Development of a Questionnaire on Self-concept, Motivational Beliefs, and Attitude Towards Programming

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ABSTRACT

Academic self-concept, motivational beliefs, and attitudes towards a school subject are relevant for learning and educational achievement. A positive self-concept in science and mathematics is argued to motivate students to persist and advance in studying these subjects. In particular, self-concept, motivational beliefs, and attitudes towards STEM domains were found to be predictive of educational achievement. Recently, programming was suggested to be a key competence in education.

To assess self-concept, motivational beliefs, and attitudes towards programming, we developed a new questionnaire based on existing scales for mathematics. The new questionnaire assesses the same aspects for programming on seven subscales, such as self-concept, belief about usefulness, and self-reported persistence when working on programming tasks.

We conducted a pilot study in which we used this questionnaire to measure self-concept, motivational beliefs, and attitudes towards programming. The study was set in the context of an extracurricular course on computational thinking (CT) for elementary school students between the ages of seven and ten years. Before the start of the course, we assessed all 31 participating students' self-concept, motivational beliefs, and attitudes towards programming using the developed questionnaire and their CT skills using the Computational Thinking test (CTt).

Our results confirmed the expected associations between the aspects assessed by our questionnaire. However, we did not find significant associations of questionnaire results and CT skills. Consequently, future research involving a larger sample is needed to better understand the association between children's actual performance and their self-concept, motivational beliefs, and attitudes towards programming.

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CCS CONCEPTS

• **Social and professional topics → Computer science education**; **K-12 education**; **Computational thinking**; *Computing literacy*; • **Applied computing** → *Education*.

KEYWORDS

computer science education, computing education, computational thinking, computing literacy

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1 INTRODUCTION

1.1 Academic Self-concept, Motivational Beliefs, and Attitude

Academic self-concept, motivational beliefs, and attitude were repeatedly observed to be significant predictors of learning progress and achievement [24, 38, 48, 51]. In particular, a positive self-concept in science and mathematics has been found to motivate students to persist and advance in their studies of science and mathematics [1, 21, 51]. Additionally, motivational beliefs and self-concept in science have been shown to reliably predict academic achievement [28, 51]. Considering this impact of academic self-concept, motivational beliefs, and attitude towards STEM (Science, Technology, Engineering, Mathematics) subjects, it seems worthwhile to measure, monitor, and foster these variables in students – in particular because individuals trained in STEM competencies have increasing employment market opportunities with high monetary compensation and social recognition [27].

Importantly, in addition to STEM competencies, the increasing importance of computer science in general and programming in particular was emphasized repeatedly in recent years (e.g., [2, 18, 34]). So far, however, few studies evaluated the relevance of students' academic self-concept, motivational beliefs, and attitude towards programming. Therefore, the current study aimed at piloting a questionnaire on academic self-concept, motivational beliefs, and attitude towards programming based on an existing one for mathematics [4, 13, 38]. The same mathematics questionnaire was previously adapted and validated for other school subjects, such as biology, physics, English, and German [14].

Because the developed questionnaire is based on existing instruments for other school subjects, it would allow for assessing academic self-concept, motivational beliefs, and attitude towards programming in relation to and comparable to the same constructs for other subjects. The availability of instruments for assessing the same constructs across various school subjects would offer possibilities for research on the relationship between self-concept, motivational beliefs, and attitude in different subjects. In the following, we will first describe the constructs assessed by the questionnaire before we report empirical results of a first pilot study.

1.1.1 Constructs Measured by the Developed Questionnaire. The questionnaire we developed assesses the following aspects of academic self-concept, motivational beliefs, and attitude towards programming as well as students' self-reported previous experience and understanding of programming on seven subscales.

i) The first subscale measures students' self-reported *previous experience and understanding of programming*. Importantly, this aspect is not modeled on the existing questionnaire on mathematics. However, we included it because this scale may provide important information on the background against which the results on the other scales need to be interpreted.

ii) *Self-concept with regard to programming* is assessed on the second subscale. Academic self-concept has been defined as a person's self-perception with respect to achievement in school [31]. Correspondingly, individuals' self-concept regarding a specific subject reflects their confidence in their own ability to do well in that subject [31, 51]. Positive self-concept was found to be an important predictor of achievement in a subject: when students have no confidence in their ability to perform well in a subject, they have no reason even attempting to succeed [28].

Motivational beliefs are individual beliefs about a subject that motivate or demotivate a student to engage with a subject and make the effort required for achieving in it. Thus, these beliefs reflect the motivational value a person attributes to a subject or task and therefore are also termed value beliefs. Positive motivational beliefs have been associated with students' persistence in attempting to perform well even when their interest and intrinsic enjoyment of the subject decrease [28]. As specified in expectancy-value theory, Eccles et al. differentiate between four aspects of motivational value belief: intrinsic value belief, attainment value belief, utility value belief, and cost belief [11, 49]. Accordingly, we assess these aspects in four further subscales:

iii) *Intrinsic value belief about programming* is measured on the third subscale. Intrinsic value belief with respect to a subject is defined as the degree to which a person intrinsically enjoys and is interested in the subject. This construct reflects a person's attitude towards the subject. While a positive attitude towards a subject is not a necessary requirement for achievement, it can support and increase a student's engagement in a subject [28]. Furthermore, intrinsic value belief about a subject is a predictor for students' voluntary engagement with a subject in their leisure time [10, 25].

iv) The fourth subscale assesses *attainment value belief about programming*. With regard to any specific subject, attainment value belief reflects the importance an individual places on a subject [13].

v) *Utility value belief about programming* is measured on the fifth subscale. Utility value belief about a subject represents an individual's expectation of the subject's usefulness in different areas of life, such as everyday life, school, future career, or social life [13].

To distinguish between the terms, intrinsic value belief and attainment value belief are considered intrinsic motivational factors, while utility value belief is seen as an extrinsic motivational factor [41]. All three of these beliefs have been linked with future career ambition and selection of classes [10].

vi) The sixth subscale assesses students' *cost belief about programming*. This belief about a subject reflects the negative consequences a person expects to result from engaging in the subject, including assumed effort and exhaustion as well as negative emotions [13, 30].

Including such a broad spectrum of motivational beliefs in the questionnaire is one of its key strengths, as covering these four dimensions makes education attitude questionnaires powerful for predicting academic choices [50]. In qualitative analyses, intrinsic value belief – or enjoyment –, utility value belief, and cost belief have already been established as important factors influencing students' decision whether or not to pursue further education in computer science [23].

vii) Finally, *compliance and persistence with regard to programming* are measured on the seventh subscale. These variables were characterized as indicators for students' thoroughness in working on a task as well as their resilience in the face of challenging tasks [38]. Correspondingly, high persistence and compliance have been linked to better learning achievement [38].

In the present study, we evaluated these seven variables' correlation with each other and with students' computational thinking

(CT) abilities as a cognitive skill underlying programming and coding. We used an adapted version of the Computational Thinking test (CTt) [33] to measure students' ability to understand and apply CT concepts.

1.2 Related Work

1.2.1 Instruments for Assessing Students' Attitude towards Computing and Programming. To allow for an assessment of students' interest in or attitudes towards computing, some questionnaires have been developed in recent years. These questionnaires may broadly be divided into two categories: one subsuming questionnaires pertaining more narrowly to computer science or computing, and the other to computer use or interaction with computing devices more generally.

The first category includes questionnaires such as the Computing Attitudes Survey (CAS). The CAS was developed to assess students' attitudes and beliefs about problem solving and the nature of knowledge within computer science [9]. Four of the instrument's 26 items assess personal interest in and enjoyment of computer science, while the remaining 22 items were designed to assess students' self-estimated computing-related abilities, such as coming up with specific problem solving strategies. Items were mostly modeled on items of existing instruments for other subjects, such as biology [12]. Validity of the CAS instrument was evaluated for target groups in post-secondary computing education [9].

Other instruments in this category include a two-part questionnaire for measuring high school students' attitudes towards computing [15] and the Computer Science Attitude Survey [16]. The former includes two scales with the same five subscales each – one scale for "computer science" and one for "information technology" [15]. The latter has been developed for assessing science and engineering students' attitudes toward computer science and is aimed at undergraduate college students [16].

These instruments are all aimed at either high school or college students and their items are phrased to be appropriate and comprehensible for this target group. However, they would be inappropriate for a target group at elementary school age for several reasons. First, regarding grammar and vocabulary, their items seem too complex for younger children. Secondly, they have in part been developed for a target group with previous experience in computer science (e.g. CAS, [9]). Second, they aim at assessing attitude toward computer science, computing, or information technology – terms and domains which are unlikely to be comprehensible or familiar for students significantly younger than high school age.

The second category of instruments includes questionnaires aimed at assessing attitudes toward computer use or interaction with computers, such as the Microcomputer Beliefs Inventory (MBI) [32]. This instrument consists of 26 items for measuring self-efficacy and outcome expectancy beliefs regarding computer use and is aimed at middle school students [32].

Another instrument from this category is a questionnaire comprising 21 items for assessing attitudes towards interacting with computers in high school students between the ages of 16 and 19 years [36].

The instruments from this second category are mostly targeted at middle or high school students and therefore at a slightly younger target group than those from the first category. Additionally, they do not require previous experience in programming or computer science. On this basis, these instruments could more easily be adapted for assessing elementary school students than instruments from the first category. However, assessing attitude towards computer use or interaction with computing devices is not equivalent to assessing attitude towards the more narrowly defined domain of computing.

For these reasons, existing instruments from either of these two categories appear unsuited for being used or adapted for assessing elementary school students' attitude towards programming, either due to being too complex and requiring too much previous knowledge and experience, or due to not being domain-specific enough.

This motivated our decision to develop a new instrument for specifically assessing academic self-concept, motivational beliefs, and attitude towards programming partly based on instruments for assessing the same constructs for other subjects in students of the same age group.

1.2.2 The Role of CT. The idea of CT was first described by Seymour Papert [29], referring to cognitive processes that play a fundamental role in the systematic development of computational procedures. Today, the term is being used more broadly.

Jeannette Wing [52] characterized CT as an essential ability for understanding, formulating, and solving complex problems, which often requires partitioning, abstraction, generalization, parameterization, modeling, and algorithmization. Such solution approaches are typically strategic, systematic, abstract, reproducible, algorithmic, and, most importantly, computable. Nevertheless, it does not matter whether a person or a machine is going to execute the resulting computation [52].

For the purpose of introducing young students to programming, such algorithmic solutions have been identified as consisting of a basic set of CT concepts, such as sequences, loops, events, conditional branching, operators, and data [3].

While some argue CT to reflect conceptual competences obtained through – and therefore intrinsically linked to – programming and studying computer science [26], others frame it as a new and fundamental way of thinking with problem-solving benefits superior to other ways of thinking, as pointed out by Denning et al. [8]. Other definitions portray CT as a cognitive skill in addition to reflecting the practical skill of programming [37] and thus emphasize the wide spectrum of CT applicability. Therefore, CT is also suggested to be a 21st century skill [45, 53], which is valuable to be acquired and developed already in early education [53].

In recent years, the idea of CT has been the focal point of continuous discussion and attention. However, the notion that underlying concepts are the most important part of computer science is not new, but has already been emphasized by Donald Knuth [20].

In summary, when we refer to CT, we consider it the conceptual core of computing describing principles and methods rather than specific tools or technological systems [26].

1.3 Aim of the Study

The present pilot study aimed at providing a first indication of the potential validity of our newly developed questionnaire for assessing children's academic self-concept, motivational beliefs, and attitude towards programming. We approach the validation process by first utilizing the instrument in this pilot study to appraise its general usability before initiating a full validation study.

We expected the questionnaire results for the seven subscales of academic self-concept, motivational beliefs, and attitude to be correlated because they are designed to measure related constructs (for similar results on mathematics, see [13]). However, we neither expected correlations to approach 1, nor all subscales to be correlated significantly because they assess different aspects of academic self-concept, motivational beliefs, and attitude towards programming. These expectations mirror the correlation pattern found for the mathematics-related questionnaire on which the developed questionnaire is based [4, 13].

In particular, we expected *programming self-concept* to correlate with *intrinsic value belief* and *compliance and persistence with respect to programming*, as well as with *CT performance*, because students' mathematics self-concept was found to strongly predict students' intrinsic value belief, persistence, and performance in mathematics (e.g., [7, 24, 40]). Furthermore, confidence as part of self-concept, and interest, which is an element of intrinsic value belief, were previously observed to be significantly correlated in computer science education [46].

We also expected a positive correlation between *programming self-concept* and *utility value belief about programming*, because positive associations were found between students' utility value belief about mathematics and their mathematics self-concept (e.g., [6, 17, 39]).

Moreover, *intrinsic value belief* about mathematics was found to be highly correlated with *cost belief* regarding mathematics [13]. Therefore we expected to replicate this association for the case of programming.

Finally, we expected *self-concept*, *motivational beliefs*, and *compliance and persistence* to be correlated with *CT performance*, as these variables have been found to be predictors of achievement in other subjects (e.g., [24, 28, 48, 51]).

2 METHODS

2.1 Participants

In this pilot study, we evaluated test and questionnaire data from 31 elementary school students between the ages of 7 and 10 years (M = 9.47; SD = 0.76) from 3rd and 4th grade who participated in a CT course at four Hector Children's Academies in Baden-Württemberg, Germany. The Hector Children's Academies offer extracurricular enrichment programs for elementary school children. Students are nominated for the program by their elementary school teachers based on their achievement in school. Nominated students can then select courses from the local academy's program and attend them free of charge. There are currently more than 60 Hector Children's Academies.

Participation in the study was voluntary. We obtained informed consent from each of the students as well as from their parents before they participated in the study.

2.2 Study Design

We piloted the questionnaire in the pretest and posttest evaluating a newly developed CT course. One week before the first course lesson, all participating students attended a pretest and one week after the end of the course, they attended a posttest session. These took place in classrooms of the children's schools. Students filled out anonymized paper tests and questionnaires.

In the present article, we focus on students' ratings of their academic self-concept, motivational beliefs, and attitudes towards programming at the pretest to evaluate their answers to the developed questionnaire before they attended the course. To identify potential effects of these variables on CT ability, we also assessed students' performance in the CTt at pre- and posttest time and calculated the increase in performance.

2.3 The CT Course

We utilized the new questionnaire in the context of a CT course consisting of ten lessons, each of them 90 minutes long, with students attending one lesson per week. The course aims to foster programming skills, systematic problem-solving ability, and interest in computation-related topics. Its purpose is to help students develop an initial understanding of basic programming concepts and their applications – both in the digital and the non-digital world.

In the course [44], students are introduced to basic concepts of CT, specifically sequencing, loops, parallelism, events, conditionals, operators, and data/variables (e.g. [3]). They course activities allow students to make use of CT processes, such as algorithmic thinking, conditional logic, decomposition, abstraction, pattern matching, parallelization, evaluation, and generalization (e.g. [18]). CT concepts and processes are taught using unplugged activities like the life-size educational board game "Crabs & Turtles: A Series of Computational Adventures" [43] as well as plugged-in activities making use of the educational visual block-programming language Scratch, the Scratch extension S4A (Scratch for Arduino), the Arduino open hardware platform and the Open Roberta Lab, a robots programming environment. Unplugged game-based methods for teaching CT were observed to support elementary school students' understanding of CT concepts [22], while plugged-in activities provide the opportunity for applying these concepts. The objective of the CT course is for students to get to know basic CT concepts and gain first experiences in programming while applying these concepts. Tsarava et al. provide a more detailed description of the CT course, its contents, methods, and learning objectives [42].

2.4 Measurements

2.4.1 *The New Questionnaire.*

The developed questionnaire assesses different aspects of academic self-concept, motivational beliefs, and attitude towards programming on seven subscales, comprising four to twelve four-point Likert-scale items each. The subscales for assessing academic self-concept, motivational beliefs, and persistence regarding programming were developed based on an existing validated questionnaire for assessing academic self-concept and motivational beliefs related to mathematics [4, 13, 38]. Items were adapted by replacing the word "mathematics" with the word "programming". The same adaptation procedure was used in previous studies for adapting the mathematics instrument for the subjects biology, physics, English, and German [14]. All four instruments developed this way were validated in a study with 830 participants [14].

In a first step, we identified critical terms to represent the focal area of the instrument. Despite the terms *programming* (German *Programmieren*) and *computer science* (German *Informatik*), we did not consider *computing* and *computational thinking*, both of which have no direct translation or commonly used equivalent in German. Other potential focal terms, such as *computer use* (German *Computernutzung*), we found too broad in scope to assess students' attitude towards computing-related activities.

To evaluate the appropriateness of the wording of the adapted questionnaire for 3rd and 4th graders (the math version was initially developed for 5th graders), we asked children attending a pre-pilot session of the CT course whether they had heard the focal terms *Informatik* or *Programmieren* before. In case they responded positively, we asked them to explain what they understood the respective word to mean. While only some of the children had heard the word *Informatik* before and none of them were able to explain its meaning, all children had heard the word *Programmieren* before and were able to either give a basic explanation or provide examples of what programming activities could look like. Thus, we decided on using the word *programming* (German *Programmieren*) as the focal word of the instrument, constituting a compromise between subject specificity and comprehensibility for 3rd and 4th grade students.

The additional subscale for assessing previous experience and understanding of programming was not modeled on the existing questionnaire on mathematics, but was developed new. We included it to provide important information on the background against which the results on the other subscales need to be interpreted.

The scales and their items are worded in German, but examples in this article are presented in English. The seven subscales were set up the following way:

- *(P1) self-reported previous programming experience and understanding*: four items, e.g. "I can explain what the word 'programming' means."
- *(P2) programming ability self-concept*: four items, e.g. "I am good at programming."
- *(P3) programming intrinsic value belief*: four items, e.g. "I enjoy programming."
- *(P4) programming attainment value belief*: seven items, e.g. "Being good at programming means a lot to me."
- *(P5) programming utility value belief*: twelve items, e.g. "Being able to program has a lot of advantages in school."
- *(P6) programming cost belief*: eleven items, e.g "After I work on programming tasks, I often feel exhausted."
- *(P7) self-reported programming compliance and persistence*: eight items, e.g. "Even when programming tasks get challenging, I try to do my best."

All items for these scales are Likert-type, therefore participants respond by means of checking one of four boxes indicating ordinal responses (1 = agree completely; 2 = rather agree; 3 = rather do not agree; 4 = do not agree at all). This means that a low result for each of the variables indicates a high score on the respective construct. For example, an average of 1.72 for *(P2)* implies students on average have a positive *self-concept in programming*.

The scales include reversed items to filter out invalid responses by detecting inconsistencies between responses to positively phrased items and potentially contradicting responses to their negatively phrased counterpart items [19]. Responses to these items were recoded prior to analysis.

2.4.2 TIMSS 2015 Context Questionnaire. Because a relevant share of correlations found in educational research can be explained by effects of socioeconomic status [27], we assessed selected aspects of students' socioeconomic background as well as their access to digital technology:

- *(lang) frequency of German language being spoken in the student's home*: four response options (from 1 = "I always speak German at home" to 4 = "I never speak German at home")
- *(soc) possession of wealth-indicating items in the student's home as an indicator of socioeconomic status*: eleven items with "yes"/"no" responses; total number of "yes" responses checked constitutes the score for this variable
- *(use) frequency of computer/tablet use at home, in school, or elsewhere*: three items, one each for home, school, and elsewhere; four response options (from 1 = "daily or almost daily" to 4 = "never or almost never")

These variables were assessed using scales 3, 5, and 6 of the Trends in International Mathematics and Science Study (TIMSS) 2015 Context Questionnaire [47].

2.4.3 CT Performance Assessment (CTt). To test students' CT ability – specifically for recognizing and understanding sequences, loops, events, conditional branching, operators, variables, and functions – we used the CTt [33], which originally consists of 28 items. However, because it has been validated for students of age 12 and 13, which is slightly above the age group of our sample, we used only the 21 items of lowest difficulty as indicated by the item difficulty ranking [33]. In particular, we selected items 1, 2, 3, 4, 5, 6, 7, 9, 10, 11,13, 14, 17, 18, 19, 20, 21, 24, 26, 27, 28.

We calculated the following variables from the CTt:

- *(prCTt) number of correctly solved CTt items at pretest time*
- *(poCTt) number of correctly solved CTt items at posttest time*
- *(gainCTt) = (postCTt) - (prCTt)*

2.5 Statistical Analysis

All statistical analyses were performed using IBM SPSS Statistics 25. To assess the relationship between the variables *(P1)*, *(P2)*, *(P3)*, *(P4)*, *(P5)*, *(P6)*, *(P7)*, *(lang)*, *(soc)*, *(use)*, *(prCTt)*, *(poCTt)*, and *(gainCTt)*, we calculated bivariate Pearson correlations.

Through a systematic search for contradictory answers to items within the same subscale using reversed items, we identified two students who each had only checked answer boxes on the same side of the Likert scale for three of the subscales. We therefore followed the suggested approach of labeling these values as invalid and excluded the variables for the respective subscales of these two students' responses from the analysis [19].

2.5.1 Missing Data. Out of 31 students participating in the course, one did not attend the pretest due to illness. Four students did not attend the posttest; three of them had been ill and one had dropped out of the course. The range of missing data due to absence, nonresponse, or invalid response was between 3.2 % and 22.6 % per item. Please note these percentages include the missing data due to absence of the five students who only attended either the pretest or posttest.

We used the multiple imputation algorithm integrated into IBM SPSS Statistics 25 to impute the missing data. When performing a multiple imputation, each missing item is replaced by a list of $m > 1$ simulated values for the respective item [35]. This generates m plausible versions of the dataset. When analyzing an imputed dataset, the same analysis is calculated for each of the m datasets and the results are combined into an overall estimate whose standard errors reflect missing-data uncertainty and finite-sample variation [35].

Multiple imputation is a mathematically sophisticated missing data treatment method which realistically models random variation [5]. It represents the state of the art of missing data treatment [35] and has been recommended for educational research [5]. Especially for smaller sample sizes, multiple imputation provides high accuracy of estimation and, on average, performs better than other missing data treatment methods [5].

3 RESULTS

Our results showed *(soc) possession of wealth-indicating items in the student's home as an indicator of socioeconomic status* (M = 4.18; SD = 1.80) and *(lang) frequency of German language use at home* (M = 1.33; SD = 0.48) to have no significant correlation with any of the self-concept, motivational beliefs, attitude, or CT performance variables. Therefore, we can conclude that language and socioeconomic status as measured by the TIMSS 2015 scales had no effect on the other variables. Consequently, we dropped *(lang)* and *(soc)* from the correlation table (see Table 1), and it was not necessary to consider them as control variables in a partial correlation analysis.

Part of the analyzed variables were non-normally distributed. Technically, this violates the assumption of normal distribution which usually needs to hold true for many analyses to be valid. However, Pearson correlation analyses specifically have a high robustness towards violation of normality and can therefore also be calculated for non-normally distributed variables (e.g. Field, 2000, p. 87).

When assessing the relationship between variables *(P1)*, *(P2)*, *(P3)*, *(P4)*, *(P5)*, *(P6)*, *(P7)*, *(lang)*, *(soc)*, *(use)*, *(prCTt)*, *(poCTt)*, and *(gainCTt)*, we found 13 significant correlations (see Table 1).

In accordance with our expectations, we found *(P2) programming self-concept* (M = 1.64; SD = 0.49) to be significantly correlated with *(P3) intrinsic value belief* (M = 1.35; SD = 0.48), *(P5) utility value belief* (M = 1.93; SD = 0.63), and significantly correlated with *(P7) self-reported compliance and persistence* (M = 1.55; SD = 0.55). Thus, children who reported high scores on programming self concept also reported high scores on intrinsic value belief, utility value belief, and compliance and persistence.

Likewise, we observed the expected correlation between)*(P3 intrinsic value belief* and *(P6) cost belief* (M = 3.23; SD = 0.54). These two variables were significantly but negatively correlated. Due to the nature and direction of these two scales, this result indicates that children who reported high interest in and enjoyment of programming on the one hand also reported little negative consequences or emotions, such as exhaustion, on the other.

In addition, our results showed *(P2) self-concept* as well as *(P7) compliance and persistence* to be correlated significantly but negatively with *(P6) cost belief*. This reflects a relationship between little expected negative consequences or emotions associated with programming and, respectively, positive programming self-concept or high compliance and persistence.

Furthermore, we found a significant correlation between *(P3) intrinsic value belief* and *(P5) utility value belief*. This means that students who reported high enjoyment of and interest in programming also considered programming to be useful.

We also found *(P4) attainment value belief* (M = 1.81; SD = 0.72) to be highly significantly correlated with *(P5) utility value belief* and significantly correlated with *(P7) compliance and persistence*. Thus, there seems to be a relationship between placing high importance on programming one one hand, and regarding programming as useful and working on programming tasks thoroughly and resiliently on the other.

The results also indicated *(P1) previous programming experience and understanding* (M = 1.66; SD = 0.57) to be significantly correlated with *(P2) self-concept* and highly significantly correlated with *(use) frequency of computer/tablet use at home, in school, or elsewhere* (M = 2.79; SD = 0.90). This result indicates that students who already have some experience in and understanding of programming also have a positive programming self-concept and tend to use computers or tablets more frequently.

Contrary to our expectations, we found no significant correlations between *CT performance at pretest* (M = 11.55; SD = 3.61), *posttest* (M = 14.22; SD = 3.79), or *CT gain* (M = 2.96; SD = 4.53), and any of the self-concept, motivational beliefs, or attitude variables. This may indicate a lack of relationship between self-concept, motivational beliefs, and attitude variables, but may also be related to other reasons, which we discuss in section 4.1 on potential limitations of the current study.

4 DISCUSSION

This pilot study set off to develop a new questionnaire on self-concept, motivational beliefs, and attitudes towards programming. We modeled several subscales of the instrument on existing instruments for other subjects and applied it in a first pilot study to evaluate the general feasibility of our approach.

As shown by the results of the correlation analysis (see Table 1), academic *self-concept with regard to programming* correlated significantly with other subscales, namely with *intrinsic value belief*, *utility value belief*, *cost belief*, and self-reported *compliance and persistence*. This is not surprising, considering the central role self-concept plays as a prerequisite for achievement in a subject and as a deciding factor in whether a person attempts to succeed in a subject or not [28].

When examining the correlation pattern for the four motivational value beliefs – *intrinsic value belief*, *attainment value belief*, *utility value belief*, and *cost belief* – it is worth noting that they correlate significantly with each other and other variables such as

Table 1: Correlation between questionnaire variables, frequency of computer/tablet use, and CTt performance

Variable name	(P1)	(P2)	(P3)	(P4)	(P5)	(P6)	(P7)	(use)	(prCTt)	(poCTt)
(P1) self-reported programming understanding										
(P2) programming ability self-concept	.415*									
(P3) programming intrinsic value belief	.358	.414*								
(P4) programming attainment value belief	.064	.312	.225							
(P5) programming utility value belief	.210	.391*	.386*	.621**						
(P6) programming cost belief	-.175	-.544**	-.373*	-.253	-.102					
(P7) programming compliance and persistence	.057	.594**	.336	.407*	.310	-.483**				
(use) frequency of computer/tablet use	.472**	.188	.393	-.016	.114	-.026	.168			
(prCTt) CTt performance before training	-.156	-.278	.023	-.069	.012	.322	-.207	.005		
(poCTt) CTt performance after training	.170	-.058	.191	-.162	.068	.102	-.254	.066	.208	
(gainCTt) CTt performance gain	.259	.172	.137	-.077	.045	-.178	-.038	.048	-.623**	.635**

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

self-concept and *compliance and persistence*. Hence, they seem to constitute an integral part of the questionnaire.

Overall, the pattern of correlations among the subscales for self-concept, motivational beliefs, and attitude towards programming was very similar to the pattern observed for the same constructs on mathematics. In turn, this implies similar relationships between the variables within the newly developed questionnaire on academic self-concept, motivational beliefs, and attitudes towards programming as compared to the validated questionnaire on mathematics. Accordingly, this is first evidence for the validity of the newly developed questionnaire.

Unsurprisingly, we found self-reported *previous experience and understanding of programming* to be significantly correlated with *frequency of computer/tablet use at home, in school, or elsewhere.* This may imply students might have uninformed assumptions about computer or tablet use being closely connected with programming skills. On the other hand, this result may also reflect that students who already have some previous programming experience also are the ones who use computers or tablets more frequently. Because of the correlational results, no causal interpretation is possible.

Because the proposed instrument for assessing self-concept, motivational beliefs, and attitude towards programming is based on existing instruments for other school subjects, it allows for these attitudinal constructs to be assessed in relation to and comparable with these other subjects. This is an asset of the new questionnaire, as it is so far not clear whether the working mechanisms underlying influences of academic self-concept, motivational beliefs, and attitude towards specific subjects are comparable across subjects or not. A questionnaire allowing for the assessment of these same constructs across different subjects would make it possible to investigate whether these factors have the same influence on programming as they do on other subjects, and whether attitudes might be correlated across subjects.

Considering the educational impact of students' academic self-concept, motivational beliefs, and attitude towards programming and the increasing importance of the topic itself, it would be desirable to assess these constructs reliably. A validated questionnaire – based on the results of the present pilot study – for measuring them would allow for the assessment of the effects of specific programming, CT, or computer science programs or curricula on these constructs, which have been observed to strongly influence students' educational achievement and academic trajectories in other subjects such as mathematics (e.g. [24, 38, 48, 51]). In turn, any changes of these variables may be regarded as an indicator for the quality of a program or curriculum in terms of teaching methodology and fostering of student motivation.

4.1 Limitations

Unlike with other subjects (e.g. [28, 51]), our expectations of finding correlations between self-concept, motivational beliefs, and attitude towards programming on one hand and CT performance variables on the other could not be confirmed. Importantly, this lack of a significant association could be caused by power limitations resulting from the small sample size. Studies reporting this association for mathematics, for instance, usually had much larger sample sizes (e.g., [13]). Therefore, we are planning to further investigate the relationship between the variables of the developed questionnaire and performance in programming and CT in future studies with larger samples.

Furthermore, it needs to be acknowledged that students who attended the course were nominated by their teachers based on their school achievements. Therefore, the sample may not be representative for the overall student population but represent a sample biased towards better performing students.

Additionally, it needs to be acknowledged that the original questionnaire on which we based the development of the current one was intended for students in 5th grade or higher. Therefore, future studies should evaluate in more detail whether the comprehensibility of the respective items is given.

4.2 Future Work

To gather further evidence and overcome power limitations, we are planning to use the developed questionnaire in a follow-up study using a randomized controlled field-trial design. This means all students participating in the study are randomly assigned to either the CT course group or the control group and all parts of course and assessment take place in actual classroom environments and thus in the contextual unpredictability of real teaching and learning situations. In such a randomized controlled field trial, it would be desirable to assess questionnaire and CT performance data of about 200 participating elementary school students. In this way, the instrument can undergo a validation process and already be utilized to analyze differential course effects on the measured constructs between the course group and the control group.

4.3 Conclusion

Being rooted in evidence-based education research and modeled on existing standardized and validated scales, the developed questionnaire goes beyond the current state of the art of attitude assessment in computer science education research at the primary and secondary education level. The relationships between the subscales of the questionnaire appear to show a similar pattern as compared to relationships between the subscales of the questionnaire it is modeled on. This provides a first implication of evidence on the validity of the developed questionnaire. However, the small sample size of this pilot study combined with the lack of observations of significant correlations between actual performance and the questionnaire's subscales for self-concept, motivational beliefs, and attitude towards programming calls for further research to fully substantiate the validity of the newly developed questionnaire.

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