On Things that Matter in Learning Programming: Towards a Scale for New Programming Students

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***Abstract*—*Full research paper*—In this paper, we report on the development of a succinct and easy-to-administer 11-item scale that quantifies students' self-efficacy, social aspect, independence, and meaning of studies, with a focus on introductory programming studies. The scale has been constructed using exploratory factor analysis of survey response data collected from students attending introductory programming courses offered by two universities. We evaluate the scale by using it to examine differences between university contexts, and assess to what extent the scale relates to students' perceived impact of the COVID-19 pandemic on studies, prior programming experience, self-assessed competence, and seeking help. Our evaluation of the scale suggests that social aspect was correlated with being more strongly influenced by the COVID-19 pandemic, while the perceived ability to work independently was correlated with reduced influence of the COVID-19 pandemic. Prior programming experience was positively correlated with self-perceived ability to work independently and with self-efficacy. Similarly, self-estimated competence was positively correlated with self-efficacy. Finally, social aspect and meaning of studies were positively correlated with help-seeking. Our evaluations show that the scale holds promise as a new tool for researchers and practitioners seeking to improve understanding of their study contexts.**

***Index Terms*—introductory programming, covid, pandemic, novice, meaningfulness, help-seeking, motivation**

I. Introduction

Learning programming is arguably an ever-more important skill in today's world, taught not solely to computer science (CS) students but also to students majoring in other subjects. Programming is generally considered a difficult topic for novices [1], evidenced both by studies looking at factors that contribute to learning outcomes as well as studies seeking to identify why students are dropping out (e.g. [2]–[5]).

A lot of effort has been put into understanding issues arising in introductory programming. Traditionally, they have been examined from a cognitive standpoint [6], [7]. Computing education research (CER) has often turned to psychology for theoretical constructs (e.g. attention and memory). In recent years, motivation has emerged as another relevant factor to examine in CS, and more specifically in introductory programming courses (CS1); see e.g. [8]. However, the challenge is to get the 'big picture' of different factors affecting the experiences of a beginning CS1 student. The issue is partly due to what could be called competing theories in motivational psychology that typically seek answers primarily to some particular aspect of our behaviour: e.g. our goals, values, self-beliefs or needs. Yet, just as with any success, also issues in our endeavours – studies or otherwise – can be down to multiple different factors at once.

As an example, withdrawing from CS1 has been examined e.g. in [2], [5], whereby some of the contributing factors are personal, especially motivation. Other factors are rather social in nature: e.g. excessive reliance on others, as well as not finding a social group to fit into. The researchers identified also situational factors: how taking up programming fits within a student's life situation [2], [5]. However, sometimes our life situation can be majorly challenged for a thoroughly non-personal reason: The COVID-19 pandemic has affected students across the world by forcing them to remarkably unusual study circumstances.

As a part of this change, the pandemic has incited ongoing research and discussions [9], [10], including how introductory programming students experience the pandemic [11] and re-thinking how courses are taught [12], [13]. To get a sense of how changes in CS1 have been received, one should ask students not just about the effect of the pandemic *per se* but also from the context of their overall stance towards independent and online studying.

In this work, we outline the development of a short and succinct scale that triangulates students' (1) motivation and meaning of studies; (2) self-efficacy of programming; and (3) perceived social aspect of their studies. The work has been conducted through a construction of a larger set of questions, which has then been reduced to a more concise set of items – a scale – using exploratory factor analysis. We further evaluate the scale through five exploratory research questions, demonstrating its applicability for explaining different aspects of the students: their context (i.e. university affiliation), their present characteristics (their a. prior b. present programming competence), their help-seeking propensity, and lastly perceived impact on their studies of the special arrangements in teaching due to the COVID-19 pandemic.

II. Background

A. Self-determination and self-efficacy

According to the self-determination theory (*SDT*) [14], our behavior can crucially be driven by two different motivators:

extrinsic and intrinsic. The extrinsic motivators can be subdivided according to the following subcategories of regulatory styles: external regulation ("Something about your external situation forced you to do it"), introjected regulation ("You made yourself do it, to avoid anxiety or guilt"), identified regulation ("Interesting or not, you felt that it expressed your true values") and integrated regulation ("You knew that what you did was in line with what you are like."). *Intrinsic* motivation, on the other hand, is expressed by feelings of enthusiasm ("You did it purely for the interest and enjoyment in doing it"); a positive, direct relationship with the focus of attention, experiencing intrinsic regulation. [15], [16]. Arguably, to become a self-determined – or autonomous - learner is to achieve intrinsic motivation to some extent in one's chosen field, whereby that extent is best thought of as a continuum and not a binary variable. Motivation can be partly intrinsic and partly extrinsic. While we seek to gauge students' level of intrinsic motivation with several items, perhaps in its purest form it is represented with the item *Do you view that ultimately you learn programming because you want to?* SDT has been employed in CER, e.g., under the rubric of gamification, usually serving as a theoretical backbone [17]–[19]. On the other hand, some studies in CER employ MSLQ (Motivated Strategies for Learning Questionnaire) – often including the SDT context items of the scale ([8], [20], [21]). While programming can be said to be instrumental for many work-life related goals, it seems far less clear from CER, whether learning programming is for at least some students something they find important in and of itself and want to learn just for the sake of it.

More typically than with self-determination theory, introductory programming students' motivation has been examined in the context of their self-efficacy (cf. [3], [4], [22], [23]) – a key construct in Bandura's social cognitive theory [24]. In the words of its creators, what sets SDT apart from e.g. social cognitive theory and its key notion of self-efficacy, is that SDT aims to look primarily into the *type* of motivation whereby self-efficacy rather into the amount of it [25]. In any case, what we find to have been lacking in CER is to view the two theories as *complementary*: both of them include an internal, personal dimension and a social-environmental dimension of motivation. In social cognitive theory, a reciprocal relationship is born between our self-efficacy, behaviour and our environment; our behaviour carries the good impact of our self-efficacy into our environment, whereby working within it will hopefully further strengthen our self-efficacy.

Students' self-efficacy beliefs as regards learning programming indeed form one important factor guiding their learning, and the programming course itself (along with feedback in it) influences their motivation [26]. We ask in our scale, whether students think they can a. become good at programming in their own right but also b. become as good as more experienced programmers. Thus, we incorporated in our scale a kind of social, comparison aspect of self-efficacy. In SDT, a reciprocal relationship between us and our environment is advanced through the fulfilment of our basic psychological needs - the need for autonomy, competence and relatedness. McGill [27] offers an astute review into the usage of motivation theories in CER. He presents Svinicki's model [28] on how to divide competing motivation theories – in the student motivation context – into three categories; first, theories gauging the value of a task, second, locus of control theories and, third, theories of self-efficacy. While SDT covers in Svinicki's view all of the three categories, social cognitive theory falls naturally into the third category.

B. Finding meaningfulness in studies

The more we experience intrinsic motivation in a given activity, the more likely we are to find doing it meaningful. Yet, meaningfulness does not equate with enthusiasm or enjoyment. We can also conceivably find our work or studies meaningful when extrinsically motivated, under identified or integrated regulation as outlined above. In [29], Martela and Pessi break down meaningfulness at work into finding significance which in turn contains self-realization (i.e a personal significance) and finding a broader purpose that is a rather universal one (cf. [30]). There is a connection between the model of motivation in self-determination theory (SDT) and the concept meaningfulness as presented by Martela and Pessi (ibid.) especially through the *value* component in the SDT. Our values, crucially, tell us what is important to us (e.g. [27], [28], [31]). Hence, to better understand learning programming, it would be relevant to ask students about how they perceive the meaning of, first, learning programming and, second, their studies as a whole.

The Martela-Pessi [29] model of meaningfulness has, in our reading, not yet been examined in student context. Yet, meaning of studies has been proposed to be one of the key elements in how students become engaged in their studies [32], [33]. Peters & Pears [34], in an interesting study on meaning in CS, found that among significant aspects creating meaning for CS students were them having a sense of being a member of their study community and having been "at home" with computers & technology from an early age. This would seem to be aligned with the theory of community of practice [35], which – among other things – discusses becoming a member of a community, starting from legitimate peripheral participation.

We argue that to keep motivated by one's studies in the long-run, one needs to find meaningfulness and value in them. Whether this is true for a skill such as programming and for a method science such as CS requires more research that continues complementing and completing the picture outlined by Peters & Pears [34].

C. Social practices and engagement

Meaning of studies is thought to be intertwined with a person's overall engagement in their studies [32], [33]. In common with both SDT and Korhonen model on student engagement [32], [33] is a social aspect, i.e. the social resources that others offer – peers and teachers alike – to enable our engagement in studies and hence our learning. According to Korhonen model, a study community's social practices are harnessed through participation in that community (cf. [33]). In SDT, that social participation is thought to be guided by the need for relatedness, i.e. belongingness ([15].

One worthwhile way to approach students' social practices and engagement is to ask students to assess their propensity to seek help from peers, teachers or others. Furthermore, students could also be asked to assess the impact that peers, teachers and the atmosphere in their study community have in their studies. To be sure, this approach concerns students' subjective experiences – similar to what e.g. [33] did. In Wenger's theory and Korhonen's model (ibid.), learning is not thought to be solely due to one's own motivation or competence rather it requires a social dimension to take place. As programming is widely known to be difficult for many newcomers, the social aspect of studying that has been known to help seems to us like an integral type of question in a scale for new programming students. Information from such question could, as an example, also provide additional light into the observed benefits of e.g. pair programming [36] and peer instruction [37].

D. CS – An inherently independent field?

It seems to us that computer science as a field has been better equipped than many other fields to counter the vastly increased demand for independence due to the COVID-19 pandemic. Computing education research has a long history of studying ways to support online and remote studying compared to many other subjects. This has been driven in part due to the large class sizes and the associated need for automated assessment and feedback [38], [39]. The topic of independent studying and how to foster it is likely more intricate than meets the eye. One should look into personal characteristics but also into the pedagogy and the study environment context. Crucially, some external changes are so enormous that they will challenge one's studies regardless of one's own study skills and abilities. The pandemic is a prime example.

What has been new is the sheer magnitude - globally - of studying remotely. We argue that generally, the pandemic has meant a profound change for students [40], [41], and yet for many studying CS there have only been rather subtle changes. Likely, one of the biggest effects has been the disappearance of casual and informal on-campus interactions, whereby increases in online education do seem to depend on one's major. Yet, many students have been left to their own devices a lot more than usually. It seems then, that the need for relatedness as per SDT and engaging in social practices have been thwarted, challenging communities of practice [35]. While the situation due to the pandemic has been novel in untold number of ways, differences and synergies of on-campus and online offerings have indeed been explored in the CER literature also in the past (e.g. [42]–[44]). On the other hand, researchers have posited that traditional surveys used in online contexts may not be directly applicable in MOOC contexts [45].

Thus, there is certainly a need to also ask students about studying online and studying independently in a general sense. Answers to such questions could provide relevant context to the question of whether the pandemic had affected individual student's studies or not, and more broadly also inform us on the extent to which various 'modes' of studying suit individual students.

III. Scale Development

A. Planning

The design and development of the scale for new programming students started when we created a broader survey that explored students' thoughts and beliefs about their studies in programming. The design was guided by the following broader objectives:

- O1 *Finding motivation and meaning in studies*: Do students in an introductory programming course learn programming because they want to and how is that related to their self-assessed meaning of A. learning programming and B. their overall studies.
- O2 *Finding self-efficacy of programming*: Do students believe they can become good at programming crucially by practicing it and is it related to how they view their motivation and meaning of studies?
- O3 *Finding a social aspect of studies*: How significant do students believe is the impact of others (e.g. teachers) on their studies and how is that impact related to their *motivation and meaning of studies* and their *self-efficacy* beliefs?

When constructing the survey, we rooted the survey items in several theoretical constructs to offer a comprehensive theoretical background for our work. The key theories and theoretical constructs employed and discussed during the survey creation process included self-determination theory (SDT) [14], meaningfulness model [29], student engagement model [33], and social cognitive theory [24], each described in Section II. Included in the first three above models is the idea that finding a personal meaning in our endeavours is crucial to our long-term wellbeing. We also explored inherent independence of computer science, witnessed in part in the long-standing research into automated assessment practices that have increased the opportunities for working at a distance. Further, while designing our scale, we discussed with introductory programming teachers and researchers to identify potential common concerns and pitfalls of CS1 students.

The effort led to a total of 34 survey items that were answered using a Likert-scale with seven answer options. This was considered to be the starting set of items that we would then start to reduce to form a more concise set.

B. Pilot data collection and adjustment

During fall of 2020, a pilot study was conducted at an introductory programming course of AU, where the survey with 34 survey items was administered to volunteering students. Upon inspecting answers from $n = 44$ students who fully completed the survey and consented to the use of their responses for research, we observed that (1) students' competence beliefs were not adequately captured by the survey, and (2) importance of other related study subjects was relatively scattered between students and did not provide insight to programming (we had asked about importance of mathematics and physics). Thus, we added six new survey items related to competence in programming, and removed two survey items related to mathematics and physics experiences.

This led to a new version of the survey with a total of 38 survey items[1].

C. Data collection

During fall of 2021, the survey with $n = 38$ items was administered to volunteering students in introductory programming courses offered by two Finnish universities, Aalto University (AU) and University of Helsinki (UH). The university contexts differ in that AU offers instruction targeted separately for computer science majors and to majors in other subjects, while UH offers an introductory programming course targeted for all, regardless of their major – at UH, the course can also be taken by non-degree students, remotely.

From the two universities, we received a total of $n = 117$ fully completed surveys with research consent.

D. Scale construction

To construct the scale, we performed Exploratory Factor Analysis (EFA) [46] on the $n = 117$ survey answers[2]. EFA was conducted to reduce the number of survey items to a more concise set and to examine the underlying factors in the survey, leading to a more concise scale. Kaiser-Meyer-Olkin (KMO) test [47] showed that the collected data was suitable for factor analysis (KMO test value > 0.5), and Bartlett's test of Sphericity [48] showed that the data was not an identity matrix ($p < 0.01$). When inspecting the underlying factors, we used a combination of the Scree test [49] and Kaiser's criteria [50] to assess the appropriate number of factors, iteratively removing survey items that poorly loaded to the identified factors (we considered loadings over 0.6 as acceptable). As a rotational method, we initially used promax [51], which is an oblique rotation method, as we considered the expected underlying theories to be at least somewhat correlated. However, we observed that varimax [51], which is an orthogonal rotation method, produced the same results as promax. Over the iterative process, we ended up with four factors that consisted of a total of 11 items, with normally distributed answers, outlined in Table I.

E. Interpretation

We interpret the factors identified through EFA and shown in Table I as follows:

1) *Self-efficacy*, indicating self-efficacy (cf. [24], [52]) and interest, but also autonomy in the self-determination theory (SDT) [14], [15]
2) *Social*, indicating a self-assessed social aspect, similar to relatedness in SDT [14], [30], [53] and social practices in the Korhonen model [32], [33]
3) *Independence*, indicating self-perceived independence and fit to online studies
4) *Meaning*, indicating meaning of studies (cf. [33]), similar to meaningful work in Martela and Pessi's work [29]

These four factors, *Self-efficacy*, *Social*, *Independence*, and *Meaning* jointly form the succinct scale for new programming students that we further evaluate in this article - *also against the backdrop of our objectives O1-O3*. The internal consistency of our scale, measured using Cronbach alpha [54], is 0.71 (95% confidence interval [0.628, 0.785]).

IV. Evaluation

A. Motivation and data

While the university context is not commonly discussed in studies related to students' experiences in introductory programming courses, studies have explored the impact of the COVID-19 pandemic (e.g. [10]–[12], [45], [55]), students' prior programming experience (e.g. [3], [56], [57]), approaches for assessing competence (e.g. [58]–[60]), and help-seeking behaviors (e.g. [61]–[63]). Many of these have been discussed from the perspective of students' performance in the introductory programming courses, but potential factors underlying the observations are often under-explored.

We sought to provide a lens through which to view the potential of the factors measured by the developed scale on the aspects highlighted above. Thus, when collecting survey data in Fall 2021 from students participating in introductory programming courses at AU and UH, we also collected additional details. They included students' university affiliation (if any), students' assessment of their programming experience, students' self-assessed competence in programming, and students' perceived tendency to ask for help. While the first question was categorical, providing an option to pick a university or to indicate no affiliation, the subsequent questions were answered using Likert-scale questions ranging from not at all to very much so.

B. Research questions and approach

We demonstrate the versatility of the new scale through an exploration of its suitability in answering the following five research questions.

RQ1 How is university context reflected in the responses to the new scale?
RQ2 To what extent do the factors in the new scale explain COVID-19 pandemic impacting studies?
RQ3 How is self-assessed prior programming experience reflected in the responses to the new scale?
RQ4 How is self-perceived competence in programming reflected in the responses to the new scale?
RQ5 How is help-seeking reflected in the responses to the new scale?

The first question is answered through a high-level analysis of differences in the factor values between the contexts, while the four subsequent questions are answered using a correlation analysis between the scale factor values and received answers to the scale items.

[1]The questions are included in an online appendix at https://osf.io/248ua/?view_only=3de361cadae7481f8408ea021cfc70d3

[2]We used the `statsmodels` Python module `v0.13.2` for the analyses.

TABLE I

FOUR-FACTOR SCALE FOR NEW PROGRAMMING STUDENTS IDENTIFIED USING EXPLORATORY FACTOR ANALYSIS ON SURVEY ANSWERS FROM STUDENTS FROM TWO UNIVERSITIES. THE TABLE SHOWS SCALE ITEMS, EFA FACTOR LOADINGS, AND THE INTEPRETED FACTOR LABELS. ALL ITEMS WERE ANSWERED USING A 7-ITEM LIKERT-LIKE SCALE RANGING FROM 1=NOT AT ALL TO 7=VERY MUCH.

#	Item	Self-efficacy	Social	Independence	Meaning
1	Do you think that you can become good at programming?	**-0.882**	0.059	-0.095	-0.262
2	Some students have prior background in programming. Do you view that you can become just as good at programming as students who have already practiced programming before?	**-0.714**	0.087	-0.097	-0.052
3	Do you view that ultimately you learn programming because you want to?	**-0.700**	-0.144	-0.250	-0.022
4	Teachers impact your studies.	-0.016	**0.663**	0.059	-0.013
5	Your study friends impact your studies.	0.060	**0.761**	0.103	-0.141
6	Some (other) aspects about your university such as the general atmosphere impact your studies.	-0.075	**0.852**	0.177	-0.197
7	Your studies contain a lot of independent studying online. How well do you think it will go along with your way of learning things?	-0.115	-0.136	**-0.873**	-0.110
8	How do you view studying independently suits you in general?	-0.173	-0.148	**-0.783**	-0.072
9	How much are you committed to your studies?	-0.109	0.111	-0.070	**-0.805**
10	How important do you view your current studies to be to yourself?	-0.183	0.122	0.052	**-0.749**
11	How meaningful do you find your studies as a whole?	-0.164	0.196	-0.314	**-0.735**

C. Statistical tests

When answering the research questions, we report p values of all statistical significance tests. As a boundary value, we use $p < 0.05$, and in accordance with the American Statistical Association's recommendations, we use p values as one piece of evidence of significance, to be used in context [64]. When reporting and discussing correlations, we use Spearman r statistic, and following [65], interpret $0.1 < abs(r) <= 0.3$ as small effect, $0.3 < abs(r) <= 0.5$ as medium effect, and $0.5 < abs(r)$ as large effect.

V. EVALUATION RESULTS

Here, we first outline differences of the scale responses between the university contexts, which is followed by presentation of correlations between the scale factors and impact of the COVID-19 pandemic, prior programming experience, competence, and help-seeking, summarized in Table III.

A. University context

Differences between the university contexts identified with the scale are presented in Table II. Overall, the highest value for the factor Self-efficacy is observed for students at UH, while the lowest Self-efficacy is observed for the students at AU, on par with students with no affiliation (when considering medians, no affiliation has lower Self-efficacy than AU). We observe the highest value for the factor Social in students at AU and the lowest value for Social in students with no affiliation. The students at AU have the lowest value for the factor Independence, while the same is highest for the students with no affiliation. The factor Meaning is highest for the students at AU and lowest for students with no affiliation.

B. The COVID-19 pandemic

The impact of the COVID-19 pandemic on respondents' studies was measured using a Likert-scale question: "The special arrangements in teaching due to the coronavirus pandemic impact your studies. (On a scale from 1 to 7, where 1 = Not at all, 7 = Very much so)". Overall, as shown in Table III, there is a medium positive effect between the factor Social and perceived impact of the pandemic ($r = 0.48$) and a medium negative effect between the factor Independence and impact of pandemic ($r = -0.41$). No effect between the factor Meaning and impact of the pandemic nor the factor Self-efficacy and impact of the pandemic is observed.

C. Prior programming experience

Students' prior programming experience was measured using a question on a Likert scale: "Studying CS inherently contains learning programming. As with anything, students have differing amounts of experience on programming. Some may have done a lot of programming before, others less so. How familiar are you with programming? (On a scale from 1 to 7, where 1 = Newcomer, 7 = Very experienced)." Overall, as shown in Table III, there is a medium positive effect between the factor Independence and prior programming experience ($r = 0.32$) and a medium positive effect between Self-efficacy and prior programming experience ($r = 0.32$). No effect between the Social factor and prior programming experience nor Meaning factor and prior programming experience is observed.

D. Self-assessed competence

Students' self-assessed competence was measured using four Likert-scale questions gauging whether students felt core concepts in programming (1. loops, 2. conditional statements, 3. functions) easy to understand with everyday reasoning and 4. to what extent they felt that they had to keep many things in mind when programming (reverse coded). For simplicity, we considered a student's competence as the average value to the four questions.

When considering competence, as shown in Table III, there is a medium positive effect between Self-efficacy and competence ($r = 0.47$). Prior to the correction for multiple comparisons, one could also have interpreted a small effect between the factor Meaning and competence ($r = 0.22$). No significant effect between Social and competence nor Independence and competence is observed.

TABLE II
MEAN, MEDIAN AND STANDARD DEVIATION (DENOTED WITH MEAN, MEDIAN AND σ) OF THE FACTOR VALUES OF THE SCALE, GROUPED BY SELF-REPORTED AFFILIATION OF THE RESPONDING STUDENTS.

	Self-efficacy			Social			Independence			Meaning		
Affiliation	mean	median	σ	mean	median	σ	mean	median	σ	mean	median	σ
AU ($n = 51$)	5.60	6.00	1.40	4.65	5.00	1.37	5.39	5.5	1.27	5.89	6.00	0.99
UH ($n = 42$)	6.10	6.33	0.87	3.88	4.33	1.78	5.69	6.0	1.20	5.74	5.83	1.20
No affiliation ($n = 24$)	5.63	5.67	1.11	3.57	3.67	1.96	6.00	6.5	1.20	4.98	5.00	1.22

E. Help-seeking

Students' help-seeking was measured using two Likert-scale questions that gauged to what extent, when needing help, students were likely to ask for help from (1) the course staff and (2) from their peers. For simplicity, we considered tendency to ask for help as the average value to the two questions.

When considering help-seeking, as shown in Table III, there is a medium positive effect between help-seeking and the Social aspect ($r = 0.43$) and a medium positive effect between help-seeking and the factor Meaning ($r = 0.32$). No significant effect between Independence and help-seeking nor Self-efficacy and help-seeking is observed.

VI. DISCUSSION

A. Motivation and meaning of studies

We set out to measure with our scale, do students find a motivation and meaning in their studies, outlined as as our first objective, O1, in Section III. Our EFA analysis revealed that indeed our data did yield a factor of meaning, albeit it only pertains to the overall meaning people find in their studies and not meaning concerning learning programming. This is interesting as this is in our reading the first time in CER that meaningfulness of learning programming has been studied alongside perceived overall meaning of studies, the latter of which being an established field of inquiry through Wenger's work (c.f. [35]). On the other hand, as stated in Section II, meaning of studies can be linked with and has indeed been researched through intrinsic motivation in the self-determination theory (SDT).

As stated in e.g. [15], [16], intrinsic motivation in SDT is about a tendency to explore and learn out of curiosity, interest and enjoyment, even in the absence of external rewards (for validation of intrinsic motivation, cf. [66], [67]). Hence, wanting to learn something is arguably a manifestation of intrinsic motivation. We asked this with our item "Do you view that ultimately you learn programming because you want to?". In our EFA, we did not find this item connected with the Meaning factor. Arguably, from a construct validity standpoint, this was somewhat surprising. Our results would imply that students view motivation towards their studies separately from that towards programming. A further interpretation for our results might be that students understand questions gauging *importance* and *meaning* on a higher abstraction level vs. wanting to do something and hence do not see the inherent connection between the topics in these questions. In practice, it could be that when contemplating on the meaning of something, people are prone to answer 'as expected' (i.e. the Hawthorne effect [68], [69]) rather than what truly reflects their values. When constructing items the question of abstraction level of the wording is important albeit challenging.

B. Self-efficacy, motivation, and meaning

The item "Ultimately learning programming because you want to" did occur - in another factor: the *self-efficacy factor*. This is perhaps in contrast to our second objective, O2, but on the other hand, we did posit that the theory of self-efficacy should best be viewed complementary with the SDT and its notions of being motivated due to intrinsic motivation.

Finding meaningfulness is arguably related to having a high proportion of intrinsic motivation in contrast to extrinsic one. However, two things are important to bear in mind here. Firstly, motivation as described in the SDT [14], is best understood as a continuum, not a binary variable. Accordingly, a student may feel differing amounts of intrinsic motivation, depending on the subject but probably also on the topic in a course. Second, it is also good to recognize that having an extrinsic motivation towards a subject or topic is not invariably a "bad thing", nor detrimental for academic performance; indeed, some researchers have even tried to tap into this through gamification and other approaches [70]. As to "commitment to studies", It is curious that it is part of our Meaning factor as it is not directly predicted by SDT nor Korhonen model [33] nor Martela-Pessi [29] model. Yet, commitment would seem to sit logically at the crossroads of being both an organized and a motivated student. Commitment is conceivably boosted by the same things that increase our self-efficacy and our intrinsic motivation.

These observations warrant further research to understand differences in how students view the pressing matters in a present course – e.g. programming – and in their studies in general, as well as research seeking to replicate our findings in new contexts to unveil tacit contextual factors that contribute to our observations.

C. On the experience of social aspect

Our third objective, O3, was to find a social aspect of studies. We observe that the social aspect of studies is a rather complicated one to ascertain to the extent that it would ultimately need some experimental setting whereby part of students actually collaborate while others do not. However, from motivational and student engagement perspective, the social aspect has in fact been studied through students' self-reported

TABLE III

SPEARMAN'S r CORRELATIONS BETWEEN THE SCALE FACTORS AND RESPONSES ON IMPACT OF PANDEMIC, PRIOR PROGRAMMING EXPERIENCE, SELF-ASSESSED COMPETENCE, AND HELP-SEEKING BEHAVIOR. CORRELATIONS WITH $p < 0.05$ ARE MARKED USING BOLD-FACE FONT AND CORRELATIONS WHERE $p < 0.05$ AFTER CORRECTING FOR MULTIPLE COMPARISONS (N=16) ARE MARKED WITH AN ASTERISK (*).

	Pandemic		Prior experience		Competence		Help-seeking	
	r	p	r	p	r	p	r	p
Self-efficacy	-0.04	0.716	(*) $\mathbf{0.32}$	0.002	(*) $\mathbf{0.47}$	$3e-6$	0.06	0.547
Social	(*) $\mathbf{0.48}$	$1e-6$	-0.10	0.370	0.01	0.915	(*) $\mathbf{0.43}$	$3e-5$
Independence	(*) $\mathbf{-0.41}$	$6e-5$	(*) $\mathbf{0.32}$	0.002	0.16	0.130	-0.21	0.051
Meaning	0.03	0.807	-0.17	0.097	$\mathbf{0.22}$	0.037	(*) $\mathbf{0.32}$	0.002

experiences (e.g. [33], [71]). Thus, our scale, with its Social factor, seems to corroborate the Korhonen student engagement model's [33] factors of self-assessed social practices and participation. That a student regards their friends or teachers to impact their studies speaks to the relevance of the topic, yet it is a neutral wording. A follow-up question could thus be to ask if students long for more impact of their peers or teachers (cf. SDT relatedness). One might also ask more in detail, in what kind of instances students see teachers' or peers' impact as especially relevant. It would also be a good idea to compare more precisely the impact of others in programming vs. other studies. As we conjectured in Section II, CS students might feel less inclined for collaboration due to the field's ordinarily independent structure.

D. Independent studying and working online

An inherent part in CS studies, especially in introductory programming courses that use automated assessment systems, is working independently – and often online. This habit has been boosted by the recent COVID-19 pandemic. We set out to also explore the extent to which students felt that independent and online studies suited them. In EFA, *Independence* did emerge as one of the factors that was separate from Self-efficacy, Social and Meaning, i.e. the other factors identified in our analysis. In general, we observed that the more the students felt that independent studies suited them, the less they felt impacted by the pandemic. This seems to corroborate the notion that at least in the studied contexts, it has been possible to study despite the pandemic – indeed, both contexts extensively rely on the use of automated assessment that help working remotely.

To some extent, independent studying and working online are conceivably connected to self-regulated learning, which has been explored, e.g., using the MSLQ scale [72] in various CS contexts (see e.g. [4], [21], [73]). Yet, it is hard to ascertain the extent to which the discipline-specific teaching practices such as the use of notional machines [74] and automated assessment [38] influences these observations. While our broader survey also had questions related to rehearsal – which were inspired and drawn from the MSLQ scale, they were ultimately omitted due to overall poor factor loading. Similar observations were made related to help-seeking, which was also excluded from the factors due to poor loadings, which has also been observed in the past in MOOC contexts [45]. It is a good question to what extent the COVID-19 pandemic has increased similarities of local but online offerings and MOOCs.

E. Limitations

Our work comes with a set of limitations, which we discuss next. First, as is always the issue with surveys, we relied on self-reported data. Possibly there are biases in responses, including selective memory and telescoping, which may influence some of the answers to the questions; it might be, e.g., that some students have de-emphasized the likelihood of asking for help from peers or course staff due to lack of recent interactions. Furthermore, it is possible that students may not always have understood a given question the way it was intended to be understood.

Second, the survey administration time was decided by the instructors at the Universities, and thus was not conducted at the same time at both Universities. This, in addition to the notion that the instructional materials, approaches and practices differ between the Universities, may have had an impact on students' responses. Similar to the first issue mentioned above, it is possible that the time and moment in a course when the students answered the surveys may have created differences between their responses; e.g. regarding questions on self-evaluated competence. Yet, prior studies have observed the utility of self-evaluating competence multiple times over a course [58].

Third, the sample size ($n = 117$) that our EFA was based on is relatively small and while our analysis entailed aggregated data from two universities, it is possible that the results do not generalize. Thus, studies that evaluate and validate the scale in other contexts are needed.

Fourth and finally, motivations and beliefs may fluctuate and transform over time; similarly, students' study skills and help-seeking behaviors may improve (or worsen) over time. In our study, we had access to a limited population and have so far administered the scale once to each population. Thus, we do not have information on how students' motivations and beliefs change over time, nor do we know which factors contribute to the changes and how.

VII. CONCLUSION

In this work, we set out to create a scale for exploring introductory programming students' thoughts and beliefs on why and how to learn programming. We created a pool of questions that we then administered to the students, iterating over the questions in a pilot study. Using Exploratory Factor

Analysis on collected responses, we identified a concise four-factor scale that measures (1) Self-efficacy, indicating self-efficacy and interest, (2) Social, indicating a self-assessed social aspect, (3) Independence, indicating a self-perceived fit to independent and online studies, and (4) Meaning, indicating meaning of studies.

We discussed the key theoretical frameworks that worked as the basis of the survey and the developed scale. One particular aspect of the scale is that each of the four factors are such that they can be used to inform decisions in educational contexts. As an example, students' self-efficacy can be used to inform instructional design, as it can – over a long time – be influenced through appropriately targeted assignments, feedback and good pedagogical practices; social aspect can be used to highlight components that have an impact on studies and that could then be paid further attention to in order to best support the students; self-evaluated independence could be used to inform, e.g., attendance and support policies; and self-evaluated meaning of studies could be used to inform, e.g., need for study mentoring or counseling.

Further, we evaluated the utility of the created scale by exploring its usefulness in providing insight into study contexts and other aspects that have previously been studied when examining, e.g., introductory programming students' study success. Namely, we explored differences in responses between students from different affiliations, and studied how the scale could be used to explain the impact of the COVID-19 pandemic on studies and the relevance of prior programming experience, self-perceived competence and help-seeking propensity while studying. Our evaluations demonstrate the usefulness of the scale as an additional tool for researchers looking into introductory programming students. In particular, one novel aspect of the scale is the factor related to online and independent fit, which we believe is highly useful for discipline-specific research that focuses on subjects such as computer science with a long tradition in developing systems that make it easier to work both independently and online.

As part of our future work, we are looking into collecting further demographic data such as educational background and study major to provide further insight into the factors identified by the scale. We are also interested in evaluating the scale in new contexts, as well as looking into collecting more data from the universities that already participated in the research.

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