Literature Review
The Influence of Early Programming on STEM Gender Gap

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> "The real explanation is obvious: Women are less drawn to science and engineering than men. [...] presumably because (by and large) they do not like these fields or (on average) do not tend to excel in them."
> (Gelernter, 1999)

Fortunately, it has been shown that the gender gap in STEM (Science, Technology, Engineering and Mathematics) is not caused by innate brain differences (Tzuriel & Egozi, 2010). The numbers are rising, but still there is an underrepresentation of women in STEM fields (Booy et al., 2012), though it differs per field. In this essay, the recruitment issue in computer science (CS) will be central.

It is important to strive for equity, because the society is missing out on potential contributions of talented women. Also, women now miss out on high status and good paying jobs.

In this essay, three studies concerning the gender gap in STEM will be discussed. The first article (Cheryan et al., 2017) introduces a theoretical model to describe factors influencing the gender gap in STEM. The second (Aivaloglou & Hermans, 2019) and third (Master et al., 2017) both performed experimental research on the effect of an early programming intervention.

1 Model gender gap in STEM

As has been mentioned in the previous paragraph, not all STEM fields observe the same width of the gender gap. Cheryan, Ziegler, Montoya, and Jiang (2017) propose a model to explain the variation in rates of women's participation between STEM fields.

The authors of the article tried to understand *why* the preferences are different. What factors are involved, and how could a change be achieved? These research questions guided the conducted literature research.

1.1 Method

To find out the reasons for the differences in women representation in the STEM fields, a literature research is conducted. The selection of articles is very extensive, with over fifty articles included. This selection is meticulously made.

First, ten common contributing factors are identified from a myriad of review papers since 1990 from psychology, education and sociology. The used databases and the search plan (with relevant keywords) is described thoroughly. This detailed explanation of their method of searching adds to the replicability.

Moreover, the collection of studies is filtered to ensure a minimum threshold for quality, by among other requiring a minimum sample size.

The study reviews the ten factors that are thought to influence the underrepresentation in STEM. Each factor is assessed by reviewing the articles from the corresponding categories. Two criteria need to be met for a factor to explain the variance of gender participation across STEM fields. First, the factor or its effects must distinguish the different STEM fields. Second, the factor should be related to the gender gap in interest, intentions to major, or participation in STEM.

1.2 Results

The results of the literature study can be summarized in figure 1.

The first factor seen in the graph is masculine culture. Note, the authors do not claim that all men are attracted and all women are repelled by it. Still, the literature review indicated that it influences the lower representation of women. Also, evidence was found that the masculine culture effected the gender gaps in self-efficacy.

The second cause that came out as a result is insufficient early experience. Students receive more early educational experience in some STEM fields than other. Mandatory early experiences could help to reduce gender gaps in self-efficacy. Even so, there are other fields that do not have early exposure, but still attract women, such as psychology. Therefore, the authors concluded, it only occurs where the lack of early experience combines with perceived masculine culture.

The last cause is self-efficacy. For this factor, the literature showed more mixed evidence.

1.3 Reflection

One should keep in mind that the goal of this paper was to investigate factors that explain the gender gap in STEM. This is not necessarily the same as researching the best practical solution to bridge the gap. Moreover, there was no direct evidence that

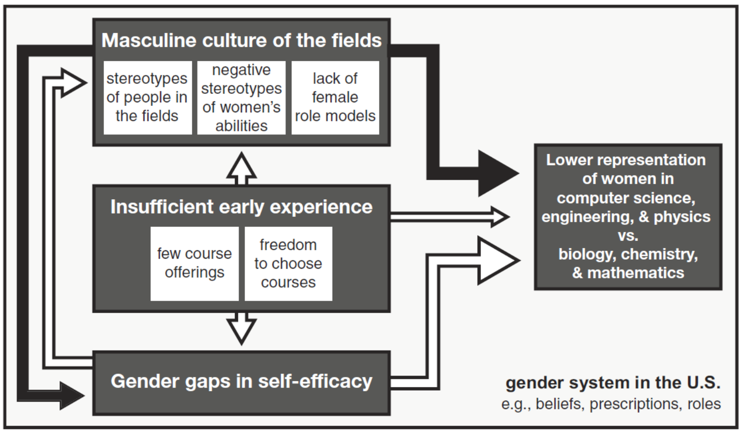

Figure 1: Cheryan et al., 2017 Solid arrows indicate the presence of evidence.

linked insufficient early experience and gender gaps in self-efficacy to a lower representation in STEM. More research on this link is discussed in the next two sections.

2 Early programming experience (twelve-year-olds)

More and more primary schools include an element of programming in their curriculum, for example using Scratch or other programming languages specifically designed for early programming education. Aivaloglou and Hermans (2019) researched a group of elementary school children that followed a Scratch programming course.

The research aims at a broad and varied range of factors, that is split up in research questions. The first relevant research question tries to establish the influence of this factors, as well as stereotypes on CS scientist on choosing programming as a future career. The second question aims to see whether age, gender and previous programming experience affect those factors.

2.1 Method

The results are collected in an eight-week programming course in Scratch, provided by the authors.

The subjects are 74 children attending two public elementary schools in the Netherlands. About half of the students (51.35%) is female, and the ages vary from eight to twelve years. The schools were selected mainly based on their proximity of the university, which is an irrelevant factor for the results of the study.

To assess the students' self-efficacy and motivation, questionnaires were used at the beginning, middle and end of the course. The students rated themselves on a seven-point likert-scale from 'does not apply at all to me' to 'very true to me'. The MSLQ orientation subscales were used for the statements to measure motivation and self-efficacy.

The questionnaire also included statements to measure the belief in four stereotypical types, namely *singularly focused, asocial, competitive and male.* To evaluate career choices, students replied to the statement "I want to become a programmer when I grow up".

2.2 Results

No significant result was found that the programming course influenced the students CS career orientation; there was no significant difference between the start and end measurements.

Self-efficacy, however, did have a strong correlation with choosing a CS career orientation ($p=0.018$ for the measurement half-way the course, and $p=0.022$ for the final self-efficacy measurement). This correlation was only found for girls.

At last, the results did not show the children to have stereotypical beliefs about computer scientists. The student's perceptions about stereotypical traits (converted to 0 to 1 scale) were found to result on average around 0.50.

2.3 Reflection

A limit of the implication of this study is their self-declared CS career orientation. This does not necessarily link with their actual career choices in a few years time.

Moreover, self-efficacy was shown to be correlated with wanting a science career. This does not show self-efficacy to cause girls to pursue a science career. Both self-efficacy and aiming for a science programming career could be caused by being good at it.

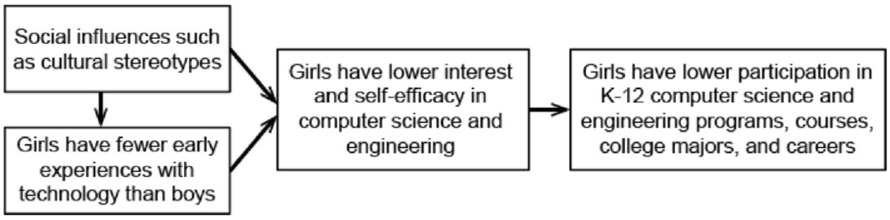

Figure 2: (Master et al., 2017) Interacting sociocultural factors.

3 Early programming experience (six-year-olds)

In the previously discussed study, no conclusive results about the direct impact of the intervention was found. Master, Cheryan, Moscatelli, and Meltzoff (2017) investigated the influence of programming experience for even younger children.

In their study, a group of 6-year-old school children are asked about their interests and stereotypes about programming, robots and their self-efficacy concerning these topics.

The study has two aims. First, the children stereotypes about computer science and engineering are researched, in comparison to other STEM fields. Second, the intervention itself and its effects on girls' immediate interests and self-efficacy are studied.

Figure 2 shows the conceptual framework as used in the study. The gender gap in motivation stems from cultural stereotypes and gender differences in experience, according to this article. Stereotypes make people, even very young people, believe to be less capable in STEM fields. Another cause of the gender gap might be that girls are less exposed to experiences related to computer science, such as spatial and science-related games.

3.1 Method

The participant group consisted of 96 children (all 6 year old), with 48 girls and 48 boys. Most were middle or upper class (93 % of the mothers were college graduates). To divide the children into groups, stratified random sampling to condition was used: the experimenter was male for half of the participants and female for the other half.

The "robot" experimental treatment group spent 20 minutes playing a game to design a "pet" robot using a smartphone. The goal was to program the robot to navigate over a path out of hexagonal tiles. For a visual reference, see figure 3.

The two control groups participated in "storytelling" activity and in "no activity". The storytelling activity asked the children to tell stories using four sets of picture cards. No difference was expected between the two control groups.

The technology motivation was measured by assessing their interest in programming, interest in robots, and self-efficacy with robots. Children were asked to value questions as "how fun is programming?" on a scale from 1 to 6 by pointing at smiling or frowning faces.

STEM-gender stereotypes were measured in the same manner, with questions as "Who is better at programming, girls or boys?".

Figure 3: (Master et al., 2017) Six-year-old girl in the robot treatment group.

3.2 Results

As the authors had predicted, girls in the robot treatment group had significantly higher ($p = 0.002$) technology motivations than the two control groups. In contrast, for boys, no significant effect on motivation was found between the three groups.

The gender gap that boys showed more technology motivation than girls, was significant in both control groups, but not in the robot treatment group.

Furthermore, results showed that 6-years reported significantly more often ($p < 0.001$) than chance that boys were better than girls at robots. However, no significant effect of groups was found on any of the children's stereotypes.

3.3 Reflection

Programming is explained as "telling the computer what to do". The same problem as in the previous article arises. The understanding what programming really is might be limited, and therefore the claims of self-efficacy and motivations for it should be seen in context.

The positive results on changes of motivation are promising. Still, the question is if these motivations are long-lasting or situational.

Next to that, stereotypes did not change. More research is needed to find ways to address the problem of stereotyping in STEM fields.

4 Conclusion

In conclusion, we will take the reflection points for the articles and formulate possible future research directions.

One of the problems that arose is the understanding of what programming means. The implications of the research might be limited. For example, how do we know if the positive effects of early programming interventions are long-lasting? Would that be enough for people to choose a different career and bridge the gap?

A research that extends over time and follows students from young age to the time of them choosing a career could possibly give insights. A start could be to perform qualitative research to ask women about their career choices and choosing factors. Is insufficient early experience a factor for lower representation, and would introducing programming early (help) bridge the gap? Future research might tell.

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