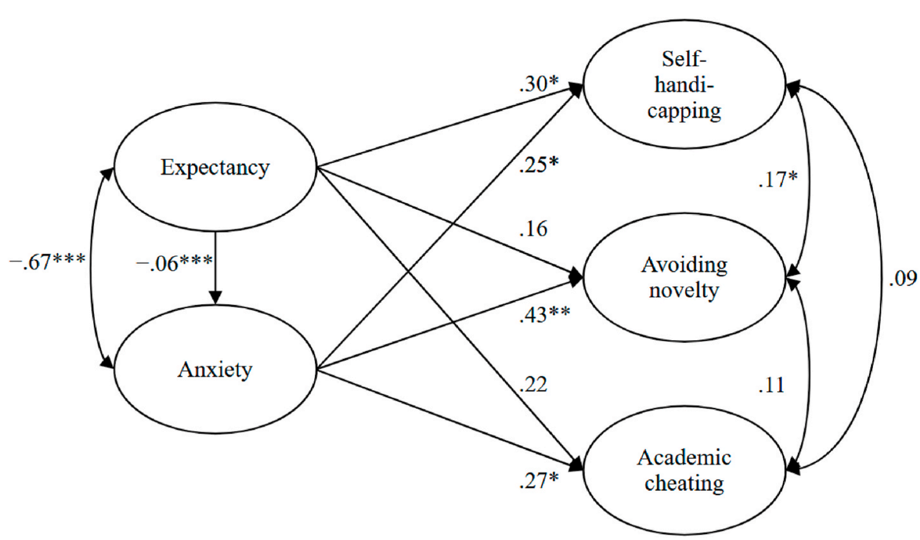

Fig. 3. Relations between expectancy, anxiety, and self-protection.

Table 4
Correlations.

	Expectancy	Anxiety	Self-handicapping	Avoiding novelty	Academic cheating
Anxiety	−.59***				
Self-handicapping	.08	.06			
Avoiding novelty	−.09	.24***	.19***		
Academic cheating	.04	.09	.12*	.15**	
Prior programming knowledge	.32***	−.26***	.06	−.02	.03

*$p < .05$. **$p < .01$. ***$p < .001$.

higher anxiety might be more likely to engage in self-protection. Last, the three self-protection scales were positively related to each other, but not to prior programming knowledge. This suggests that people who engage in one self-protective behaviour are more likely to engage in others as well. However, their prior programming knowledge does not seem to be indicative of self-protection.

4.2. Relations of anxiety and expectancy with self-protection

To investigate the relations between anxiety and expectancy with self-protection, we specified a SEM that yielded a good fit, $\chi^2 = 439.18$, $df = 241$, $p < .001$, CFI = 0.94, RMSEA = 0.05, $p = .404$, SRMR = 0.05. The hypothesised relations between the variables are presented in Fig. 3, and the direct and indirect effects are presented in Table 5.

Regarding research question 1, whether higher programming anxiety is associated with higher self-protection, the model shows positive direct effects of programming anxiety on all three self-protection scales; self-handicapping, $\beta = .25$, $p = .034$; avoiding novelty, $\beta = .43$, $p = .006$; academic cheating, $\beta = .27$, $p = .038$. This indicates that participants with higher programming anxiety were more likely to report self-protective strategies.

Regarding research question 2, whether lower expectancy is related to higher self-protection, the results of the SEM suggest that the direct effect of expectancy on self-handicapping was positive, $\beta = .30$, $p = .016$. However, expectancy had no direct effect on either avoiding novelty, $\beta = .16$, $p = .282$, or academic cheating, $\beta = .22$, $p = .115$. This implies that student teachers with higher expectancies are more likely to engage in self-handicapping, but not other self-protective behaviours.

Last, research question 3 was concerned with a possible mediating effect of anxiety on the relationships between expectancy and self-protection. The Monte Carlo confidence intervals showed that the indirect effects of programming expectancy via programming anxiety on all three self-protection scales were different from 0. This suggests significant negative indirect effects of programming expectancy on all self-protection scales. The total effect was not significant, which might be explained by the negative indirect but positive direct effect of expectancy on the self-protection scales. More specifically, if the indirect effect is negative and the main effect of a predictor is positive, these effects oppose each other and thus the total effect mathematically will be either weakly positive or negative. This can lead to significant direct and indirect effects with the total effect being nonsignificant. According to Preacher and Hayes (2008), the indirect effect is more important when interpreting the mediation model than the total effect. Thus, taken together, the results suggest that anxiety mediates the effect of programming expectancy on self-protection.

Table 5
Results of the SEM.

	Direct effects		Indirect effect of expectancy	Total effect
Outcome variables	Anxiety	Expectancy	Via anxiety [95% CI]	
Total	–	–	–	.56
Anxiety	–	−.06***	–	–
Self-handicapping	.25*	.30*	−.02 [−.03; −.00]	–
Avoiding novelty	.43**	.16	−.03 [−.06; −.01]	–
Academic cheating	.27*	.22	−.02 [−.05; −.00]	–

Notes. CI = Confidence intervals obtained by the Monte Carlo method, *p*-values are not available for this method.
*$p < .05$. **$p < .01$. ***$p < .001$.

5. Discussion

Implementation of CT into primary school classrooms can only be successful, if the teachers are on board with teaching the subject (Butler & Leahy, 2021; Weber et al., 2022; Yadav et al., 2014). Therefore, investigating underlying reasons for possible personal hindrances such as potential self-worth threats can inform the design of university teacher education curricula to alleviate anxiety and increase expectancies of success. Thus, in this study, we examined whether engaging with CT can pose a self-worth threat to primary school student teachers in a sample of $N = 323$ with generally low prior programming knowledge. On the backdrop of three research questions, the results suggest that (a) programming anxiety was positively related to higher levels of self-protective behaviours, (b) programming expectancy was related positively to self-handicapping but not to other self-protective behaviours, (c) programming anxiety mediates the effect of programming expectancy on self-protective behaviours. These findings contribute to the literature on preparing student teachers to implement CT as a 21st century skill into future primary school classrooms.

In line with the literature and our assumptions that students who report programming anxiety would also be more likely to report self-protective behaviours (research question 1), we found that programming anxiety and self-protective behaviours were positively related (Covington, 2009; Del Ferradás et al., 2019; Fairlamb et al., 2022). The results suggest that preschool teachers with higher levels of anxiety reported higher levels of all three self-protective behaviours that were assessed, i.e., self-handicapping, avoiding novelty, and academic cheating.

Contrary to the literature (Lee et al., 2013) and our expectations that lower expectancy would be related to higher levels of self-protective behaviours (research question 2), expectancy had a positive direct effect on self-handicapping behaviour, whereas the direct effects on avoiding novelty and academic cheating were non-significant. This is also in line with the manifest correlations we found (see Table 4), which showed no relation between expectancy and self-protective behaviours. However, when the indirect effect via anxiety was accounted for, expectancy had a negative effect on all three self-protective behaviours (research question 3, Lee et al., 2013). Thus, the relation between expectancy and self-protective behaviours is only negative if anxiety has been accounted for. A reason might be that low expectancy is only a driving force for self-worth threats if an individual experiences anxiety (Del Ferradás et al., 2019; Fairlamb et al., 2022; Jiang et al., 2020; Lee et al., 2013). The results support the work by Covington (2009) and suggest that low expectancy per se is not a reason for experiencing a self-worth threat as students might just not care whether they will fail in a subject or task (*failure acceptors*). However, if they are highly anxious about failure, they are likely to experience a self-worth threat (*self-protectors*) and engage in self-protective behaviours.

Taking a closer look at the negative indirect effect of expectancy via anxiety on the self-protective behaviours, the results suggest that over-strivers (high expectancy, high anxiety) tend to engage less in self-protective behaviours. These students tend to experience low levels of self-worth threats (Covington, 2009; Leis et al., 2022; Martin et al., 2003), and instead of engaging in self-protective behaviours, they tend to invest effort driven by their higher expectancies and anxiety of failure. However, the indirect effect also suggests that self-protectors (high anxiety, low expectancy) engage in self-protective behaviours more frequently and were thus more likely to, e.g., report self-handicapping as in creating obstacles to invest low effort into CT. For example, they reported going out the evening before an important assignment was due or waiting until the last minute to work on a task. In general, self-handicapping might be the most effective self-protection strategy. When a student fails, they can attribute their failure to their lack of preparation. However, if they succeed, they can be especially proud of the result they did not adequately prepare for, because it must mean that they are very capable in the subject at hand (Schwinger et al., 2014). Moreover, as shown in the inter-correlational relationships between three self-protection scales, self-protectors were also more likely to report a general dislike of novelty, e.g., that they would have preferred learning about a STEM subject they were already familiar with instead of CT. This might point to a general fear of novelty. Future research might establish a link to the openness and neuroticism factors of the Big 5 model. Last, self-protectors were also more likely to report academic cheating, underlining that they would rather not engage with CT at all, but find solutions online or copy from other students. With all these behaviours, anxious students seemingly try not to engage with CT in order to avoid failure (Lee et al., 2013). In consequence, they probably will not acquire the CT skills necessary to teach CT to their future students.

5.1. Limitations

Limitations of the study concern the sample and the assessment of the measures. First, the sample consisted of primary school student teachers who were primarily female. Studies have shown that women tend to face increased levels of anxiety and low expectancies towards STEM subjects such as CT (Marsh et al., 2019; Weber et al., 2022). Potentially, results would have differed in a sample consisting of a similar ratio of women to men. Nevertheless, in Germany most primary school teachers are female, similar to most other OECD countries as well (OECD, 2021). Therefore, the results are relevant in this context.

Regarding the assessment, we did not assess CT skills and thus cannot make any statements on whether CT skills might have affected the experience of self-worth threats or the relations between self-protective behaviours and expectancy or anxiety. In general, the sample had little prior programming experience, yet even though programming is an integral part of CT, CT also encompasses broader problem-solving competencies (Shute et al., 2017). Maybe student teachers with higher CT or problem-solving skills had higher expectancies and lower anxiety levels and thus were less likely to experience a self-worth threat. This finding could have far-reaching practical implications for university education and even school education and could be investigated in a future study.

Last, we only used self-report measures in this study. Therefore, we do not know whether the student teachers followed through with the self-protective strategies they reported. A future study could investigate self-protective behaviours in a more behaviour-based way.

6. Conclusion

Our results have practical relevance for (primary school) teacher education. To help student teachers benefit the most from their university education, especially in subjects like CT where they might feel less confident and more anxious, specific measures can be implemented. These measures aim to prevent students from experiencing a self-worth threat, ensuring their active engagement with the content. This can then support students' learning of the subject at hand, in our case of CT. To achieve this, students' anxiety should be alleviated, and their expectancies increased. In the field of CT, some researchers have already started to target students' expectancies (Jaipal-Jamani & Angeli, 2017; Yadav et al., 2014) as well as anxiety (Weber et al., 2022). They found that helping student teachers to engage with the subject in meaningful ways, such as working with robots in a science teaching class, and using block-based programming languages (e.g., Scratch, NEPO) that are easy to implement in the classroom (Kong & Lai, 2022; Weber et al., 2022), increase expectancies of success and decrease anxiety. Our study highlights the importance of such programmes to ensure that student teachers do not fall behind on the acquisition of important skills because they engage in self-protective behaviours. Future research can investigate ways to engage student teachers in CT without leaving anyone behind.

In conclusion, our study sheds light on underlying reasons for primary school teachers' hesitancy to teach CT to children and offers insights into possible ways of alleviating self-worth threats. Our results caution against student teachers' potential self-worth threats in STEM topics and the way they can potentially affect teaching practice and children's learning in the 21st century.

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Veronika Barkela: Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Areum Han:** Writing – review & editing, Visualization, Methodology, Formal analysis, Data curation. **Anke Maria Weber:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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