



Universiteit
Leiden
The Netherlands

Children's implicit and explicit stereotypes on the gender, social skills, and interests of a computer scientist

Wit, S. de; Hermans, F.F.J.; Aivaloglou, E.; Ko, A.J.; Vahrenhold, J.; McCauley, R.; Hauswirth, M.

Citation

Wit, S. de, Hermans, F. F. J., & Aivaloglou, E. (2021). Children's implicit and explicit stereotypes on the gender, social skills, and interests of a computer scientist. *Proceedings Of The 17Th Acm Conference On International Computing Education Research*, 239-251.
doi:10.1145/3446871.3469753

Version: Publisher's Version
License: [Creative Commons CC BY 4.0 license](#)
Downloaded from: <https://hdl.handle.net/1887/3250270>

Note: To cite this publication please use the final published version (if applicable).

Children’s Implicit and Explicit Stereotypes on the Gender, Social Skills, and Interests of a Computer Scientist

Shirley de Wit
s.de.wit@liacs.leidenuniv.nl
Leiden University
The Netherlands
Stichting VHTO
The Netherlands

Felienne Hermans
f.f.j.hermans@liacs.leidenuniv.nl
Leiden University
The Netherlands

Efthimia Aivaloglou
e.aivaloglou@liacs.leidenuniv.nl
Leiden University
The Netherlands
Open Universiteit
The Netherlands

ABSTRACT

Motivation Only 27% of computer and mathematical scientists in the United States and 18% of IT specialists in Europe are women. The under-representation of women in the field of Computer Science is, among other things, influenced by stereotypes of computer scientists. These stereotypes include being male, asocial and having an (obsessive) interest in computers. Even though stereotypical beliefs can develop at an early age, research on children’s stereotypes of computer scientists is sparse and inconclusive.

Objectives Stereotypes we hold can be implicit or unconscious beliefs, or explicit or conscious beliefs. In this study, we focus on children’s implicit and explicit stereotypes regarding computer scientists’ gender, social skills and interests. We also study whether explaining what a computer scientist does affects these stereotypes.

Method We study the implicit stereotypes through the reduced-length Child Implicit Association Test and the explicit stereotypes through self-reported absolute and relative Likert scale questions. We gathered data on 564 children between the age of 7 and 18 who were visiting a science museum. The participants in the *experiment group* (n=352) watch a video of either a man or woman explaining what a computer scientist does at the start of the study.

Results We found weak implicit stereotypical beliefs on computer scientists’ social skills and moderate implicit stereotypical beliefs on computer scientists’ interests. We also found explicit stereotypes on computer scientists’ gender, social skills and interests. Measuring the effects of the intervention, we found significant differences between the *control* and *experiment group* in their explicit stereotypes on computer scientists’ social skills.

Discussion The amount of scientific work on children’s stereotypes regarding computer scientists is still limited. Applying the reduced-length Child Implicit Association Test to measure children’s stereotypes on computer scientists has, to our knowledge, not been done before. Understanding children’s stereotypes and how to tackle them contributes to closing the gender gap in Computer Science.

CCS CONCEPTS

• **Social and professional topics** → **User characteristics; Computing occupations.**

KEYWORDS

stereotypes, gender, social skills, interests, computer scientist, programmer

ACM Reference Format:

Shirley de Wit, Felienne Hermans, and Efthimia Aivaloglou. 2021. Children’s Implicit and Explicit Stereotypes on the Gender, Social Skills, and Interests of a Computer Scientist. In *Proceedings of the 17th ACM Conference on International Computing Education Research (ICER 2021), August 16–19, 2021, Virtual Event, USA*. ACM, New York, NY, USA, 13 pages. <https://doi.org/10.1145/3446871.3469753>

1 INTRODUCTION

Women are underrepresented in the field of Computer Science [5, 19, 24, 29, 30, 36]. In the United States, women accounted for 27% of computer and mathematical scientists [27]. In Europe, 18% of IT specialists are women [9]. Reasons for women to not pursue a Computer Science career include low self-efficacy [1, 18, 26, 38], low interest [18, 26, 30] and lack of fit [18, 29, 30, 38] which are all factors influenced by stereotypes [5, 11, 30, 36, 38]. Adults stereotype computer scientists as being male, asocial and technological oriented [5, 6, 16, 29].

We know that stereotypes develop at an early age [3, 37], however research on the stereotypical beliefs that children hold about computer scientists is sparse [24, 30] and inconclusive. A study with the Draw-A-Computer-Scientist-Test revealed that children (aged 8-11) stereotype a computer scientist as being a male who works alone and predominantly uses computers [24]. However, a study where children (aged 8-12) were explicitly asked whether they believe that computer scientists are male, asocial, and singularly focused on computer science did not result in the identification of stereotypical beliefs [1]. These inconsistent findings might be explained by the difference between implicit and explicit stereotypes. An implicit stereotype is relatively inaccessible through conscious awareness and thus can not be measured by directly asking participants about it [10]. An explicit stereotype, on the other hand, is one we can deliberately think and report about and thus can be measured by asking participants about it.

In this study, we aim to gain an understanding of children’s implicit and explicit stereotypes regarding computer scientists. We focus on the stereotypes concerning gender, social skills and interests. We thereby aim to answer the following research questions:



This work is licensed under a Creative Commons Attribution International 4.0 License.

ICER 2021, August 16–19, 2021, Virtual Event, USA
© 2021 Copyright held by the owner/author(s).
ACM ISBN 978-1-4503-8326-4/21/08.
<https://doi.org/10.1145/3446871.3469753>

RQ1. To what extent do children hold implicit stereotypes on computer scientists’ a) gender, b) social skills and c) interests?

RQ2. To what extent do children hold explicit stereotypes on computer scientists’ a) gender, b) social skills and c) interests?

We hypothesize that not all children know what a computer scientist does, supported by [23, 24, 26], which might influence their stereotypical beliefs. Therefore we also study whether explaining what a computer scientist does influences children’s stereotypes, resulting in our third research question:

RQ3. How does an explanation of what a computer scientist does affect children’s implicit and explicit stereotypes on computer scientists’ a) gender, b) social skills and c) interests?

To answer our research questions, we conduct a quantitative study in a science museum with 564 children between the age of 7 and 18. We use the reduced-length Child Implicit Association Test to measure children’s implicit stereotypes and 5-point Likert scale questions to measure children’s explicit stereotypes. Participants in the *experiment group* (n=352) start the study with a video in which either a man or woman explains what a computer scientist does.

We found that children hold weak implicit stereotypical beliefs on computer scientists’ social skills (being social instead of asocial) and moderate implicit stereotypical beliefs on computer scientists’ interests. We also found explicit stereotypes on computer scientists’ gender, social skills and interests. Measuring the effects of the intervention, we found significant differences between the *control* and *experiment group* in their explicit stereotypes on computer scientists’ social skills.

2 BACKGROUND

2.1 Stereotypes in Computer Science

Computer scientists are often stereotyped as being male, asocial and having an (obsessive) interest in computers [5, 6, 16, 29]. Other stereotypical traits of computer scientists include being intelligent [6], having specific physical features such as wearing glasses [6, 24], and being competitive [29].

Stereotypes regarding computer scientists can be transmitted through the physical environment, the media, and the people in the field [6]. It has been found that a Computer Science classroom without stereotypical objects such as electronics, tech magazines and video games increase girls’ interest in taking computer science courses [30]. Stereotypes show through the stereotypical clothing, hobbies and favourite movies of the people in the field [7]. Stereotypical hobbies include playing video games, watching anime, and programming. While non-stereotypical hobbies included playing sports, hanging out with friends, and listening to music. In a study, undergraduate students interacted with either a stereotypical or non-stereotypical role model for, on average, less than 2 minutes [4]. Women who encountered a role model who embodied computer science stereotypes were less interested in majoring in computer science and felt less belonging in the field compared to women who interacted with a non-stereotypical role model or no role model.

The work on children’s stereotypical beliefs about computer scientists is sparse [24, 30], but researched by some. A study with the Draw-A-Computer-Scientist-Test showed that children (aged 8-11) stereotyped computer scientists as being male, working alone

and predominantly using computers [24]. Children in this study drew a vague set of tasks and 25% of them drew a scientist (with a lab coat and exploding chemicals) who uses a computer. In another study, a Draw-A-Programmer Test with students aged 12-14, 62.5% of the boys depicted only male programmers in their drawings while 75.3% of the girls included at least one female programmer [28]. Despite the instruction to draw colleagues, 20.1% of the students drew a single programmer. In a survey, girls (aged 14-16) described computer scientists as ‘geeky’ and ‘not athletic (sitting in front of a computer all day does that to you)’ [19]. Another study shows that 6-year-old children think that boys are better than girls at robotics and programming [31]. However, in another study measuring explicit stereotypical beliefs, students (aged 8-12) were not inclined towards any particular beliefs of a computer scientist being singular focused, asocial, competitive or male [1].

2.2 Measuring implicit and explicit stereotypes

An implicit stereotype is relatively inaccessible through conscious awareness and thus can not be measured by directly asking participants about it [10]. The most widely-used way of measuring implicit stereotypes is the Implicit Association Test (IAT) [17]. The IAT is a computerized test that determines the implicit association between concepts [20], for instance between flowers/insects and attitude. The test asks participants to categorise stimuli (such as words or pictures) to the left or right by pressing corresponding keyboard responses. The response time is used to determine the strength of the association. The traditional IAT consists of 7 blocks of which 5 blocks are meant for participants to practice the controls and 2 blocks are used to measure implicit association through response time. The trials within a block are the stimuli that the participant needs to categorise. An example of a 7-block IAT measuring the attitude towards flowers and insects is shown in Table 1. Participants who have a faster response time in block 4 than in block 7 have a more positive implicit attitude towards flowers than toward insects.

The IAT is designed for adults, but with some adjustments can be used to measure children’s implicit stereotypes. These include improving usability by replacing the keyboard responses with two large response buttons [14], replacing a keypad with a mouse [35], and attaching arrows to the computer screen [35]. Written stimuli can be replaced with recordings of spoken words [14] or with images and pictures resulting in a completely pictorial-based version of the IAT [35]. Rutland et al. [35] made a shorter version of the IAT for children: it contains 5 blocks instead of 7 blocks, 12 instead of 20 trials per practice block and 32 instead of 40 trials per test block. Williams and Steele [41] concluded that the reliability of this reduced-length Child Implicit Association Test is comparable to the reliability of the traditional IAT completed by adults.

An explicit stereotype is one we can deliberately think and report about. These stereotypes can be measured by asking questions to participants, for instance via Likert scale questions as done by others [1, 12, 40]. The questions asked can be absolute or relative [25], where absolute questions measure just one target concept (for instance evaluating flowers) and relative questions measure two concepts compared to each other (for instance, evaluating flowers in comparison to insects).

Table 1: 7-block IAT measuring attitude towards flowers and insects

Block	Trials	Function	Left response	Right response
1	20	Practice	Flowers	Insects
2	20	Practice	Pleasant	Unpleasant
3	20	Practice	Flowers + pleasant	Insects + unpleasant
4	40	Test	Flowers + pleasant	Insects + unpleasant
5	20	Practice	Unpleasant	Pleasant
6	20	Practice	Flowers + unpleasant	Insects + pleasant
7	40	Test	Flowers + unpleasant	Insects + pleasant

3 RESEARCH DESIGN

We conduct an experiment with a between-subject design, which means that each participant is in a single group and thus exposed to only a single condition. The study is conducted in the Dutch language. In this study, we use ‘programmer’ instead of ‘computer scientist’ since the term computer scientist is not commonly used in the Netherlands.

The research consists of several components: a video intervention, reduced-length Child Implicit Association Tests, explicit Likert-scale questions, questions about experiences with programming and programmers, and demographics¹. All participants did an IAT in which we measure their implicit gender stereotypes (referred to as the gender-profession IAT), followed by either an IAT in which we measure their implicit social skills stereotype (referred to as the social-profession IAT) or an IAT in which we measure their implicit interests stereotype (referred to as the interests-profession IAT). We include two instead of three IATs per participant to limit the amount of time spent on the study as well as retaining their focus.

The intervention consists of a short video in which a programmer explains what a programmer does. We made two versions of the video, one with a male programmer and one with a female programmer. They both used the same script. Participants in the *experiment group* see one of these videos at the beginning of the study, while the *control group* sees the video at the end. Figure 1 gives a graphical overview of the order of the components in this study per group.

Before conducting the study, we performed a pilot to test the materials including the usability of the open-source application we developed to gather the data. We discuss the findings of the pilot in Section 3.4.

The design of the study is approved by the ethics committee of Leiden University.

3.1 Implicit stereotypes

We measure the implicit stereotypes by the use of the reduced-length Child-IAT [35, 41] which consists of 5-blocks with a reduced number of trials and only pictorial stimuli. The structure of this reduced-length Child IAT, with gender-profession IAT as an example, is shown in Table 2. The order in which the stereotype consistent block (block 3 in Table 2) and stereotype inconsistent

block (block 5 in Table 2) are presented is counterbalanced, as suggested by [35, 41]. The order of the stimuli (images) is random. Each image is shown an equal number of times to all participants and the same image does not appear twice in a row. The participants use the ‘e’ key to categorize an image to the left, and the ‘i’ key to categorize an image to the right. On both the ‘e’ and ‘i’ key yellow stickers with a bigger ‘e’ and ‘i’ are placed to increase ease of use. When a child makes a mistake, feedback is provided for incorrect responses; a blue ‘x’ remains on-screen until the correct response is given.

Each of the concepts consists of two categories, shown in Table 3. We use four images per category, as suggested to be the minimum amount of stimuli [33]. A sample of the images is shown in Figure 2.

For the profession concept, we use the categories programmer and writer. As mentioned before, we use the term ‘programmer’ instead of ‘computer scientist’ since the term computer scientist is not commonly used in the Netherlands. We compare a programmer to a writer in line with other IAT studies [12, 32, 42], where science and mathematics are contrasted with language. We also consider a programmer to be the creator of software where a writer is the creator of new texts. Since both professions can use similar tools such as computers, we decide to use images of products a programmer or a writer creates.

For the gender concept, we use the categories boy and girl. Although gender is not binary, the boy and girl gender are contradictory and a division most children can relate to. The categories are depicted by drawings of boys and girls.

For the social skills concept, we use the categories alone and together which are depicted by either one person or two persons. We use the same four drawn persons in both categories, where each person appears an equal amount of times in each category and the distribution is gender-balanced.

For the interests concept, we use the categories video gaming and tennis. We choose video gaming because this is one of the stereotypical hobbies described by [7, 30] and is consistent with having a singular focus on computers. One of the non-stereotypical hobbies is playing sports [7]. A sport that is evenly popular among boys and girls, as well as among major and minority groups, in the Netherlands is tennis [15] and therefore chosen as the second category in the interests concept.

3.2 Explicit stereotypes

We ask participants about their explicit stereotypes regarding programmers’ gender, social skills and interests. We do so with both relative and absolute questions. In the relative questions children

¹Materials including the questions and software, scripts and anonymized dataset can be found at <https://shirleydewit.com/icer2021>

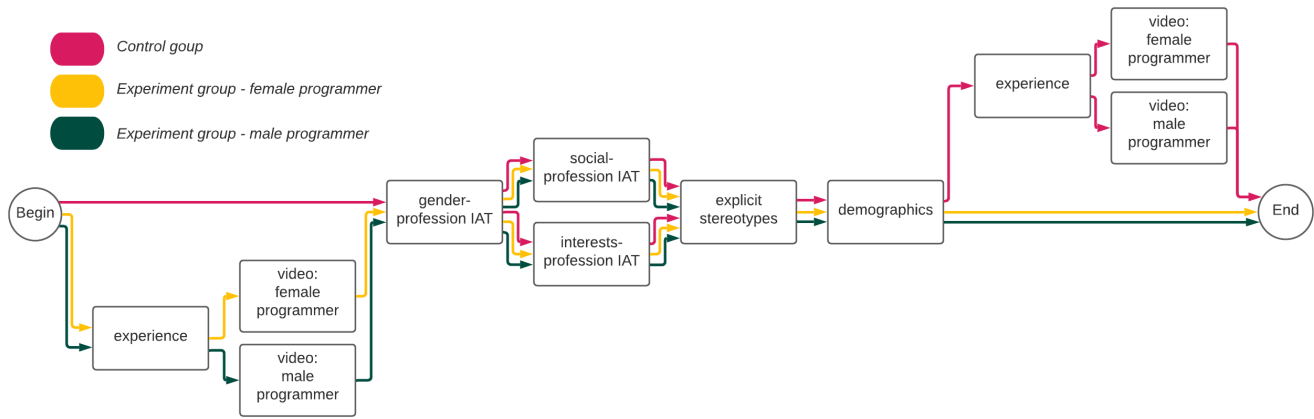


Figure 1: Overview of the study design

Table 2: The structure of the reduced-length Child-IAT with the gender-profession IAT as example

Block	Trials	Function	Left response	Right response
1	16	Practice	Programmer	Writer
2	16	Practice	Boy	Girl
3	32	Test	Programmer + boy	Writer + girl
4	16	Practice	Girl	Boy
5	32	Test	Programmer + girl	Writer + boy

Table 3: Concepts, categories and images used in the gender-profession, social-profession and interests-profession IAT

Concept	Category	Images
Profession	Programmer	Website, video streaming, video calling, social media
	Writer	Magazine, book, newspaper, papers
Gender	Boy	Four different boys
	Girl	Four different girls
Social skills	Alone	Four persons standing alone
	Together	Four groups of two persons standing
Interests	Video gaming	Four different video game controllers
	Tennis	Tennis racket, ball, shoe, net

indicate whether a statement applies to programmers or writers for example *Which profession do you think is for girls?* (translated from Dutch). In the absolute questions children indicate whether a statement applies to programmers only for example *Being a programmer, that is a profession for...* (translated from Dutch). All explicit questions are answered with a 5-point Likert scale and inspired by [1].

3.3 Experiences and demographics

We ask participants about their experiences with programming and programmers. For their programming experiences, we ask if they have any experiences and also if they obtained them at school, at home with family or friends, or at out-of-school activities such as in libraries or code clubs. Children who do not know what programming is fall in the category ‘no experiences’. For their experience with programmers, we ask participants if they know a programmer and see this person often, not often, or via media such as movies.

The children who do not know what a programmer is, fall in the category ‘not knowing a programmer’. For both the experiences with programming and with programmers, children are allowed to select more than one answer.

The demographics include children’s age and gender as well as the country of birth of their parents or guardians.

3.4 Materials and pilot

To conduct this research, we developed software, videos and images¹. We tested the materials during a two day pilot in the same science museum where the experiment is conducted. Seventeen children participated in this pilot. The following paragraphs describe the materials and the adjustments made according to the feedback gathered during the pilot.

Software. Together with a group of students, we developed open-source software that gathers informed consent forms, assigns

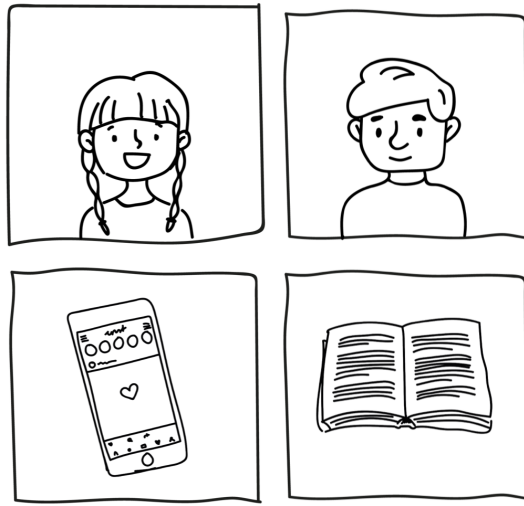


Figure 2: Sample of the images used in the IATs for gender (top) and profession (bottom)

participants randomly to a group and gathers the research data. The online informed consent form is accessible for guardians on their own devices via a QR code, which was preferable due to COVID-19 regulations. The software that gathers the data is developed with a focus on usability, data security, and having a neutral environment without distractions. The application is in black and white and only displays the components of the study. For the video, participants can not click ‘next’ before the end of the video. During the pilot we saw that some of the buttons were too small for children, so we enlarged them. They also had trouble with a question where scrolling was needed to see all answers, so we adjusted the layout of this question. In the pilot, we included an open question but it took a lot of time and effort from the children to fill this in so we removed it. Some children asked the researcher to read aloud the explanation texts. Therefore we added a read-aloud functionality to the software for all included texts. The children who press the read-aloud button will have a female computer voice reading the displayed explanation text or question aloud. Some children asked multiple times which keys on the keyboard they needed to press in the IAT, but once they understood the controls they had no problem using them. Therefore we introduced the opportunity for children to practice the fruit-vegetable categorization task before entering the research space. We also added yellow stickers with ‘e’ and ‘i’ on the keyboards to help children recognize which keys to use. We observed in the experiment that these additions solved the usability issues.

Video. In the two intervention videos, all aspects, besides the gender of the presenter, are kept the same. Both the female and male programmer were named Robin, they said the same text, stood before the same neutral background and had similar physical characters such as clothing, skin and hair colour. We took the following description of a computer scientists as a starting point for the script: ‘A computer scientist knows about computers. A computer scientist can fix computers and develop new programs and apps to use

for work and fun.’ [36]. In the video, Robin introduces himself or herself as a programmer. Robin explains that computers are all sort of devices that can not think by themselves. The task of the programmer is to program these devices such that they know what to do. Examples Robin mentions include social media, video streaming services, and websites. The length of both videos is under one minute. In the pilot, we asked children if they understood (one of) the video’s and could explain what a programmer does. We also discussed with the children what software applications they know and use. Children mentioned video calling applications which they use for remote learning due to COVID-19. This resulted in adding a video calling application as an example mentioned in the video as well as an image for the programmer category within the IAT.

Images. For the stimuli of the IAT, we used artist drawn images designed for this study. We decided on using images and not pictures because of the reduced-length Child-IAT having only pictorial stimuli and because of having more control over what is shown. We consciously picked black and white line drawings to have all stimuli in a similar style. During the pilot, we asked children to categorize the printed out images of the gender and social skills concepts into a boy, girl and gender-neutral pile. We observed that the gender images we designed were not logical for children. One of the boys got frustrated because in his opinion the gender categorization presented in the IAT was not correct. Two things stood out. First that even when children were in doubt about the gender they felt the urge to categorize an image as either boy or girl. Secondly, long hair equals a girl and short equals a boy for almost all children in the pilot. Therefore we gave all girls long hair and all boys short hair in the study. For the interests concept, the children did not recognize one of the video gaming consoles so we updated this illustration as well.

3.5 Environment and participant recruitment

We conducted the research at NEMO Science Museum in Amsterdam for 14 days in a row during the summer of 2020. At the museum, we recruited participants by pointing out the opportunity to participate via screens at the entrance of the museum, as well as by asking visitors who walked by the research space to participate. We mentioned that the research was about professions, without disclosing what we measured and for which professions. Participants (and their families) could ask questions about the purpose of the study after finishing the study.

For all participants under the age of 16, a guardian needed to sign an informed consent form. Before entering the research room, participants were asked to practice controls for the IAT with a fruit-vegetable categorization task, see Figure 3a. Guardians were asked to wait in another room. A few (young) children who found participating apprehensive had an adult joining them. The researchers in the room made sure the adults did not influence the study. There was always a researcher in the room to answer questions and help out if needed.

The room itself was not decorated and only contained materials for the experiment, see Figure 3b. When sitting at the desk, participants faced the wall. We collected data via our software running on laptops. The participants could use an external mouse to make navigation easier. Furthermore, we asked participants to use the

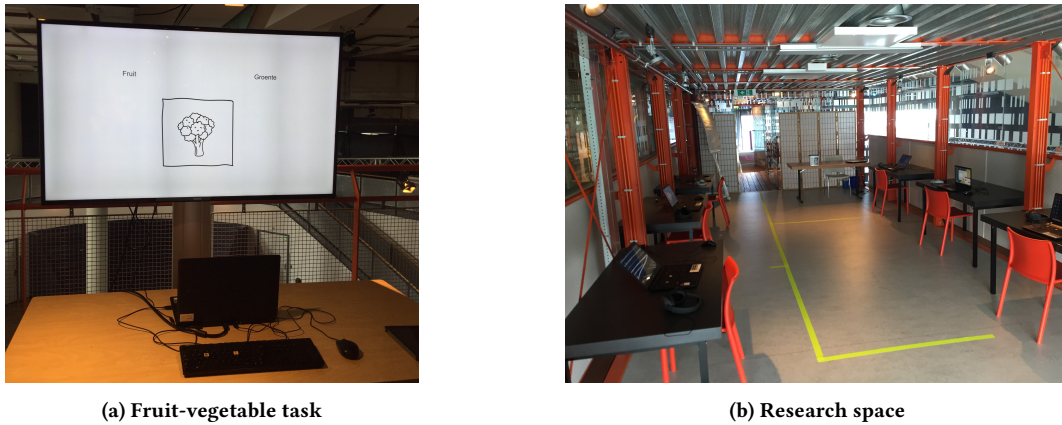


Figure 3: Research environment

headphones we provided. At the end of the experiment, participants received a certificate stating that they were ‘science rabbits’ proving they participated in scientific research. All materials were cleaned after every single use because of COVID-19 regulations.

During the 14 days, we had a team of eight women who conducted the research in the museum. Every day there were at least three people present and, besides the first day, we made sure that there was no complete new team per day to ensure consistency in the recruitment and support process. Except for one day (due to health problems), at least one of the authors of this paper was present.

3.6 Participants

During the 14 days of data collection, 611 children between the age of 7 and 18 started the study. Of these children, 564 (or 92%) completed the entire study. We observed (mostly younger) children quitting for various reasons including lack of focus, slow pace and thereby longer duration, impatient parents, and siblings or friends finishing earlier. The data from the 564 children that completed the study are used in the remainder of this paper. The age of the participants varied from 7 to 18 with a mean of 10.19 and a median of 10. The age distribution can be found in Figure 4.

Of the participants, 266 (or 47%) of the children identified themselves as girls, 262 (or 46%) as boys, 8 (or 0,014%) as neither a boy nor girl and 28 (or 0,050%) preferred to not disclose their gender. Most children indicated that both (447 or 79%) or one (51 or 9%) of their parents are born in the Netherlands. All the children were able to read in Dutch, which is the language used in the study. Over half of the children has previous programming experience (310 or 55%), where most of these children gained experience at school (230 or 74% of the children with programming experiences). Furthermore, 97 (or 31% of children with programming experiences) gained experience at home and 72 (or 23% of the children with programming experiences) children gained experience at out-of-school activities. The majority of the children, 385 (or 68%) responded that they do not know any programmer. Of the 180 (or 32%) children that do know a programmer, 55 (or 31% of the children who know a programmer) interact often with this person, 73 (or 41% of the children

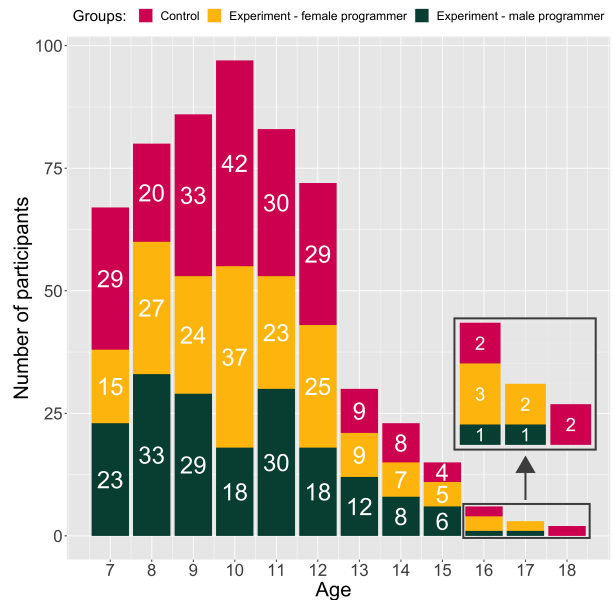


Figure 4: Age distribution of the children who completed the study (n=564)

who know a programmer) do not interact with this person often, and 73 (or 41% of the children who know a programmer) indicate they know a programmer via the media.

3.7 Data analysis

We analyse the data of the participants using R¹. To determine whether participants completed the study, we check whether they filled in their age and gender which were the last questions asked to participants from all groups (see Figure 1). We also exclude eight participants who we helped to skip the second IAT due to lack of concentration, which was written down in the research notes. To answer RQ1 and RQ2 in Section 4.1 and Section 4.2, we use the data

of the participants in the *control group* only. In Section 4.3, we use the data from all the groups.

We use age in two different ways in our analysis. Firstly, we use age as a continuous variable. Secondly, we divide the participants into three age categories: young (age 7, 8, 9 and 10), middle (age 11, 12 and 13) and older (age 14, 15, 16, 17 and 18). These categories are based on the school system in the Netherlands. Where the younger participants are in primary school, the middle group is either in the last year of primary school or the first year of secondary school, and the older participants are in secondary school.

3.7.1 Implicit stereotypes. For the implicit stereotypes, we look at the response time and calculate the D measure [22]. To determine whether the response time of the consistent and inconsistent blocks differ, we use a t-test to compare the means of the two blocks. The D measure, usually between -2 and 2, indicates the strength of the implicit association. As a rule of thumb, an absolute value of the D measure above 0.15 indicates a weak implicit association, above 0.35 a moderate implicit association and above 0.65 a strong implicit association [2]. To calculate the D measure with the improved scoring algorithm [22] for a reduced-length Child-IAT, we label the first 12 of the 32 trials within block 3 and 5 as training trials and the other 20 trials as critical as suggested by [41]. We eliminate trials with a latency above 10.000 ms and remove participants who have a latency below 300 ms for more than 10% of their trials within a single IAT. This resulted in the removal of three participants in the social-profession IAT and one participant in the interests-profession IAT. Within the improved scoring algorithm, a 600 ms penalty is given when a participant entered the wrong response. However, the algorithm suggests not to add this penalty when a correct response is needed to continue the task. Since this is the case in our set-up, we do not add a 600 ms penalty when an error occurred. We also investigate whether gender, age, and experiences of the participants result in different D measures by using Pearson correlation for the continuous age variable and t-test for the other variables.

3.7.2 Explicit stereotypes. For the explicit stereotypes, we analyse the scores of the 5-point Likert scale questions. We compare the answers with a one-sample t-test to 3, since 3 represents a neutral attitude in the 5-point Likert scale. We use t-tests to analyse whether gender, age, and experiences of the participants result in different scores. We use a Pearson correlation to analyse the correlation between the scores and the continuous age variable. Additionally, we use Cohen's d to calculate the effect size and its 95% Confidence Interval (95% CI). An effect size of 0.2 indicates a small effect, 0.5 indicates a medium effect and 0.8 indicates a large effect [8].

3.7.3 Intervention. For the intervention, we compare the *control group* with the *experiment group* as a whole, the *experiment group - female programmer* and the *experiment group - male programmer*. Furthermore, we compare the *experiment group - female programmer* to the *experiment group - male programmer*. We use t-tests to look for differences between groups' D measures for the implicit stereotypes and differences between groups' scores for the explicit stereotypes. We also compare subsets based on gender, age, and experiences, for example the boys in the *control group* compared to the boys in the *experiment group*.

4 RESULTS

4.1 RQ1: Implicit stereotypes

A complete overview of the response times and D measures for the implicit stereotypes in the control group can be found in Table 4. Three participants were excluded for the social skills stereotype and one participant for the interests stereotype due to many fast responses, which is within the exclusion criteria (see Section 3.7).

a) Gender stereotype. On average, participants in the *control group* have no association between programmers and gender. Although they did respond faster when combining programmer and boy images than when combining programmer and girl images ($p=0.0034$), the difference was not big enough to conclude an implicit association (D measure = 0.072). The boxplot of the D measures is shown in Figure 5a.

We found no significant differences in D measures based on participants gender, age or experiences.

b) Social skills stereotype. On average, participants in the *control group* have a weak implicit association between the categories programmer and together; they responded faster when combining programmers and together (and writers and alone) with $p=1.41 e^{-9}$ and D measure=-0.27. The boxplot of the D measures is shown in Figure 5b.

We found that the older the participant, the stronger the association between the categories programmer and together. The correlation between the D measure and the age of the participants is -0.29 ($p=0.0034$, 95% CI [-0.46 -0.099]) and the correlation between the D measure and the age categories is -0.22 ($p=0.022$, 95% CI [-0.41, -0.034]). The correlation between age and D measure is shown in Figure 6. Please note that the oldest participant in this group is 15 years old ($n=1$).

We found no significant differences in the D measures for the social skills stereotype based on participants gender or experiences.

c) Interests stereotype. On average, participants in the *control group* have a moderate implicit association between programmers and video games; they responded faster when combining programmer and video gaming than when combining programmer and tennis with $p<2.2 e^{-16}$ and a D measure of 0.45. Figure 5c depicts a boxplot of the D measures. Participants who indicated knowing programmers from media have a stronger association between programmers and video games ($p=0.031$).

We found no significant differences in the D measures for the interests stereotype based on participants gender, age or programming experiences.

Our findings for RQ1 indicate that the participating group of children hold no implicit stereotypes on computer scientists' gender, weak implicit stereotypes on programmers being social, and moderate implicit stereotypes on programmers playing video games.

4.2 RQ2: Explicit stereotypes

The features we measured for the explicit stereotypes are described in Table 5. This table includes the mean, whether the score differs from the 'neutral' score 3, and the distribution of the answers given by the *control group*. Table 6 shows the mean per feature based on the age, gender and experiences of the participants.

a) Gender stereotype. For the participants in the *control group*, we found for the gender-girls, gender-boys and gender-programmer

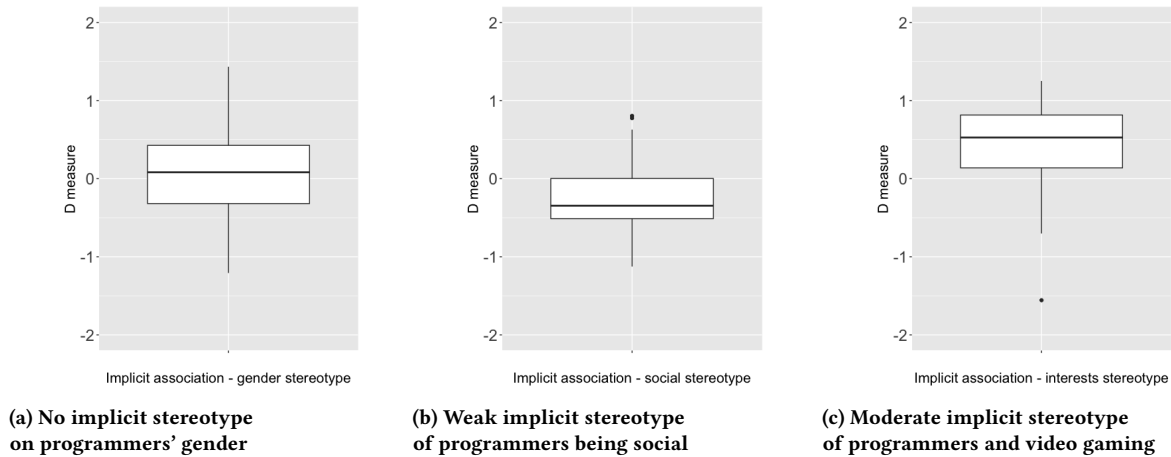


Figure 5: D measures of the *control group* for all three stereotypes

Table 4: Implicit measurements on all three stereotypes from participants in the *control group*

	Gender				Social Skills				Interests			
	N	Response time consistent block (in ms)	Response time in-consistent block (in ms)	D	N	Response time consistent block (in ms)	Response time in-consistent block (in ms)	D	N	Response time consistent block (in ms)	Response time in-consistent block (in ms)	D
All	208	2863	2926	0.072	100	3161	2960	-0.27	104	2695	2379	0.45
Gender												
Boy	89	2797	2858	0.11	43	3116	2852	-0.31	43	2587	2989	0.45
Girl	101	2897	2922	0.0089	49	3195	3034	-0.26	51	2758	3183	0.45
Neither	4	2744	2719	0.10	1	3594	3954	0.31	3	2323	3064	0.75
Unknown	14	3075	3444	0.29	7	3135	2977	-0.19	7	3073	3476	0.38
Age												
Young	124	3123	3179	0.051	66	3306	3143	-0.21	56	2981	3393	0.39
Middle	68	2553	2596	0.063	30	2911	2650	-0.36	37	2396	2861	0.56
Old	16	2204	2387	0.28	4	2696	2327	-0.58	11	2274	2609	0.40
Experience - programming												
Yes	120	2714	2805	0.11	58	3021	2827	-0.26	59	2574	3004	0.44
Yes - out-of-school	21	2468	2628	0.22	8	2492	2379	-0.19	13	2628	3025	0.32
Yes - home	37	3021	3159	0.16	18	3430	3214	-0.23	18	2767	3146	0.33
Yes - school	84	2661	2.712	0.065	40	3006	2795	-0.29	42	2470	2917	0.48
No	89	3064	3088	0.017	42	3358	3147	-0.29	46	2841	3257	0.48
Experience - programmer												
Yes	66	2664	2792	0.16	32	2967	2699	-0.36	32	2538	2959	0.41
Yes - often	23	2746	2953	0.19	13	3157	2924	-0.32	9	2581	2766	0.18
Yes - not often	22	2661	2745	0.19	8	2839	2618	-0.39	14	2556	3063	0.41
Yes - media	25	2559	2652	0.10	13	2786	2465	-0.40	11	2440	3040	0.69
No	142	2957	2988	0.03	68	3252	3085	-0.23	72	2765	3188	0.47

features, as described in Table 5, the explicit belief that programmers are more likely to be men.





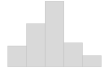

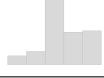
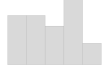
We found that boys think that being a writer is more for girls than girls themselves ($p=0.00029$, $d=0.52$ (medium), 95% CI [0.23, 0.82]). Boys also think programming is more for boys than it is for girls more strongly than girls themselves do ($p=0.0012$, $d=-0.48$ (small), 95% CI [-0.77, -0.19]).

Participants who know a programmer but do not see this person often have a stronger explicit belief towards programming being for boys than children who know a programmer and see this person often ($p=0.039$, $d=-0.64$ (medium), 95% CI [-1.3, -0.024]).

No other significant differences were found based on participants age, gender and experiences for the three gender features.

b) Social skills stereotype. Participants agree with the statement that programmers make friends easily.

Table 5: Features measuring explicit stereotypes including the mean, whether the mean differs the neutral belief and distribution of the answers by participants in control group

Feature	Description	n	Mean	Different from 3?	Distribution
Gender-girls	Profession for girls 1= programmer, 5 = writer	208	3.62	Yes $p=1.8 e^{-14}$	
Gender-boys	Profession for boys 1= programmer, 5 = writer	208	2.23	Yes $p<2.2 e^{-16}$	
Gender-programmer	Programming is a profession for 1=boys, 5=girls	208	2.56	Yes $p=4.9e^{-12}$	
Social	Makes friends easier and prefers to work together 1= programmer, 5 = writer	103	2.86	No $p=0.18$	
Social-programmer	Programmers make friends easily and prefer to work together 1=agree, 5=disagree	103	2.77	Yes $p=0.029$	
Interests-videogaming	Likes to play video games 1=programmer, 5=writer	105	1.57	Yes $p<2.2 e^{-16}$	
Interests-tennis	Likes to play tennis 1=programmer, 5=writer	105	3.48	Yes $p=6.4e^{-05}$	
Interests-programmer	Programmers like computers and have little other interests 1=agree, 5-disagree	105	2.83	No $p=0.19$	

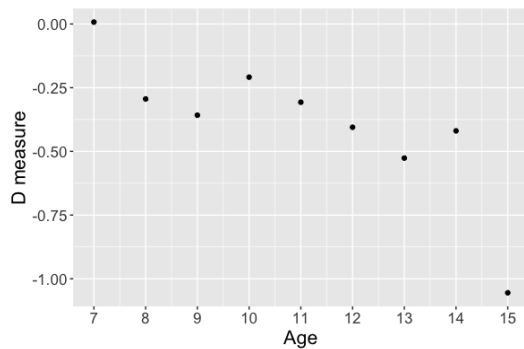


Figure 6: The older the participants, the stronger the implicit stereotype of programmers being social

The older the participant, the less they agreed with this statement depicted in a correlation of 0.24 ($p=0.016$, 95% CI=[0.045, 0.41], see in Figure 7.

No other significant differences were found based on participants age, gender and experiences for the social and social-programmer features.

c) *Interests stereotype.* Participants think that a programmer prefers to play video games more than a writer does and that a writer prefers to play tennis more than a programmer does.

The older the participant, the stronger their explicit stereotype that video gaming is for programmers with a correlation of -0.23

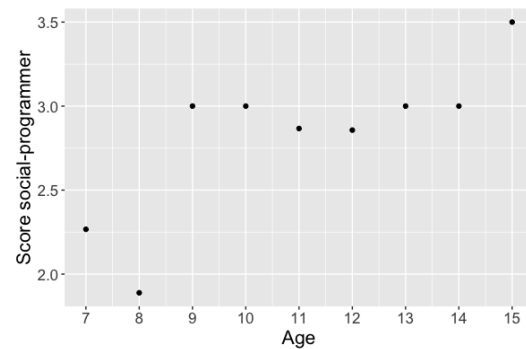


Figure 7: Younger participants agree more on programmers being social than older participants

($p=0.020$, 95% CI [-0.40, -0.037]), see also Figure 8. When participants fall in older age categories, they agree more with programmers being singularly focused with a correlation of 0.19 ($p=0.048$, 95% CI [0.0020, 0.37]).

No other significant differences were found based on participants age, gender and experiences for the three interests features.

Our findings for RQ2 indicate that the participating group of children have the explicit belief of a programmer being male, social and interested in video games.

Table 6: Explicit measurements on all features on a 5-point Likert scale from participants in the control group, with progr. being an abbreviation for programmer

	N	Gender -girls	Gender -boys	Gender -progr.	N	Social	Social -progr.	N	Interests -videogaming	Interests -tennis	Interests -progr.
All	208	3.62	2.23	2.56	103	2.86	2.77	105	1.57	3.45	2.83
Gender											
Boy	89	3.92	2.02	2.35	46	2.70	2.76	43	1.51	3.37	2.93
Girl	101	3.39	2.28	2.75	49	2.98	2.80	52	1.54	3.48	2.81
Neither	4	4.25	2.50	2.25	1	3.00	3.00	3	2.67	4.67	2.33
Unknown	14	3.21	3.14	2.64	7	3.14	2.57	7	1.71	3.14	2.57
Age											
Young	124	3.69	2.17	2.55	67	2.87	2.69	57	1.70	3.40	2.56
Middle	68	3.53	2.31	2.57	31	2.87	2.88	37	1.43	3.49	3.16
Old	16	3.50	2.38	2.63	5	2.80	3.20	11	1.36	3.55	3.09
Experience - programming											
Yes	120	3.60	2.24	2.53	60	2.85	2.73	60	1.52	3.48	2.88
Yes - out-of-school	21	3.67	2.24	2.43	8	2.75	2.75	13	1.85	3.69	2.54
Yes - home	37	3.65	2.14	2.54	18	2.78	3.06	19	1.47	3.79	2.68
Yes - school	84	3.54	2.26	2.58	42	2.98	2.67	42	1.50	3.31	3.07
No	89	3.64	2.21	2.61	43	2.88	2.81	46	1.63	3.39	2.74
Experience - programmer											
Yes	66	3.70	2.17	2.53	34	2.79	2.74	32	1.50	3.59	2.94
Yes - often	23	3.48	2.35	2.74	14	2.71	2.79	9	1.44	3.78	3.11
Yes - not often	22	4.00	2.00	2.27	8	2.88	2.63	14	1.50	3.43	2.50
Yes - media	25	3.64	2.16	2.52	14	2.93	2.71	11	1.64	3.73	3.45
No	142	3.58	2.26	2.58	69	2.90	2.78	73	1.60	3.38	2.78

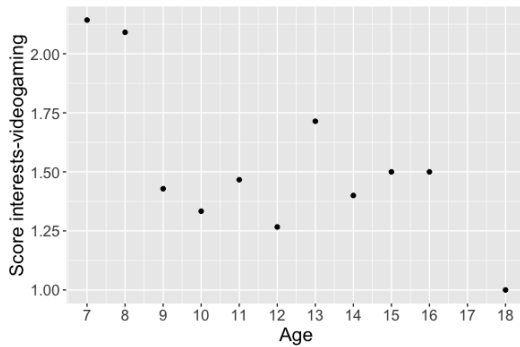


Figure 8: The older the participant, the stronger their explicit association between programmers and video gaming

4.3 RQ3: Intervention

4.3.1 Implicit stereotypes. We did not find any significant differences in the implicit stereotypes between the groups. The D measure per group is shown in Table 7. However, we did find some differences between groups for the interests stereotype based on participants age and experience groups.

Participants in the middle age category have a stronger association between programmers and video games in the *experiment group - female programmer* (D measure=0.81) compared to the *control group* (D measure=0.56) with $p=0.038$ and compared to the *experiment group - male programmer* (D measure=0.52) with $p=0.026$.

The participants who know a programmer have a weaker association between programmers and video games in the *control group*

Table 7: D measure per stereotype per group

Group	Gender	Social	Interests
<i>Control</i>	0.072 (n=208)	-0.27 (n=100)	0.45 (n=104)
<i>Experiment</i>	0.049 (n=352)	-0.27 (n=178)	0.51 (n=174)
<i>Experiment - female programmer</i>	0.033 (n=176)	-0.30 (n=91)	0.53 (n=84)
<i>Experiment - male programmer</i>	0.066 (n=176)	-0.24 (n=87)	0.49 (n=90)

(D measure=0.41) than in the *experiment group - female programmer* (D measure=0.68) with $p=0.047$.

4.3.2 Explicit stereotypes. When comparing the different groups with each other, we only found differences in the social skills stereotype (see Table 8 for all mean scores explicit feature). Participants in the *experiment group* as well as participants only in the *experiment group - male programmer* agreed more to a programmer being social than the *control group* with $p=0.10$, $d=0.33$ (small) and 95% CI of [0.081, 0.57]. Below we discuss the significant differences (with $p<0.03$) with at least a medium effect size based on participants age, gender and experiences. The table with all significant differences can be found online ¹.

For the gender stereotype, we found that participants who know a programmer but do not see this person often think a profession for girls is less likely to be a programmer after seeing a female programmer in the video (mean=3.86) than when seeing a female programmer (mean=3.41) with $p=0.036$, $d=-0.60$ (medium) and 95%

Table 8: Score on a 5-point Likert scale per the explicit features per group

Group	Gender -girls	Gender -boys	Gender -programmer	Social	Social -programmer	Interests -videogaming	Interests -tennis	Interests -programmer
<i>Control</i>	3.62	2.23	2.56	2.86	2.77	1.57	3.45	2.83
<i>Experiment</i>	3.67	2.39	2.61	2.82	2.43	1.67	3.67	2.85
<i>Experiment - female programmer</i>	3.58	2.38	2.65	2.84	2.49	1.64	3.71	2.78
<i>Experiment - male programmer</i>	3.76	2.40	2.57	2.81	2.36	1.69	3.62	2.91

CI=[-1.19, -0.015]. Participants who know a programmer via media in the *experiment group - male programmer* (mean=2.94) have a less strong opinion about a profession for boys being a programmer than the *control group* (mean=2.16, $p=0.036$, $d=-0.88$ (large), 95% CI=[-1.56, -0.21]) and than the *experiment group - female programmer* (mean=2.21, $p=0.016$, $d=-0.72$ (medium), 95% CI=[-1.39, -0.047]).

For the social skills stereotype, we found participants in the middle age group to believe that programmers are more social when they are in the *experiment group* (mean=2.34) or in the *experiment group - female programmer* (mean=2.26) than when they are in the *control group* (mean=2.87) with $p=0.012$, $d=0.56$ (medium), 95% CI=[0.12, 1.00] and with $p=0.016$, $d=0.61$ (medium), 95% CI=[0.10, 1.12] respectively. Within the older age group, we found that when participants saw a video with a female programmer they agreed more to programmers being social (mean=2.33) than participants in the *control group* (mean=3.20) with $p=0.046$, $d=1.01$ and 95% CI=[-0.27, 2.30].

For participants with programming experienced, which they obtained at home, they agreed more to programmer being social when they saw a video (mean=2.32, $p=0.018$, $d=0.76$ (medium), 95% CI=[0.13, 1.39]) or the male programmer video specifically (mean=2.21, $p=0.035$, $d=0.80$ (large), 95% CI=[0.043, 1.55]) compared to the *control group* (mean=3.06).

Participants who know a programmer in the *control group* have a weaker belief about programmers being social (mean=2.74) compared to the participants who saw the intervention video (mean=2.19, $p=0.014$, $d=0.57$ (medium), 95% CI=[0.13, 1.00]) or specifically the female programmer intervention video (mean=2.13, $p=0.016$, $d=0.61$ (medium), 95% CI=[0.099, 1.12]). Participants who saw a video at the beginning of the study and see a programmer often have a stronger belief of a programmer being social (mean=2.00) than the participants in the *control group* (mean=2.79) with $p=0.047$, $d=0.76$ (medium) and 95% CI=[0.0036, 1.51].

Based on these findings, we can answer RQ3 by stating that the intervention did not result in differences for the implicit stereotypes, except for participants in the middle age category and participants who know a programmer. For the explicit stereotypes an explanation of what a programmer does results in participants perceiving a programmer as more social. The intervention can also result in different beliefs for participants of a specific age, gender and experiences of the participants.

5 DISCUSSION

In this paper, we research implicit and explicit stereotypes on computer scientist's gender, social skills and interests. We also study whether an explanation video on what a computer scientist does results in different implicit and explicit stereotypes. The amount of scientific work on children's stereotypes regarding computer scientists is still limited [24, 30]. This study contributes to closing this gap in the literature. Applying the Implicit Association Test to measure children's stereotypes on computer scientists has, to our knowledge, not been done before. By applying the IAT in this study and by providing the open-source software we developed, we open a way to use this instrument in Computer Science Education research. Furthermore, we would like to stress the importance of researching stereotypes to understand if and when they develop as well as how to tackle them. This will contribute to closing the gender gap in Computer Science [5, 11, 30, 36, 38].

5.1 Reflections on the results

The implicit and explicit stereotypes we found are not always consistent. This is not uncommon in related literature, for example [21, 34]. An implicit stereotype measurement may differ from a self-reported stereotype because people are unaware of it, do not endorse it, or do not wish to reveal that they endorse it [34, 40].

5.1.1 Gender stereotype. We found that children do not hold implicit stereotypes about programmers' gender, but we did find explicit stereotypes with a medium effect size. The intervention did not result in different implicit stereotypes but did result in different explicit stereotypes in some groups. Not finding implicit stereotypes is in contrast with findings of, for example, the Draw-A-Computer-Scientist-Test in which 71% of the students drew a male computer scientist [24]. This inconsistency might originate from almost all team members present in the museum being women, which might have influenced the participants' unconscious beliefs. A study researching stereotypes found that only a small minority of students spontaneously described computer science students as male or masculine [6], resulting in masculine not being in the top three stereotypes mentioned. Children explicitly indicating programming is more for boys than for girls indicates that we need to tackle this gender stereotype at an early age to close the gender gap in Computer Science. The gender of the programmer in the video almost not affecting the results indicates that the development of stereotypes is more complex than exposing children to a single video.

5.1.2 Social skills stereotype. We found that children do hold a weak implicit stereotype regarding programmers' social skills, but not how we expected it: we found an implicit association between programmers and being social. A similar pattern is found in explicit stereotypes. Thereby it supports earlier research [1], where no social stereotypes were found among children. However, this finding might also relate to the stereotypes children have on the writer profession. The intervention strengthened this stereotype of a programmer being social. This might be because of seeing an actual person, while this was not the case for the writer. The applications mentioned in the video such as social media might also contribute. That especially younger children see programmers as social while many studies show that adults do not, indicates that this association is created at a later age and might relate to the way we teach programming and the interaction between students we facilitate such as pair programming [29].

5.1.3 Interests stereotype. The finding of a moderate implicit stereotype of programmers being associated more with video gaming than tennis is consistent with [7, 30]. We also found an explicit stereotype that programmers like to play video games. However, we did not find explicit stereotypes for the statement that programmers like computers and have little other interests. No gender differences were found within this stereotype, which is in line with a study that found that both genders have similar associations to the word 'Computer Science' including the association 'game' [39]. The association of programming and video gaming might limit children who do not have an interest in video gaming to consider a career in IT. This association might be strengthened by computer game programming increasingly being used as an educational strategy [13] and thus is something we can take into consideration when creating new programming materials.

5.2 Limitations

One of the limitations is that our sample consists of science museum visitors, which might not be representative. One of the indicators for this is that over half of the children indicated to have programming experience via school, which is higher than the average in the Netherlands. The COVID-19 regulations might also have an impact on the sample. However, the science museum does have visitors from different parts of the country making the sample less geographically biased.

Another limitation is the comparison of programmers with only writers. The writer profession might come with its own stereotypes. Furthermore, children do have language as a subject at school while this is not the case for programming. However, due to practical reasons, it was needed to pick one specific profession and we do believe that other professions will come with other or similar limitations.

Even though we tested the pictures in the pilot, it should be noted that the pictures we choose might result in different associations than the one we were aiming at. It is, however, out of the scope of this study to create a verified instrument.

Stereotypes can change per nation or culture. This makes it harder to generalise the results, although it also strengthens the contribution of this research since not much is known about stereotypes on computer scientists in the Netherlands. The cultural aspect

also made us decide on 'programmer' in the study instead of computer scientists. Despite these professions having some overlap, they are not the same.

6 CONCLUSION AND FUTURE WORK

Women are under-represented in the field of Computer Science which is, among other things, influenced by stereotypes on computer scientists. However, little work has been done on the stereotypical beliefs children hold. In this study, we aimed to answer the following research questions:

- RQ1.** To what extend do children hold implicit stereotypes on computer scientists' a) gender, b) social skills and c) interests?
- RQ2.** To what extend do children hold explicit stereotypes on computer scientists' a) gender, b) social skills and c) interests?
- RQ3.** How does an explanation of what a computer scientist does affect children's implicit and explicit stereotypes on computer scientists' a) gender, b) social skills and c) interests?

To answer our research questions, we conducted a quantitative study in a science museum with 564 children between the age of 7 and 18 participating. We used the reduced-length Child Implicit Association Tests to measure children's implicit stereotypes and 5-point Likert scale questions to measure children's explicit stereotypes. The participants in the *experiment group* (n=352) started the study with a video in which either a man or woman explained what a computer scientist does.

We found a weak implicit stereotype on computer scientists' social skills and a mediate implicit stereotype on computer scientists' interests. Thus, the participating group of children unconsciously think that computer scientists are social and like to play video games. We found explicit stereotypes on computer scientists' gender, social skills and interests. Thus, the participating group of children consciously think that computer scientists are male, social and like to play video games.

Watching an explanation video did not result in different implicit stereotypes, except for participants aged 11, 12 and 13 and participants who know a programmer: they both have a stronger association between programmers and video games after seeing a female programmer. For the explicit stereotypes an explanation of what a programmer does results in participants seeing a programmer as more social. The intervention also results in different beliefs for participants of a specific age, gender and experiences.

We have several suggestions for future work. When doing research in a similar setting, we suggest measuring the stereotypes of both children and parents. We also suggest doing similar research in another context, for instance at schools or code clubs. Expanding the research with other professions would also be of value. Future work could also include a quantitative study on what children think a programmer does and how this relates to implicit and explicit stereotypes. Finally, we suggest researching current computer science education practices and their impact on the development of stereotypes and career orientation. Our research and future work on this topic contribute to understanding the stereotypes children have at different ages, the influence on career orientation and thereby tackling the gender gap in Computer Science.

ACKNOWLEDGMENTS

We would like to thank all participants, students, colleagues and parties involved in this research. With a special thanks to VSNU Digital Society and COMMIT/ who funded this research, Prof. dr. Belle Derks for her advice on the research design, Science Live at NEMO Science Museum in Amsterdam providing us with the research space, and Alexandru Manolache, Alin Dondera, Andrei Geadau, Dragos Vecerdea and Ionut Constantinescu who developed the open-source software under our supervision.

REFERENCES

- [1] Efthimia Aivaloglou and Felienne Hermans. 2019. Early programming education and career orientation: the effects of gender, self-efficacy, motivation and stereotypes. In *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*. 679–685.
- [2] Hart Blanton, James Jaccard, and Christopher N Burrows. 2015. Implications of the implicit association test D-transformation for psychological assessment. *Assessment* 22, 4 (2015), 429–440.
- [3] Jennie S Brotman and Felicia M Moore. 2008. Girls and science: A review of four themes in the science education literature. *Journal of Research in Science Teaching: The Official Journal of the National Association for Research in Science Teaching* 45, 9 (2008), 971–1002.
- [4] Sapna Cheryan, Benjamin J Drury, and Marissa Vichayapai. 2013. Enduring influence of stereotypical computer science role models on women's academic aspirations. *Psychology of Women Quarterly* 37, 1 (2013), 72–79.
- [5] Sapna Cheryan, Allison Master, and Andrew N Meltzoff. 2015. Cultural stereotypes as gatekeepers: Increasing girls' interest in computer science and engineering by diversifying stereotypes. *Frontiers in psychology* 6 (2015), 49.
- [6] Sapna Cheryan, Victoria C Plaut, Caitlin Handron, and Lauren Hudson. 2013. The stereotypical computer scientist: Gendered media representations as a barrier to inclusion for women. *Sex roles* 69, 1 (2013), 58–71.
- [7] Sapna Cheryan, John Oliver Siy, Marissa Vichayapai, Benjamin J Drury, and Saenam Kim. 2011. Do female and male role models who embody STEM stereotypes hinder women's anticipated success in STEM? *Social psychological and personality science* 2, 6 (2011), 656–664.
- [8] Jacob Cohen. 1992. A power primer. *Psychological bulletin* 112, 1 (1992), 155.
- [9] European Commission. 2020. Women in digital scoreboard 2020. <https://ec.europa.eu/digital-single-market/en/news/women-digital-scoreboard-2020>. Accessed: March 2021.
- [10] IAT Corp. [n.d.]. Implicit Association Test FAQ. <https://implicit.harvard.edu/implicit/canada/background/faqs.html>. Accessed: March 2021.
- [11] Shelley J Correll. 2001. Gender and the career choice process: The role of biased self-assessments. *American journal of Sociology* 106, 6 (2001), 1691–1730.
- [12] Dario Cvencek, Andrew N Meltzoff, and Anthony G Greenwald. 2011. Math-gender stereotypes in elementary school children. *Child development* 82, 3 (2011), 766–779.
- [13] Jill Denner, Shannon Campe, and Linda Werner. 2019. Does computer game design and programming benefit children? A meta-synthesis of research. *ACM Transactions on Computing Education (TOCE)* 19, 3 (2019), 1–35.
- [14] Yarrow Dunham, Andrew Scott Baron, and Mahzarin R Banaji. 2006. From American city to Japanese village: A cross-cultural investigation of implicit race attitudes. *Child development* 77, 5 (2006), 1268–1281.
- [15] Agnes Elling and Annelies Knoppers. 2005. Sport, gender and ethnicity: Practises of symbolic inclusion/exclusion. *Journal of youth and adolescence* 34, 3 (2005), 257–268.
- [16] Nathan Ensmenger. 2015. "Beards, sandals, and other signs of rugged individualism": masculine culture within the computing professions. *Osiris* 30, 1 (2015), 38–65.
- [17] Chloé FitzGerald, Angela Martin, Delphine Berner, and Samia Hurst. 2019. Interventions designed to reduce implicit prejudices and implicit stereotypes in real world contexts: a systematic review. *BMC psychology* 7, 1 (2019), 1–12.
- [18] Michelle Friend. 2015. Middle school girls' envisioned future in computing. *Computer Science Education* 25, 2 (2015), 152–173.
- [19] Sandy Graham and Celine Latulipe. 2003. CS girls rock: sparking interest in computer science and debunking the stereotypes. In *Proceedings of the 34th SIGCSE technical symposium on Computer science education*. 322–326.
- [20] Anthony G Greenwald, Debbie E McGhee, and Jordan LK Schwartz. 1998. Measuring individual differences in implicit cognition: the implicit association test. *Journal of personality and social psychology* 74, 6 (1998), 1464.
- [21] Anthony G Greenwald and Brian A Nosek. 2001. Health of the Implicit Association Test at age 3. (2001).
- [22] Anthony G Greenwald, Brian A Nosek, and Mahzarin R Banaji. 2003. Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of personality and social psychology* 85, 2 (2003), 197.
- [23] Francisco J Gutierrez, Jocelyn Simmonds, Cecilia Casanova, Cecilia Sotomayor, and Nancy Hitschfeld. 2018. Coding or hacking? exploring inaccurate views on computing and computer scientists among K-6 learners in Chile. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education*. 993–998.
- [24] Alexandria K Hansen, Hilary A Dwyer, Ashley Iveland, Mia Talesfore, Lacy Wright, Danielle B Harlow, and Diana Franklin. 2017. Assessing children's understanding of the work of computer scientists: The draw-a-computer-scientist test. In *Proceedings of the 2017 ACM SIGCSE technical symposium on computer science education*. 279–284.
- [25] Wilhelm Hofmann, Bertram Gawronski, Tobias Gschwendner, Huy Le, and Manfred Schmitt. 2005. A meta-analysis on the correlation between the Implicit Association Test and explicit self-report measures. *Personality and Social Psychology Bulletin* 31, 10 (2005), 1369–1385.
- [26] Jung Won Hur, Carey E Andrzejewski, and Daniela Marghitu. 2017. Girls and computer science: experiences, perceptions, and career aspirations. *Computer Science Education* 27, 2 (2017), 100–120.
- [27] Beethika Khan, Carol Robbins, and Abigail Okrent. 2020. The State of U.S. Science and Engineering 2020. <https://nces.nsf.gov/pubs/nsb20201>. Accessed: March 2021.
- [28] Zuzana Kubincová, Martin Homola, Ming-Hsiu Mia Chen, and Teng-Hui Lu. 2020. DRAW-A-PROGRAMMER TEST AND FIRST RESULTS IN SLOVAKIA. In *Proceedings of EDULEARN20 Conference*, Vol. 6. 7th.
- [29] Colleen M Lewis, Ruth E Anderson, and Ken Yasuhara. 2016. "I Don't Code All Day" Fitting in Computer Science When the Stereotypes Don't Fit. In *Proceedings of the 2016 ACM conference on international computing education research*. 23–32.
- [30] Allison Master, Sapna Cheryan, and Andrew N Meltzoff. 2016. Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science. *Journal of Educational Psychology* 108, 3 (2016), 424.
- [31] Allison Master, Sapna Cheryan, Adriana Moscatelli, and Andrew N Meltzoff. 2017. Programming experience promotes higher STEM motivation among first-grade girls. *Journal of experimental child psychology* 160 (2017), 92–106.
- [32] Brian A Nosek, Mahzarin R Banaji, and Anthony G Greenwald. 2002. Math= male, me= female, therefore math≠ me. *Journal of personality and social psychology* 83, 1 (2002), 44.
- [33] Brian A Nosek, Anthony G Greenwald, and Mahzarin R Banaji. 2005. Understanding and using the Implicit Association Test: II. Method variables and construct validity. *Personality and Social Psychology Bulletin* 31, 2 (2005), 166–180.
- [34] Brian A Nosek, Frederick L Smyth, Natarajan Sriram, Nicole M Lindner, Thierry Devos, Alfonso Ayala, Yoav Bar-Anan, Robin Bergh, Huajian Cai, Karen Gonssalkorale, et al. 2009. National differences in gender–science stereotypes predict national sex differences in science and math achievement. *Proceedings of the National Academy of Sciences* 106, 26 (2009), 10593–10597.
- [35] Adam Rutland, Lindsey Cameron, Alan Milne, and Peter McGeorge. 2005. Social norms and self-presentation: Children's implicit and explicit intergroup attitudes. *Child development* 76, 2 (2005), 451–466.
- [36] Christine K Shenouda. 2014. *Effects of Gender Stereotypes on Children's Beliefs, Interests, and Performance in STEM Fields*. Michigan State University. Psychology-Doctor of Philosophy.
- [37] Cary Stacy Smith and Li-Ching Hung. 2008. Stereotype threat: Effects on education. *Social Psychology of Education* 11, 3 (2008), 243–257.
- [38] Una Tellhed, Martin Bäckström, and Fredrik Björklund. 2017. Will I fit in and do well? The importance of social belongingness and self-efficacy for explaining gender differences in interest in STEM and HEED majors. *Sex roles* 77, 1 (2017), 86–96.
- [39] Tina Vrieler, Aletta Nylén, and Åsa Cajander. 2020. Computer science club for girls and boys—a survey study on gender differences. *Computer Science Education* (2020), 1–31.
- [40] Michael J White and Gwendolen B White. 2006. Implicit and explicit occupational gender stereotypes. *Sex roles* 55, 3 (2006), 259–266.
- [41] Amanda Williams and Jennifer R Steele. 2016. The reliability of child-friendly race-attitude implicit association tests. *Frontiers in psychology* 7 (2016), 1576.
- [42] Hila Zitely, Michal Shalom, and Yoav Bar-Anan. 2017. What is the implicit gender-science stereotype? Exploring correlations between the gender-science IAT and self-report measures. *Social Psychological and Personality Science* 8, 7 (2017), 719–735.