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Socioeconomic background influences children's attitudes and learning in creative programming workshop

Gabriella Tisza[1] · Panos Markopoulos[1] · Heather King[2]

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Abstract

Programming and creative thinking are important skills for the twenty-first century. A large body of evidence suggests that a playful approach to learning helps children engage deeply with programming, improves their creative thinking skills, and shapes a positive attitude towards programming. However, such research has rarely considered how differences in socioeconomic background impact the way children experience such programming activities. The theoretical perspective of science capital suggests that children from high income families will hold more positive attitudes towards science and technology and will perform better in programming than children from lower income families based on their generally higher exposure to experiences involving computing technology. To examine this assumption, we designed and implemented single-occasion programming workshops lasting two hours that followed the Lifelong Kindergarten Approach and investigated differences in children's attitudes, their learning outcomes (measured by a pre-post-test, perceived learning, and task-based performance), and the fun they experienced during the workshops. We collected data from three primary schools in three distinct socioeconomic neighborhoods (i.e., high-, middle-, and low-income areas), involving, in total, 138 children. Findings indicate that the workshops had a positive effect on the children's attitude towards programming in the middle- and low-income schools only. The self-reported learning was similar in the three schools, but children from the low-income school significantly outperformed children from the high-income school in their task-based performance. Children from the middle-income school had the most fun, however, the experience of fun only significantly affected the low-income school children's perceived learning scores. We conclude that children from the middle- and low-income schools profited the most from the playful programming workshop and call on future research to investigate further underlying factors of perception, acceptance, and enjoyment of out-of-school programming activities in relation to participants' socioeconomic background when studying children's participation of programming in school.

Keywords SES · Programming · Attitudes · Learning outcomes · Fun

Extended author information available on the last page of the article

1 Introduction

In recent decades, out-of-school STEM learning, aimed at teaching Science, Technology, Engineering and Mathematics (STEM) subjects in a playful and engaging way has gained ground through learners' participation in maker spaces,[1] Fab Labs,[2] programming clubs and science museums (Pienimäki et al., 2021; Rushton & King, 2020). These venues typically provide children with a collaborative (work)space that enables exploring, learning, creating, and sharing. In case of maker spaces and Fab Labs, the emphasis is on making. Such settings offer a wide range of readily available tools from high-tech to no-tech. In programming clubs, the focus is on programming and robotics, whilst in science museums, a variety of scientific topics may be addressed, including making and programming. The overarching approach for out-of-school learning, is to develop learning environments that support learners' intrinsic motivation and trigger their curiosity.

This trend relates to a worldwide pursuit to increase children's interest in scientific topics, and especially in computer science, as computational thinking and programming are frequently seen as the literacy skills of the twenty-first century (Papavlasopoulou et al., 2018). According to Sáez-López et al. (2016) "the ability to be a creator rather than just a consumer of technology is increasingly seen as an essential skill in order to participate fully in a digital society" (p. 131). This observation reflects the need to cultivate creativity from early age on. Non-curricular and out-of-school programming clubs can play a significant role in teaching children to program as programming is not yet an integral part of the primary school curricula. The UK, Estonia, Spain, and Finland are examples from Europe where programming is already a compulsory subject in primary education. In other countries, such as the Netherlands, primary schools can decide whether to teach programming to their pupils or not.

Despite this worldwide pursuit, we know little about what influences children's interest and willingness to participate in such activities. This study aimed to broaden our knowledge on possible underlying factors for children's participation in programming-related activities, and hence provide cues for a more successful design and implementation of such activities. We focused this examination around the possible effect of children's socioeconomic background, as earlier research shows that it has an effect on children's academic achievement in general (e.g., Sirin, 2005; Warschauer et al., 2004), and in their STEM interest specifically (Blums et al., 2017; Niu, 2017; Yerdelen et al., 2016). However, we know very little about the relationship between children's socioeconomic background and their participation and learning to program. To this end, we designed and implemented a 2-h-long, playful, programming workshop to introduce programming with micro:bits to primary school children. We investigated how children's socioeconomic background and their attitude toward programming influenced the fun they experienced while learning to program, and ultimately, their learning outcomes.

1 http://www.makerspaceforeducation.com/makerspace.html

2 https://fabfoundation.org/getting-started/#fablabs-full

2 Theoretical background

2.1 Lifelong Kindergarten

The Lifelong Kindergarten is an often-used approach for teaching programming to children. It is described as being "ideally suited to the needs of the twenty-first century, helping learners to develop the creative thinking skills that are critical to success and satisfaction in today's [digital] society" (Resnick, 2007, p. 1). This approach emulates a traditional kindergarten environment where, during play, children design, create, experiment, and explore continuously. In this approach, learning takes place through a spiraling process that starts with imagining, and followed by creating, playing, sharing, reflecting, before returning to imagining, and so on. The widely used visual programming environment Scratch (Maloney et al., 2010; Resnick et al., 2003), provides a framework which applies the key elements of the Lifelong Kindergarten for those learning to program. Since this approach has been argued to be universally suitable (Resnick, 2007), and given that for the workshop we used a visual-programming interface, we hypothesized that all the children would find the workshop equally fun regardless of their gender or socioeconomic background (H1).

2.2 Attitude, fun and learning

Besides an appropriate teaching method, having a positive attitude towards the subject can arguably play a key role in obtaining high (academic) achievements. Moreover, previous research with university students found that their attitude towards programming not only influenced their academic achievement, but also affected their career choices (Cetin & Ozden, 2015).

To examine the question of attitude and learning, Bakar et al. (2010) investigated university students' attitude and academic performance and found a significant positive correlation between the two. Narmadha and Chamundeswari (2013) investigated secondary school students' science-related attitudes and their academic achievement in science class and found a positive correlation between attitude towards learning science and students' academic achievement in science class. With respect to technology-related learning, Gunbatar and Karalar (2018) found that programming with a visual programming environment—called mBlock—had a positive influence on middle school students' attitudes towards programming. Sáz-López et al. (2016) found the same association with primary school children: after students learned to program with Scratch, their motivation and commitment about programming increased significantly. Tisza and Markopoulos (2021a) investigated primary school children's attitude towards programming and the learning outcomes of a programming workshop and found that a more positive attitude towards programming was associated with higher levels of learning. They also report that having fun while learning to code significantly and positively influenced children's attitude towards programming and their learning outcomes. Based on these latter findings, we hypothesized that the experienced fun while learning will have a positive effect on children's learning outcomes (H2).

2.3 Socioeconomic status and learning

Despite the vast evidence that has accumulated regarding the importance of children's positive attitude towards programming, we know little about what influences attitudes beyond learning to code with a visual programming interface. Arguably, socioeconomic background may play a role as, we suggest, children from lower socio-economic backgrounds will have limited to programming opportunities. This affect may be more pronounced in countries where computer science or programming is not yet a compulsory subject in primary education.

The concept of *science capital* has been coined by Archer et al. in 2015 (Archer et al., 2015). The concept provides an explanation as to how children's socioeconomic background could influence their science-related attitudes and interests. S*cience capital* encapsulates "all science related knowledge, attitudes, experiences and social contacts that an individual may have" (Godec et al., 2017, p. 5). Grounded in Bourdieusian notions of capital and accrued privilege, the concept science capital acknowledges that particular advantages, such as socioeconomic status, will positively affect the science-related resources, contacts and experiences that a learner holds (Archer et al., 2015). Other factors, such as ethnicity and gender, have been shown to shape one's science capital (DeWitt & Archer, 2015), and research mapping the intersectional affects – gender, ethnicity and social class – of learners' participation with science, technology and engineering is ongoing (Moote et al., 2020). Since 2015, the concept of science capital has gained considerable traction in STEM education research, practice and policy (Nomikou et al., 2017) as findings have indicated that the higher one's science capital the more likely one is to engage with science and STEM related activities and to have a 'science identity', the latter indicating an increased likeliness to continue with science related studies after age 16 (Archer et al., 2020).

With respect to the relationship between socioeconomic status (SES) and academic achievement in general, the meta-analysis of Sirin (2005) concluded that there is an overall positive correlation. In another meta-analysis of early research on this topic, White, (1982) noted that the strength of the relationship between SES and academic achievement depended on how SES is defined and what is considered as the unit of analysis, with weak correlations found when the individual student is the unit of analysis and stronger correlations when the unit of analysis is the school. In this paper we adopt the definition of Sirin, who considers socioeconomic status to be "an individual's or a family's ranking on a hierarchy according to access to or control over some combination of valued commodities such as wealth, power, and social status" (Sirin, 2005, p. 418).

In the specific domain of ICT literacy, a few studies have examined the effect of socioeconomic differences. Hatlevik and Christophersen (2013) identified SES as a significant influencer on secondary school students' digital competence, with students from higher socioeconomic backgrounds having higher levels of competence than students from lower socioeconomic backgrounds. Senkbeil et al. (2013) found in their study with lower secondary school students that students' ICT literacy was dependent on their family's social background and school achievement (mathematics and German grade). Another qualitative study involving secondary school students (Warschauer et al., 2004) observed that ICT-related knowledge and skills are dependent on socioeconomic status, with young, well-educated people of a higher SES having the highest knowledge and the most skills. In their recent meta-analysis, Scherer and Siddiq (2019) concluded that ICT literacy is dependent on students' socioeconomic status, however, they emphasize that the relationship between SES and ICT literacy was weaker than those reported in other educational subjects such as mathematics or reading.

Regarding STEM education, the study of Niu (2017) with college students found that low-SES students were disadvantaged in pursuing a STEM major, as they may not possess the skills and/or information (or indeed, science capital) required to make a well-informed decision on STEM enrollment. Niu also found that gender and racial gaps in STEM enrollment narrow for high SES students. The study of Yerdelen et al. (2016) investigated low SES middle school students' STEM career interests and found that they had positive attitudes towards pursuing a STEM career, however, they did not compare these results with students from different socioeconomic background, hence it is difficult to assess how students' SES influenced their attitudes. The study of Blums et al. (2017) aimed to examine early SES and later STEM achievement on a large, longitudinal data set. Their study results indicated that maternal education (as an often-used factor to determine SES) had a strong influence on children's cognitive abilities which are, on the long term, related to children's STEM achievement.

Based on the research reviewed, and building on the theory of science capital, we hypothesized that children from high income schools would perform better based on their higher exposure to STEM in general, and to computing and programming experiences specifically (H3) and would thus hold more positive attitudes towards programming (H4).

2.4 Study aim and hypotheses

In this multiple-case study we set out to investigate children's attitudes towards programming and their learning outcomes in relation to their socioeconomic status. More specifically, we aimed to examine whether children with different socioeconomic backgrounds profit evenly from a non-curricular creative programming workshop. Based on the above detailed earlier research we hypothesized that:

- All the children will find the workshop equally fun regardless of their gender or socioeconomic background (H1).
- The experienced fun while learning has a positive effect on children's learning outcomes (H2).

Table 1 Descriptive statistics of the three schools

	High-income school	Middle-income school	Low-income school
Nr. of children	60	16	76
Age (*M*)	8.88 (*SD* = 0.640)	10.53 (*SD* = 0.516)	10.81 (*SD* = 0.696)
Gender distribution	31 boys (51.7%) 29 girls (48.3%)	10 boys (62.5%) 6 girls (37.5%)	39 boys (51.3%) 36 girls (47.4%) 1 missing (1.3%)
Average yearly income in the neighbourhood of the school	€ 31.800	€ 26.600	€ 20.200

- Children from high income schools will perform better on the programming tasks, in other words, will have higher learning outcomes in comparison with children from lower income schools (H3).
- Children from high income schools hold more positive attitudes towards programming in comparison with children from lower income schools (H4).

3 Method

3.1 Participants

The study was conducted in February 2020 in the Netherlands. Figures from 2019 indicate that the average yearly income per person in the Netherlands was 26 140 euro.[3] Accordingly, for the workshop and hence for participation in this study, we selected three socioeconomically distinct neighbourhoods with a low, an average, and a high yearly income,[4] and recruited primary school classes from the selected neighbourhoods. In the rest of the paper, we will refer to the schools as low-income, middle-income, and high-income schools. Detailed descriptive information about the schools can be found in Table 1 below. In total, three schools participated with six school classes and 138 children. The average age of the participants was 9.89 years ($SD = 1.124$). The gender distribution was relatively balanced, with 73 boys (52.9%), 64 girls (46.4%) and one who did not specify their gender (0.7%).

From the pre-workshop data collected examining prior experiences in programming, we found that most of the children participating in the activity were novices. A total of 22.5% of the children reported having no idea about programming, and 36.2% of the children reported knowing a bit. This is also reflected in the sample mean for the 5-step scale ($M = 2.39$, which translates to ‘a bit’; $SD = 1.114$). In other words, almost 60% of the children were new to programming. When comparing the

[3] https://allecijfers.nl/ranglijst/gemiddeld-inkomen-per-provincie-in-nederland/

[4] Source: https://allecijfers.nl; Average gross yearly income per habitant in the neighbourhood of the school (2019), used as an indication for socioeconomic background. In case of the international school, we used the data of the city not the neighbourhood as we assumed that it attracts children from a wider range than a small city school where usually children attend the primary school in their neighbourhood.

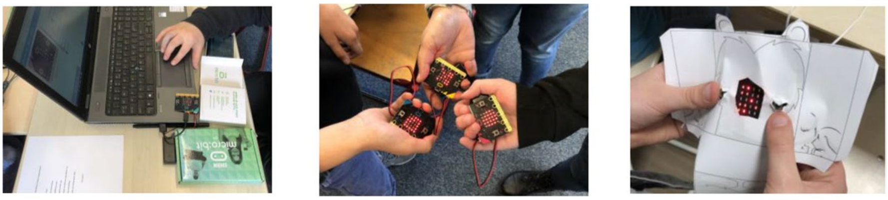


Fig. 1 The three programming tasks (from left to right): Program your name; Program stone-paper-scissors game; Program a micropet

three schools we found that there was a significant difference between children's prior knowledge or understanding of programming ($p = 0.005$, $F(2, 147) = 5.451$, $\eta^2 = 0.069$). Namely, children from the middle-income school reported the highest values ($M = 3.31$, $SD = 1.352$), followed by the high-income school children ($M = 2.47$, $SD = 1.033$) and, lastly, the low-income school children ($M = 2.31$, $SD = 1.097$).

A total of 39.1% of the children reported never having participated in a programming activity, and 23.9% reported having participated in one programming activity only. These numbers reflect the current situation in the Netherlands in that programming is not a compulsory subject in primary education and schools can decide whether to teach it or not. Importantly, programming was not taught in any of the three schools. When comparing children's previous experience with programming activities between the schools we found a significant difference ($p < 0.001$, $F(2, 146) = 11.598$, $\eta^2 = 0.137$). Namely, children from the middle-income school had the highest average reported ($M = 3.06$, $SD = 1.526$), followed by the high-income school children ($M = 2.46$, $SD = 1.222$) and the low-income school children ($M = 1.78$, $SD = 0.896$).

To summarise, there is a clear difference in children's experience and self-reported initial knowledge between the three schools. Namely, children from the lowest socioeconomic neighborhood had on average the least previous experience with programming while children from the middle-income school had the most. However, most of the children across the total sample were novices to programming.

3.2 Procedure

In collaboration with SkillsDojo (a foundation that produces open-source STEM learning materials for children between 6 and 14) we designed a single-occasion, two-hour-long creative programming workshop for primary school children. The workshop aimed to introduce programming with BBC micro:bits (www.microbit.org) for children. We prepared three tasks of increasing complexity and difficulty levels. In the first, introductory task children wrote a program to display their names. In the second, they created a stone-paper-scissors game. In the third task, they either created a 'micropet' that reacted to kinetic stimuli, or they could decide to choose themselves what to code. Examples from the workshop for the programming tasks are shown on Fig. 1.

The workshops were held in a classroom but were not part of the school's formal curriculum. The activity was designed with and based on interactive video guides that follow the Lifelong Kindergarten approach to introduce programming to children. Accordingly, children's imagination and curiosity were triggered through the use of micro:bits, and during the whole workshop children were encouraged to play, share, and reflect on their codes, games and artefacts, for example, by helping each other with debugging of the code. Once code had been developed, children could play together with the game they had made, and if they wished, they could refine the code further. In line with the Lifelong Kindergarten approach, the workshop aim was not only to learn to program with micro:bits, but to do so in a creative and deeply engaging way.

During the workshop, children were equipped with their own laptops/Chromebooks which further supported the personal authorship of the activity. Nevertheless, children were allowed and encouraged to work with each other, thereby fostering communication and collaboration, prompting, sharing, and reflecting (Vrikki et al., 2019). In addition, children were also permitted to move freely around the room, ask questions as they liked—of each other and/or the facilitators—and interact with each other. This aimed to further foster a sense of agency and to disrupt traditional classroom structures pivoted on getting answers right.

Three researchers and the teacher were present during the workshop. At the beginning of the workshop and after the introduction the researchers handed out the pre-workshop questionnaire to the children. While children were busy filling the questionnaire, the researchers prepared the Chromebooks/laptops and distributed the micro:bits and a printed step-by-step guide. Once the questionnaires were collected, children were asked to explore the micro:bits, and then assemble and plug them in the Chromebooks/laptops. Thereafter, children were asked to open the website of the videos (www.skillsdojo.nl/workshop (Dutch) or www.kidzcourse.com/workshop (English)) and the website from which they could programme the micro:bit (i.e., programming interface; www.makecode.microbit.org). The researchers helped children with these steps and encouraged them to start watching the videos and follow the instructions. When the time was over, children were asked to tidy up their tables and the post-workshop questionnaire was handed to them.

3.3 Materials

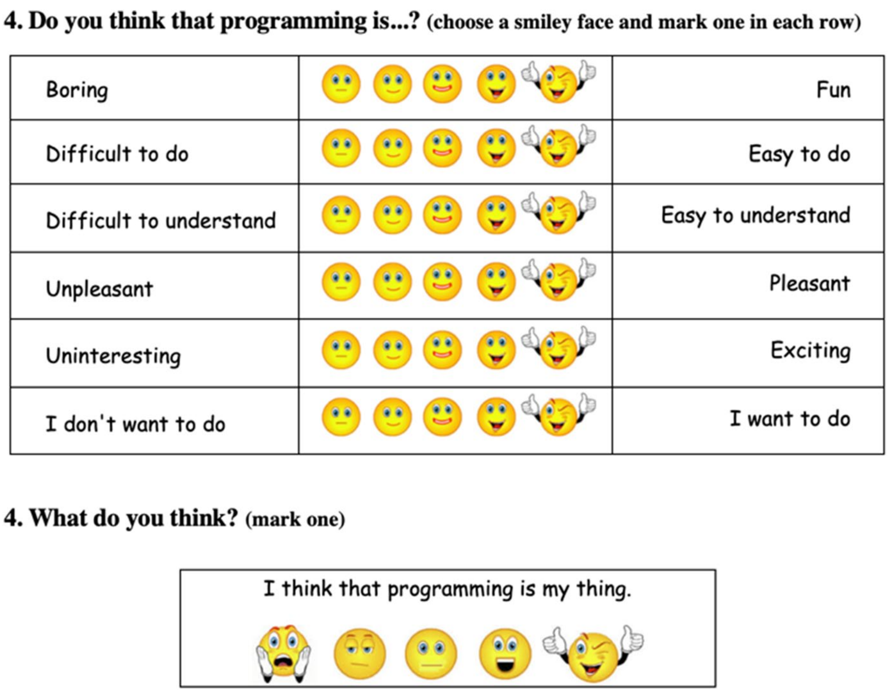
As noted earlier, children followed a how-to video guide to complete the programming tasks described as a set of SkillsDojo missions. This video guide was created by the SkillsDojo Foundation implementing the Lifelong Kindergarten approach where participants learn how technology works through a digital or physical project, building on twenty-first century skills e.g., working together, problem solving, critical thinking. All SkillsDojo missions have a 'low floor' making it easy for everyone to begin and to complete the mission, a 'high ceiling' so that in each mission there is plenty of room to grow and children are constantly being challenged, and 'wide walls' so that anyone can make any mission relevant to themselves.

The videos build on the dual programming principle, namely, the videos use two channels (audio and picture) and this supports double-barreled learning and, in line with the cognitive load theory prevent overloading working memory by following the segmentation principle (i.e., they are built of ’chunks’) and signaling (highlighting the important parts). Students can set their own pace and follow a declining guidance strategy (phasing out guidance). Finally, the videos use the redundancy principle i.e., combination of audio and picture instead of audio and word and the worked-example effect, the learning effect observed when working examples are used as part of the instruction.

3.4 Measures

For the assessment of children’s socioeconomic background, and to stratify our sample, we used the average gross yearly income per habitant in the neighbourhood of the school. We decided to use this measure for multiple reasons. First of all, in educational contexts this method has been applied successfully before (e.g., Warschauer et al., 2004). Second, obtaining precise data from the parents about their SES would have introduced unnecessary ethical concerns, raising questions of anonymity and issues with willingness for participation, ultimately resulting in the introduction of sampling bias. Third, previous findings consistently indicate a positive association between children’s educational outcomes and their schools’ neighbourhood SES (for a systemic review, see Nieuwenhuis and Hooimeijer (2016); example studies in the Dutch context are Kuyvenhoven and Boterman (2021) and Sykes and Musterd (2011)). Fourth, previous research (White, 1982) found that the relationship between SES and academic achievement is stronger when the unit of the analysis is the school in comparison with the individual. Therefore, we concluded that using the average yearly income in the neighbourhood of the school is a reliable proxy for children’s socioeconomic background and it is a suitable method for the assessment of differences in learning outcomes. Nevertheless, the consequences and possible limitations of this decision are thoroughly discussed in the Limitations section of the paper.

In the pre-workshop questionnaire, we measured children’s self-reported knowledge on programming by two questions: ’Do you have any idea about programming?’ ((1) not at all –- (5) I’m a pro)) and ‘How many programming activities have you participated before? ((1) none –- (5)-six or more). Additionally, we measured children’s attitude towards programming across six bi-polar items (Papavlasopoulou et al., 2016, 2018) both at the beginning and the end of the workshop (see Fig. 2). By collecting responses on these items both before and after the workshop we aimed to understand whether the workshop had a positive effect on children’s attitude about programming. For the attitude items we used the smiley-face scale designed and validated by Hall et al. (Hall et al., 2016). In addition to these six specific attitude items, we used a more general item (‘Programming is my thing’), which we adopted from earlier research (Tisza & Markopoulos, 2021a) where it has been shown to be a reliable measure for children’s general programming-related attitude, and which was evaluated on a 5-point scale. The internal consistency of the seven attitude


4. Do you think that programming is...? **(choose a smiley face and mark one in each row)**

Boring		Fun
Difficult to do		Easy to do
Difficult to understand		Easy to understand
Unpleasant		Pleasant
Uninteresting		Exciting
I don't want to do		I want to do

4. What do you think? **(mark one)**

I think that programming is my thing.

Fig. 2 Attitude questions of the pre- and post-workshop questionnaires

dimensions appeared to be adequate both before and after the workshop ((Cronbach, 1951); $\alpha_{pre\text{-}workshop}=0.781$, $\alpha_{post\text{-}workshop}=0.833$).

Since earlier research mostly either pertained to reported or measured learning,—and those who used the combination of these found that the two measures do not necessarily align (Iten & Petko, 2016; Tisza et al., 2021)—in order to gain a comprehensive picture, we decided to use for the assessment of learning three measures that reflect three levels of learning according to Bloom's taxonomy (Bloom, 1956). Accordingly, we recorded a knowledge assessment test both before and after the workshop and calculated the *measured learning* scores by subtracting the pre-workshop scores from the post-workshop scores (*knowledge* level of Bloom's taxonomy). Additionally, at the end of the workshop children self-reported on their *perceived* level of *learning* ('Have you learned something new today about programming?', (1) not at all -- (5) a whole lot; *evaluation* level of Bloom's taxonomy). As a third measure, we calculated children's *task-based performance* on the second task (*application* level of Bloom's taxonomy). We have chosen the second task as it was expected to be the most reliable part of the workshop for task-based performance, given that the first task had an introductory nature and that many children decided to develop their own code after the second task. For rating the task-based performance, due to resource limitations, eleven randomly selected children's screens could be captured in each of the six classes, from which 54 could be used to rate children's task-based performance. Twelve screen captures were damaged or lost during the data recording or saving process due to overheating of laptops and/or freezing of the system and/or freezing of the screen-capture program. Since the second task involved five distinct steps to complete, children were rated on a scale of 0–5 by two raters on their performance. For each correctly conducted step, 1 point could be earned. The inter-rater agreement was 100%.

For assessing children's perceived level of fun during the workshop, we used the FunQ (Tisza & Markopoulos, 2021b) instrument after the activity. We consider FunQ to be an appropriate questionnaire for the evaluation of fun because it has been developed for the assessment of fun in learning activities, and it is specifically tailored for young respondents. The validated FunQ instrument evaluates fun along 6 dimensions (Autonomy, Challenge, Delight, Immersion, Loss of Social Barriers, and Stress) and 18 items on a 5-step Likert-type scale. The internal consistency of the FunQ appears to be adequate on our sample ((Cronbach, 1951); $\alpha = 0.833$).

3.5 Ethical considerations

Participation in the learning activity was compulsory as it took place during school hours in the classroom setting, but participation in the study (i.e., responding to the questionnaires) was voluntary. The data was collected anonymously, nevertheless, informed consent was obtained across the schools from both the children and their parents / caregivers. Neither the school nor the children received any incentives for participating in the study. The study was approved on 10 January 2020 by the Ethics Review Board of the Eindhoven University of Technology, Department of Industrial Design.

3.6 Data analysis

For the analysis of children's pre- and post-workshop questionnaire data we applied quantitative data analysis techniques, including one-way ANOVA, multivariate general linear models, and repeated measures general linear models. For the data analysis we used the SPSS Statistics version 27 software.

4 Results

4.1 Fun (H1)

To assess the level of fun children experienced, we recorded FunQ after the workshop. For testing H1, we applied one-way ANOVA to compare the FunQ scores across schools and genders. The overall minimum FunQ score was 39 and the maximum was 90 in our sample ($M = 70.48$, $SD = 10.205$). According to Leven's test, equal variances across the three schools were assumed ($p = 0.071$). Our results indicate that there is a significant difference in the level of fun experienced between schools ($p = 0.001$, $F(2, 116) = 7.493$, $\eta^2 = 0.114$). The average FunQ score for the high-income school children was 70.33 ($SD = 8.832$), for the middle-income school children was 79.20 ($SD = 6.05$), and for the low-income school children was 68.34

($SD = 10.971$), meaning that children from the middle-income school—where we have seen the most positive attitudes about programming—experienced the most fun during the workshop. We found no gender difference in the level of fun experienced ($p = 0.436$, $F(1, 116) = 0.612$, $\eta^2 = 0.005$, $M_{boys} = 71.19$ ($SD = 10.619$), $M_{girls} = 69.71$ ($SD = 9.839$)).

In sum, children experienced the workshops as fun rating them in the upper third of the range, however, the level of fun they experienced varied across the schools significantly (children from the middle-income school experienced the workshops as most fun), while the experienced fun was not gender dependent. Therefore, H1 is only partially supported, as we expected that all the children will find the workshop equally fun regardless of their socioeconomic background or gender.

4.2 Learning (H2 and H3)

As discussed above, we used three measures to address children's learning that indicate different level of learning according to Bloom's taxonomy (Bloom, 1956). For testing H2 we examined the effect of fun on the three levels of learning, and for testing H3 we addressed how the school, as a proxy for children's SES, influenced children's learning outcomes.

4.2.1 Measured learning

The sample mean for the measured learning is 0.733 ($SD = 1.41$) and we did not find a significant gender difference ($p = 0.175$, F (1, 128) $= 1.857$, $\eta^2 = 0.014$). The average measured learning score in the high-income school is 0.833 ($SD = 1.68$), it is 1.067 ($SD = 0.88$) in the middle-income school and 0.565 ($SD = 1.25$) in the low-income school. We did not encounter a ceiling effect. One-way ANOVA test indicates that these differences are not statistically significant ($p = 0.373$, $F(2, 128) = 0.995$, $\eta^2 = 0.015$), however, we see that children from the lowest socioeconomic neighborhood performed the worst.

To assess whether having fun while learning affected children's measured learning, we conducted linear regression analyses. We found that fun is not a significant predictor of children's measured learning (high-income school: $p = 0.855$, $\beta_{std} = 0.029$; middle-income school: $p = 0.289$, $\beta_{std} = 0.305$; low-income school: $p = 0.165$, $\beta_{std} = 0.198$). When investigating the differences by applying univariate general linear model with fixed factors 'school' and 'fun', we find that neither fun ($p = 0.574$, $F(37, 69) = 0.940$, partial $\eta^2 = 0.471$) nor the school ($p = 0.399$, $F(2, 104) = 0.941$, partial $\eta^2 = 0.046$) or their interaction effect ($p = 0.349$, $F(27, 79) = 0.773$, partial $\eta^2 = 0.349$) is significant.

In sum, we found that children from the middle-income school outperformed children from the other two schools in the learning assessment test. However, we did not find a significant link between having fun while learning and the learning outcomes in any of the schools.

4.2.2 Perceived learning

We recorded children's perceived learning at the end of the workshop. To test the differences between the schools, we applied one-way ANOVA According to the Leven's test, equal variances across the three schools were assumed (p = 0.166). The average perceived learning in the high-income school was 3.95 (SD = 0.934), it was 3.50 (SD = 1.155) in the middle-income school, and 3.84 (SD = 1.153) in the low-income school. In other words, children from the middle-income school report on having learnt the least. Nevertheless, these differences are not statistically significant ($p = 0.335$, $F(2, 135) = 1.101$, $\eta^2 = 0.016$). We add that we did not encounter a ceiling effect.

To assess how having fun while learning affected children's perceived learning, we firstly conducted a regression analysis for each school. In the high-income school, the perceived fun while learning is not a significant predictor for perceived learning ($p = 0.163$, $\beta_{std} = 0.216$). It also accounts for less than 5% of the variance in the learning scores ($R^2 = 0.047$). In the middle-income school we see a similar tendency. Fun is not a significant predictor for children's perceived level of learning ($p = 0.099$, $\beta_{std} = -0.442$). In the low-income school, however, having fun while learning accounts for approx. 50% of the learning scores ($R^2 = 0.519$), and hence, fun is a significant predictor of the perceived learning ($p < 0.001$, $\beta_{std} = 0.721$).

When investigating the differences by applying univariate general linear model with fixed factors 'school' and 'fun', we see that fun has a significant effect on children's perceived level of learning ($p = 0.017$, $F(38, 74) = 1.968$, partial $\eta^2 = 0.640$), however, neither the school ($p = 0.110$, $F(2, 110) = 2.328$, partial $\eta^2 = 0.100$), nor the interaction effect between fun and the school ($p = 0.265$, $F(29, 83) = 1.230$, partial $\eta^2 = 0.459$) is significant.

In sum, we found no significant difference among the schools in children's perceived level of learning. However, we found that fun affected differently children's perceived learning depending on their socioeconomic background as indicated by the schools they attend. Accordingly, for low-income school children, having fun while learning had a strong influence on their perceived learning, while this is not true for children from the two other socioeconomically better situated schools.

4.2.3 Task-based performance

The mean task-based performance of them is 4.02 (SD = 1.754) and the scores vary between 0 and 5. The average task-based performance in the high-income school was 3.07 (SD = 2.086), it was 4.38 (SD = 1.768) in the middle-income school, and 4.37 (SD = 1.450) in the low-income school. One-way ANOVA indicates a significant difference in the task-based performance between schools ($p = 0.05$, $F(2, 50) = 3.169$, $\eta^2 = 0.112$). Children from the high-income school performed significantly worse than children from the low-income school ($p = 0.019$, $F(1, 43) = 6.670$, Cohen's d = -0.772).

To assess how fun influenced children task-based performance, we conducted regression analysis. We found that fun is not a significant predictor for children's task-based performance in either of the schools (high-income school: $p = 0.185$, $\beta_{std} = 0.185$;

middle-income school: $p=0.902$, $\beta_{std}=0.058$; low-income school: $p=0.060$, $\beta_{std}=0.417$).

When investigating the differences by applying univariate general linear model with fixed factors 'school' and 'fun', we see that neither fun ($p=0.511$, $F(26, 14)=1.074$, partial $\eta^2=0.823$), nor the school ($p=0.245$, $F(2, 38)=1.795$, partial $\eta^2=0.374$), or their interaction effect ($p=0.542$, $F(5, 35)=0.889$, partial $\eta^2=0.426$) has a significant influence on children's task-based performance.

To summarize, we found that children from the high-income school performed significantly worse on the task-based performance than the other two schools. However, we did not find a significant relationship between children's perceived fun while learning and their task-based performance in any of the schools.

To conclude on learning, we found that children from the low-income school thought that they have learnt the least (i.e., perceived learning) compared with children from the high-income school. This is also supported by the measured learning scores as children from the low-income school gained less knowledge than children from the high-income school. However, children from the low-income school significantly outperformed children from the high-income school on the task-based performance. Interestingly, children from the middle-income school thought that they have learnt the least (i.e., perceived learning), yet they outperformed children from the other schools on both the measured learning and the tasked-based performance scores. Therefore, H3, in which we expected that children from high-income schools would perform better based on their higher exposure to computing is supported in case of the perceived- and the measured learning, but is rejected in case of the task-based performance. The average measured learning, perceived learning, and task-based performance scores are displayed in Fig. 3. Regarding H2, in which we expected that the experienced fun while learning would have a positive effect on children's learning outcomes, our results are partially supported as we found that fun had a positive effect only in case of the low-income school and children's perceived learning scores.

4.3 Attitude toward programming (H4)

To test H4 and to investigate the development of science-related attitudes, and specifically, children's attitude toward programming, we asked them before and after the workshop across six bi-polar scales and a 5-step Likert scale, and compared the results along the schools, which we used as a proxy for children's SES. All statistical results are displayed in Tables 3, 4, 5, 6 in Appendix A.

4.3.1 Pre-workshop attitudes

We investigated whether there is a difference across the three schools controlling for students' gender in the pre-workshop attitude scores by applying multivariate general linear model with fixed factors 'school' and 'gender'. We see that children from the middle-income school scored on average higher on all items than children from the other schools. The effect of school is thus accordingly significant in all but the 'difficult to do/easy to do' ($p=0.267$, $F(2, 142)=1.336$, *partial* $\eta^2=0.020$) and

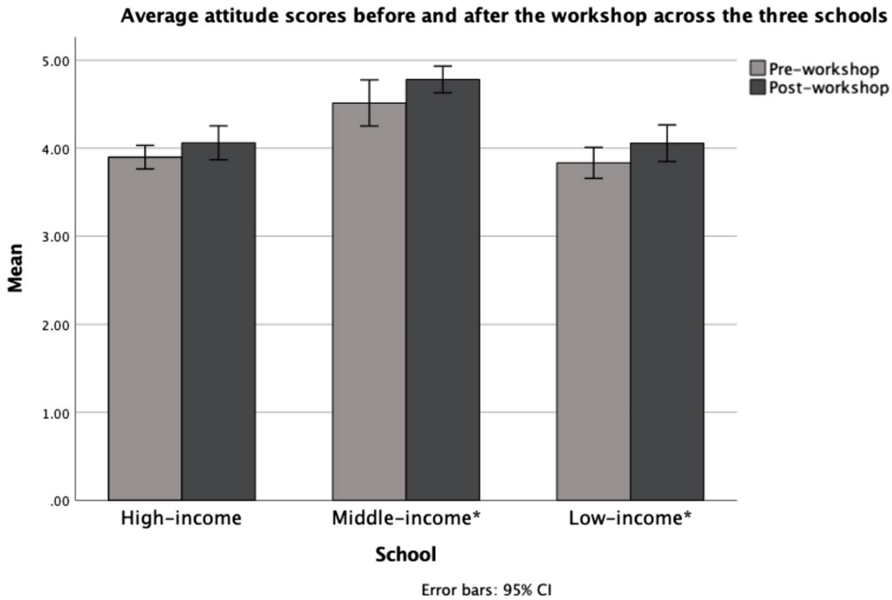


Fig. 3 Average measured learning, perceived learning, and task-based performance across the three schools

'I don't want to do/I want to do' ($p=0.111$, $F(2, 138)=2.232$, *partial* $\eta^2=0.033$) attitude scores. The effect of gender on the attitude questions was not significant ($p=0.392$, $F(1, 131)=0.737$, $\eta^2=0.006$).

4.3.2 Post-workshop attitudes

Here again we applied the multivariate general linear model with fixed factors 'school' and 'gender', to test the difference between the schools, controlling for students' gender. We see that, in general, children from the middle-income school scored on average higher in all attitude items than children from the other two schools. The effect of 'school' is thus significant in all but one ('I don't want to do again/I want to do again', $p=0.087$; $F(2, 142)=2.490$, $\eta^2=0.034$) attitude score. The effect of gender was not significant ($p=0.317$, $F(1, 133)=1.011$, $\eta^2=0.008$).

4.3.3 Attitude change

We applied the repeated measures general linear model to test whether children's attitude had changed differently across the schools, and to see whether there is a gender effect.

For the bi-polar scale *Do you think that programming is boring/fun* we found no significant change in the pre- and post-workshop scores (within subject effect; $p=0.693$, $F(1, 135)=0.156$, partial $\eta^2=0.001$). The effect of school ($p=0.003$, $F(2, 134)=6.033$; *partial* $\eta^2=0.081$) was however significant, but the effect of gender ($p=0.867$; $F(1, 135)=0.135$; *partial* $\eta^2<0.001$) was not. In other words, children's attitude regarding whether programming is boring or fun was not significantly affected by the workshop, however, children's attitude differed between the three schools.

For the bi-polar scale *Do you think that programming is difficult to do/easy to do* we found a significant change in the pre- and post-workshop scores (within subject effect; $p < 0.001$, $F(1, 133) = 20.241$, *partial* $\eta^2 = 0.131$). The effect of school ($p = 0.001$, $F(2, 132) = 7.125$, *partial* $\eta^2 = 0.096$) is also significant, but the effect of gender ($p = 0.298$, $F(1, 133) = 1.094$, *partial* $\eta^2 = 0.008$) is not. In other words, children's attitudes on whether programming is difficult or easy to do was significantly and positively affected by the workshop and was different among the three schools.

For the bi-polar scale *Do you think that programming is difficult to understand/easy to understand* we found a significant change in the pre- and post-workshop scores (within subject effect; $p < 0.001$, $F(1, 132) = 20.679$, *partial* $\eta^2 = 0.134$). The effect of school ($p < 0.001$, $F(2, 132) = 10.489$, *partial* $\eta^2 = 0.135$) is also significant, but the effect of gender ($p = 0.186$, $F(1, 133) = 1.767$, *partial* $\eta^2 = 0.013$) is not. In other words, children's attitude whether programming is difficult or easy to understand was significantly and positively affected by the workshop. Moreover, children's attitude was different among the three schools.

For the bi-polar scale *Do you think that programming is unpleasant/pleasant* we found no significant change in the pre- and post-workshop scores (within subject effect; $p = 0.282$, $F(1, 130) = 1.168$, *partial* $\eta^2 = 0.009$). The effect of school ($p = 0.001$, $F(2, 129) = 7.033$, *partial* $\eta^2 = 0.097$) is however significant, but the effect of gender ($p = 0.879$, $F(1, 130) = 0.023$, *partial* $\eta^2 < 0.001$) is not. In other words, children attitude as to whether programming is unpleasant or pleasant was not significantly affected by the workshop, however, children's attitude was different among the three schools.

For the bi-polar scale *Do you think that programming is uninteresting/interesting* we found no significant change in the pre- and post-workshop scores (within subject effect; $p = 0.485$, $F(1, 131) = 0.490$, *partial* $\eta^2 = 0.004$). The effect of school ($p = 0.001$, $F(2, 130)$, $\eta^2 = 7.104$, *partial* $\eta^2 = 0.097$) is however significant, but the effect of gender ($p = 0.756$, $F(1, 131) = 0.097$, *partial* $\eta^2 = 0.001$) is not. In other words, children attitude whether programming is uninteresting or interesting was not significantly affected by the workshop, however, children's attitude was different among the three schools.

For the bi-polar scale *Programming is something I don't want to do/I want to do* we found no significant change in the pre- and post-workshop scores (within subject effect; $p = 0.135$, $F(1, 129) = 2.259$, *partial* $\eta^2 = 0.017$). The effect of school ($p = 0.039$, $F(2, 128) = 3.329$, *partial* $\eta^2 = 0.049$) is however significant, but the effect of gender ($p = 0.735$, $F(1, 129) = 0.115$, *partial* $\eta^2 = 0.001$) is not. In other words, children attitude whether programming is something they want to do or not was not significantly affected by the workshop, however, children's attitude was different among the three schools.

For the 5-step Likert scale *Programming is my thing* we found no significant change in the pre- and post-workshop scores (within subject effect; $p = 0.144$, $F(1, 128) = 2.158$, *partial* $\eta^2 = 0.017$). The effect of school ($p = 0.001$, $F(2, 125) = 7.459$, *partial* $\eta^2 = 0.105$) is however significant, but the effect of gender ($p = 0.452$, $F(1, 126) = 0.452$, *partial* $\eta^2 = 0.004$) is not. In other words, children's attitudes regarding whether programming is their 'thing', or not, was not significantly affected by the workshop, however, children's attitudes differed between the three schools. A summary of the scores on the seven attitude dimensions, before and after the workshop, according to the schools is displayed in Table 2.

For a general impression on the attitude change across the three schools, we calculated the average aggregate score (i.e., compound score) on all seven attitude dimensions (see Fig. 4). We found that children's general attitude about programming has increased significantly in case of the middle- and low-income school, but not in the high-income school.

In sum, we see a tendency that children's attitude scores were positively influenced by the participation in the workshop, and this positive influence was significant in case of the 'difficult to do/easy to do' and 'difficult to understand/easy to understand' items. Considering the aggregated average attitude scores, we conclude that the workshop had a significant positive effect on students' attitude about programming at the middle- ($p=0.008$, $t=3.068$, *Cohen's* $d=0.792$) and low-income ($p=0.021$, $t=2.384$, *Cohen's* $d=0.327$) school, but not at the high-income school ($p=0.138$, $t=1.506$, *Cohen's* $d=0.201$). Further, the effect of school was overall significant, in other words, children's attitude score was dependent on the school they attended. In case of the middle-income school the effect size indicates a strong relationship with students' attitude about programming, while in case of the low- and high-income schools the effect is considered to be small. However, we did not find a gender difference in any of the attitude scores and score changes.

5 Discussion

In this study we aimed to investigate whether children with different socioeconomic backgrounds profit evenly from a non-curricular creative programming workshop that follows the Lifelong Kindergarten approach. We evaluated children's attitude about programming and their learning outcomes, while controlling for gender differences. Our research results indicate that both children's attitudes about programming and their learning outcomes were affected by their socioeconomic status, as this is indicated by the average yearly income of the neighborhood of the schools. This influence though was not as expected based on previous literature.

Programming and creative thinking are frequently seen as the most important skills of the twenty-first century (Papavlasopoulou et al., 2018; Resnick, 2007; Sáez-López et al., 2016). As computer science or programming is still not a mandatory subject in primary education around the world, non-curricular learning activities play a crucial role in introducing programming to children in a playful and engaging way. Previous research indicated that adopting the Lifelong Kindergarten approach (Resnick, 2007) and using a visual programming interface (Gunbatar & Karalar, 2018; Sáez-López et al., 2016) as the way of introducing programming provides learners with the possibility to deeply engage with the topic, to improve creative thinking skills, and to develop a positive attitude about programming. Our research results partially support these previous findings as we found that participation in the visual-programming interface- based creative programming workshop significantly increased the low- and middle-income school children's general attitude about the topic (i.e., compound score), but it did not have a significant effect on the high-income school children. Since earlier research did not provide a quantitative comparison of attitudes of children from different socioeconomic backgrounds, we call for a replication of this study in different setups for a wider

Table 2 Average scores on the attitude dimensions before and after the workshop across the three schools. * indicates significant change ($p < 0.05$)

Attitude dimension	High income school		Middle-income school		Low-income school	
	Pre	Post	Pre	Post	Pre	Post
Boring – Fun	$M=4.56$ ($SD=0.676$)	$M=4.58$ ($SD=0.889$)	$M=4.88$ ($SD=0.500$)	$M=4.94$ ($SD=0.250$)	$M=4.33$ ($SD=0.822$)	$M=4.33$ ($SD=1.048$)
Difficult to do—Easy to do	$M=3.05$ ($SD=0.860$)	$M=3.13$ ($SD=1.241$)	$M=3.56$ ($SD=1.094$)	$M=4.19$* ($SD=1.047$)	$M=3.09$ ($SD=1.018$)	$M=4.00$* ($SD=0.986$)
Difficult to understand—Easy to understand	$M=3.08$ ($SD=0.952$)	$M=3.40$ ($SD=1.224$)	$M=4.06$ ($SD=0.854$)	$M=4.75$* ($SD=0.577$)	$M=3.23$ ($SD=1.085$)	$M=3.90$* ($SD=1.024$)
Unpleasant – Pleasant	$M=4.25$ ($SD=0.863$)	$M=4.30$ ($SD=1.046$)	$M=4.81$ ($SD=0.544$)	$M=5.00$ ($SD=0.000$)	$M=4.14$ ($SD=0.857$)	$M=4.19$ ($SD=0.928$)
Uninteresting – Exciting	$M=4.05$ ($SD=0.782$)	$M=4.02$ ($SD=1.084$)	$M=4.88$ ($SD=0.342$)	$M=4.88$ ($SD=0.342$)	$M=4.13$ ($SD=0.984$)	$M=4.01$ ($SD=1.110$)
I don't want to do—I want to do	$M=4.19$ ($SD=1.051$)	$M=4.41$ ($SD=1.131$)	$M=4.81$ ($SD=0.403$)	$M=5.00$ ($SD=0.000$)	$M=4.27$ ($SD=0.994$)	$M=4.39$ ($SD=1.040$)
I think that programming is my thing	$M=4.02$ ($SD=0.881$)	$M=4.10$ ($SD=1.115$)	$M=4.56$ (SD$=0.512$)	$M=4.80$ ($SD=0.414$)	$M=3.65$ ($SD=0.905$)	$M=3.84$ ($SD=1.163$)

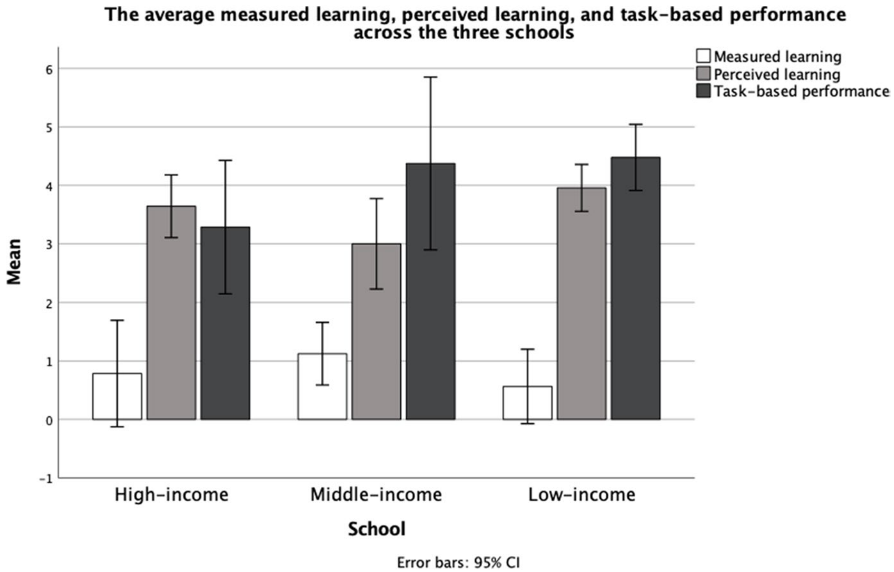


Fig. 4 Average attitude score before and after the workshop across the three schools. * indicates a significant change ($p < 0.05$)

understanding of factors affecting children's attitudes about programming. Nevertheless, our findings suggest that changing children's perception about the difficulty of programming is a key element to attract them to similar activities in the future. This is especially true for children from a low socioeconomic background, as they had on average the least previous experience with programming before the workshop.

We also saw that children from the middle-income school reported on average higher attitude scores (both before and after the workshop) than children from the other two schools. This finding complements that of Yerdelen et al. (2016), whose investigation of low SES students found that they had a generally positive attitude toward pursuing a STEM career. However, our findings question assumptions based on theory of science capital (Archer et al., 2015) which would suggest that children from high income families with greater access to science and technology related resources and contacts will hold more positive attitudes towards science (and by extension science and technology-related disciplines) in general compared with children from lower income families. As a possible explanation for these findings, we speculate that the middle-income school children have well-educated parents that grant values and interest in new technologies alongside a reasonable income to enable access to a variety of related activities, but we propose that such experiences are still sufficiently unusual to prompt novelty and more positive attitudes. On the other hand, children form the high-income school are more likely to have had high exposure to new technologies at home, and hence the workshop could have had less novelty and offered less challenge prompting minimal attitudinal affects. This speculation is supported by our finding that their attitude about programming did not change significantly in any of the seven investigated dimensions.

Children from the low-income school reported the lowest attitude scores before the workshop. However, the workshop was as effective as for children in the middle-income school in terms of attitude change as in both cases children's attitude about programming has changed significantly in two out of the seven investigated dimensions. Based on these findings we conclude that children's attitude about programing, and the effect of the playful programming workshop is dependent on children's socioeconomic background, with middle- and low-income school children profiting the most, regardless of their gender. These results align with that of earlier research on the positive association between SES and STEM interest (Blums et al., 2017; Niu, 2017; Yerdelen et al., 2016), however, our study goes a step further by focusing on the specific topic of learning to program, and provides new insights relating to primary aged children's participation in programming.

To address the effect of the workshop on children's learning, we investigated three levels of learning according to Bloom's taxonomy (1956). Regarding children's performance on the knowledge assessment test (i.e., measured learning) we found no statistically significant difference between the children from the three schools. Nevertheless, we see that children from the lowest socioeconomic neighborhood had the lowest learning gain scores. These findings align well with previous studies with secondary and college students that indicated a positive association between socioeconomic status and academic achievement (Scherer & Siddiq, 2019; Sirin, 2005; Warschauer et al., 2004). Sirin (2005) report on an overall positive relationship between socioeconomic status and academic achievement in their meta-analytic review. Warschauer et al. (2004) investigated access and use of new technologies in a group of low- and high-SES high schools and based on interviews with teachers and students they concluded that children from low-SES schools were more often assessed as being below grade-level in English and mathematics than children from the high-SES schools. The meta-analysis of Scherer and Siddiq (2019) suggested a difference in ICT literacy between children from different socioeconomic background. Our study extends these findings, by investigating programming-related learning outcomes in a programming workshop in relation to the participating children's socioeconomic background and with primary school students.

Regarding the perceived learning scores, we found no statistically significant difference in the scores between the schools. However, we see that children from the middle-income school reported the lowest scores for their perceived level of learning (meanwhile they scored the highest on the knowledge assessment test). This result is only based on comparing three schools and would need further replication before we can generalize this conclusion. Regarding the task-based performance, we found that children from the high-income school performed significantly worse than children from the low-income school. This finding, we argue, might be related to children's engagement with the activity, and accordingly, we suggest that children from the high-income school (with some prior programming experience) found the workshop less engaging than children from the middle- and low-income schools, which is reflected in their task-based performance. Another possible confounding element is the academic level or general intelligence of the children, which we did not investigate in this study. Accordingly, future studies addressing this question could shed light on further factors that influence children's programming-related learning outcomes.

In sum, we found that the playful programming workshop was partially successful in terms of learning, as we found no statistically significant difference in children's measured- and perceived learning between the three schools, but we found that the task-based performance of children from the high-income school was significantly lower than that of the low-income school children. This is a novel finding as previous studies did not directly investigate the relationship between socioeconomic background and programming-related learning outcomes.

We also aimed to understand better whether the enjoyment of the workshop had an influence on children's learning. We found that children from the middle-income school experienced the workshops as most fun, while the experienced fun was not gender dependent. This is a novel perspective on playful learning, as previous literature has not examined the fun experienced in out-of-school programming activities in relation to participants' socioeconomic background. While this result is only based on comparing three schools and would need further replication before we can generalize this conclusion, we argue that this perspective is key to better understanding what sort of activities are appreciated in different socioeconomic contexts.

Regarding the effect of fun on learning, previous research with primary school children suggested a positive association between having fun while learning to code and children's perceived learning (Tisza & Markopoulos, 2021a). On the other hand, the research of Tisza et al. (2021) with secondary school students in the field of digital game-based learning found the same positive association between students' perceived learning and the fun they experienced while learning, however, they did not find the same effect in case of measured learning.

In this study we found no significant association in either of the schools between fun and the measured learning or the task-based performance, which, in general, aligns with the research with Tisza et al. (2021), but it extends those findings by providing a more nuanced picture by investigating children from different socioeconomic background. Similarly, our finding that having fun while learning to code had a significant and positive effect on children's perceived learning in the low-income school, but not in the other two extends the results reported by Tisza and Markopoulos (2021a), with a more nuanced picture that takes SES into account. Considering the role played by SES is important as it demonstrates that playful programming workshops can contribute to a more positive perception of programming among low-income school children. Since we know very little about the aforementioned relationship, we call on future research to explore how exactly fun affects children with different socioeconomic background to learn to program.

As a final discussion point, we address the assessment of children's socioeconomic status. We must state that in case of young children, the assessment of their socioeconomic status is difficult, as children are unlikely to know their own relative status or understand differences between individuals. knowledge about it. In addition, involving the parents to clarify the situation is not always possible, and thus the response rate could be low, and further it may undermine the anonymity of the data collection. A possible way to overcome this issues is using the average yearly income of the neighborhood of the school (Warschauer et al., 2004) – the protocol we have followed in this study. However, this approach assumes that most children go to the school in their neighborhood, and that people in the same neighborhood have an approximately equal yearly income, and hence, approximately equal socioeconomic status. While the former is in general true in Holland (i.e., the majority of children attend the closest school in their neighborhood), the latter is only an assumption, which is nonetheless frequently used in the field of sociology. To further strengthen the findings of this study, future research could adopt different ways for the assessment of students' socioeconomic background, for example, surveying the parents, or using other proxies, such as the Family Affluence Scale (Torsheim et al., 2016).

6 Limitations and future work

While our study results are partially supported by previous research, our findings are still limited to the study location. Namely, the data was collected in the Netherlands, which is a relatively wealthy, Western European country. Accordingly, future research should investigate children from a broader spectrum regarding their socioeconomic status, and eventually, in other, less wealthy countries than the Netherlands to get a more general picture on the effect of socioeconomic background on learning to program.

Additionally, our study involved a 2-h long intervention, due to which we could only expect a limited effect on children's attitude, and we did not investigate the permanence of this effect. We speculate that more interventions are required to substantially contribute to the worldwide pursuit of increasing children's interest in STEM and programming. Therefore, we call on further studies to examine children's STEM and programming-related attitudes over time, and especially to investigate the long-term effect of similar interventions, and the required minimum number of hours of intervention for a long-term effect.

Furthermore, we selected three schools based on the socioeconomic neighborhood they are located in. However, this choice has some limitations as there could have been other factors that could have differentiated the schools, for example the school pedagogy that we were not aware of, the academic level of the participating students or their general intelligence. Accordingly, the structure of the workshop and the applied Lifelong Kindergarten pedagogy could have been variably suitable for the different schools, perhaps because of the school itself, and not because of the socioeconomic status. Whilst none of the schools expressed following a specific pedagogy, we acknowledge that the freedom provided in the Netherlands for schools to organize their curriculum and way of teaching may have created pedagogical differences. Therefore, to completely exclude these limitations, a future study should compare schools not only based on their socioeconomic neighborhood, but their applied pedagogy as well, possibly investigating schools with a specific pedagogy like Montessori or Dalton Plan schools.

Another possible factor that could have affected children's performance is the time of the day in which children were asked to code. One could expect that performance and learning may fluctuate at different times of the day, especially as children may get tired after several hours of schooling. This fluctuation, however, is equally affected the high-income and low-income schools as in both schools the workshop was given during both the morning and the afternoon hours. In the middle-income school, we only gave the workshop during the morning hours.

Additionally, future research should address the underlying mechanisms that drive the herein introduced associations. While our research has linked socioeconomic background to children's attitude about programming and their learning outcomes, we know little about the underlying mechanisms of these associations. As a possible explanation we propose that science capital plays a role in how children from different socioeconomic background think about programming and how they learn from related activities. Linked to this, children's expectations about themselves, what they perceive as self-actualization, and the way prior experiences determine what one considers as fun or as learning can also be part of the underlying influential factors. Therefore, we call on future research to investigate these, and eventually other underlying influential factors for herein revealed association between children's socioeconomic background and their learning outcomes and programming-related attitudes to further contemporary research.

At last, knowing the found relationships, and assuming the transformative purpose of education, we call on future research to conceptualize and validate an educational approach that addresses children from low socioeconomic background.

7 Conclusions

We designed and implemented a series of single-occasion playful programming workshops that followed the Playful Kindergarten Approach (Resnick, 2007) to introduce programming in a playful and engaging way to primary school children. In this setup, we aimed to investigate whether children from different socioeconomic neighborhoods profit differently from such learning activities, taking into account gender differences. Our findings indicate that children's socioeconomic background is related to their pre-workshop attitude about programming, and it has an influence on how children's attitude changed during the workshop. Accordingly, the workshop did not cause a significant change in children's attitude about programming in the high-income school, but it did have a positive effect on children's attitude in the middle- and low-income school. Regarding children's learning outcomes we also found that the workshop was the least effective with children from the high-income school, while children from the low-income school outperformed children from the high-income school in terms of their task-based performance. Our findings, thus, shed light on the previously understudied effect of the socioeconomic background and children attitude about programming and their learning outcomes during the course of a non-curricular playful programming workshop. Based on our findings we suggest that targeting with similar activities middle- and low-income children is more beneficial in terms of attitude change and learning outcomes than targeting high-income children.

Appendix A All statistical results regarding the pre- and post-workshop attitude items and the effect of school and gender

Table 3 All statistical results of the effect of school on the pre-workshop attitude items

Attitude dimension	F (df)	p	partial η^2
Boring—Fun	3.803(2)	0.025	0.055
Difficult to do—Easy to do	1.336(2)	0.267	0.020
Difficult to understand—Easy to understand	5.217(2)	0.007	0.074
Unpleasant—Pleasant	4.292(2)	0.016	0.062
Uninteresting—Exciting	6.233(2)	0.003	0.088
I don't want to do—I want to do	2.232(2)	0.111	0.033

Table 4 All statistical results of the effect of gender on the pre-workshop attitude items

Attitude dimension	F (df)	p	partial η^2
Boring—Fun	0.647(1)	0.423	0.005
Difficult to do—Easy to do	0.500(1)	0.481	0.004
Difficult to understand—Easy to understand	0.527(1)	0.469	0.004
Unpleasant—Pleasant	0.000(1)	0.991	< 0.000
Uninteresting—Exciting	0.016(1)	0.899	< 0.000
I don't want to do—I want to do	0.597(1)	0.441	0.005

Table 5 All statistical results of the effect of school on the post-workshop attitude items

Attitude dimension	F (df)	p	partial η^2
Boring—Fun	3.342(2)	0.038	0.049
Difficult to do—Easy to do	11.094(2)	< 0.000	0.147
Difficult to understand—Easy to understand	7.132(2)	0.001	0.100
Unpleasant—Pleasant	4.308(2)	0.015	0.063
Uninteresting—Exciting	3.804(2)	0.025	0.056
I don't want to do—I want to do	2.411(2)	0.094	0.036
I think that programming is my thing	3.853(2)	0.024	0.056

Table 6 All statistical results of the effect of gender on the post-workshop attitude items

Attitude dimension	F (df)	p	Partial η^2
Boring—Fun	0.529(1)	0.468	0.004
Difficult to do—Easy to do	1.849(1)	0.176	0.014
Difficult to understand—Easy to understand	1.807(1)	0.181	0.014
Unpleasant—Pleasant	0.062(1)	0.804	0.000
Uninteresting—Exciting	0.875(1)	0.351	0.007
I don't want to do—I want to do	1.945(1)	0.166	0.015
I think that programming is my thing	0.023(1)	0.880	0.000

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent Informed consent was obtained across the schools from both the children and their parents / caregivers. The study (ref. nr. ERB2020ID2) was approved on 10 January 2020 by the Ethics Review Board of the Eindhoven University of Technology, Department of Industrial Design.

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Authors and Affiliations

Gabriella Tisza[1] · Panos Markopoulos[1] · Heather King[2]

Gabriella Tisza
g.tisza@tue.nl

Panos Markopoulos
p.markopoulos@tue.nl

Heather King
heather.1.king@kcl.ac.uk

[1] Department of Industrial Design, Eindhoven University of Technology, Eindhoven, Netherlands

[2] King's College London, London, UK