What do We Know about Computing Education for K-12 in Non-formal Settings? A Systematic Literature Review of Recent Research

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ABSTRACT

Background and context. Non-formal learning for K-12 computing education enables young people to learn about computing outside the formal curriculum. Many studies have reported on non-formal initiatives but it is not always clear what children and young people have gained from their participation.

Objectives. This study set out to investigate non-formal learning initiatives by means of a systematic literature review. The two research questions addressed by the study are: (1) What has been the focus of recent computing education research about K-12 initiatives for young people and (2) What is the impact of non-formal K-12 computing initiatives?

Method. A systematic literature review of computing education research was conducted, focused on non-formal initiatives for young people. Research was included from any country, but must be published in English between January 2015 and April 2021. Searches using key terms were performed across three databases. 88 studies were synthesised from over 400 initial results.

Findings. The vast majority of studies reported on immersive multi-day settings such as summer camps run by universities (n= 67), with fewer (n=21) reporting on regular ongoing after-school or weekend clubs. The most popular affective outcomes measured by studies were self-efficacy (n=25) and interest (n=22). Measurement of cognitive outcomes, such as knowledge (n= 13) and skills (n=17), was less prevalent. 22 different topics were identified from the studies, with most studies being programming-heavy. The majority of papers measured the short-term impact of these interventions, and generally there was an inconsistent or incomplete reporting of learner characteristics across the studies.

Implications. The lack of papers investigating regular after-school initiatives suggests that the majority of non-formal learners are not being studied or that summer school findings are being wrongly extrapolated to this setting. More rigorous research is needed for regular after-school and short-term non-formal contexts to ensure that this set of learners' experiences is understood and potentially improved.

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CCS CONCEPTS

• **Social and professional topics** → **Informal education**; **K-12 education**; **Computer science education**.

KEYWORDS

computing education, informal learning,K-12 education,non-formal learning, systematic literature review

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1 INTRODUCTION

Providing opportunities for young people to develop knowledge, skills and enjoyment of computing is becoming increasingly important. Non-formal computing education, which involves structured or semi-structured learning opportunities outside of formal schooling, is viewed by some as being central to engaging and inspiring young people in computing and digital innovation. To ensure that non-formal education is effective, it should be evidence-led as research may provide insights into teaching and learning approaches that can be used and may contribute to improvements in outcomes for learners.

The level of formal computing education provided in schools differs greatly between countries. For example, in England there is a mandatory computing curriculum for all children aged 5-16. Other countries may have a varied coverage of computing before high school or may focus on digital skills, including using computer software and internet safety [103]. With the variation in formal computing education, non-formal learning opportunities become a way to reach young people and support the development of their computing knowledge, skills and confidence, as well as offering a complementary experience alongside formal schooling.

Non-formal education can be defined as *"institutionalised, intentional and planned by an education provider. The defining characteristic of non-formal education is that it is an addition, alternative and/or complement to formal education within the process of lifelong learning of individuals"* [37, p.11]. This contrasts with informal learning, which tends to be described as individualised and driven by the learner, usually without a set curriculum or external agenda [94].

While there is some degree of overlap between the different types of learning and settings, this paper focuses on non-formal computing education in particular. Examples of education providers could include university outreach programs, national or international non-profit or charity organisations, and commercial clubs or camp providers. Libraries, museums, maker spaces and community centres, which are often settings for informal learning, may also meet the criteria for providing non-formal computing education.

This paper reports on a systematic review of computing education research conducted in any country but published in English, published between January 2015 and April 2021, relating to non-formal learning in computing. The objective is to provide an overview of recent research in non-formal computing education with young people of school age, in order to better understand the goals, methods and impacts of non-formal computing education. This provides a starting point for more rigorous research conducted in this area and will enable us to set a research agenda around non-formal learning in computing.

2 RELATED WORK

Previous literature reviews within computing education have identified difficulties generalising across studies due to imprecise reporting of a range of key variables, such as instructional methods, demographic information, and impact measurement [43, 70, 71]. Furthermore, previous reviews have often included both formal and non-formal computing education and reported results without accounting for the age of participants. Here we provide an overview and synthesis of the previous reviews in relation to non-formal computing education in school-age samples.

A search of the literature revealed a number of review papers on computing education which included non-formal and formal settings and school-aged and older students, but that did not provide a breakdown of their findings in relation to these specific variables. For example, Jayathirtha and Kafai [46] synthesised results from 46 studies on the use of electronic textiles in computing education. Summary descriptive statistics identified that more than half of the studies were based in non-formal settings and that 36/46 studies involved young people aged 18 and under. The authors identified key themes across the studies: increased engagement and attitudes towards computing, greater involvement in the activities by typically underrepresented groups, and deep learning of circuitry and computing by participants. However, this synthesis did not differentiate between studies in non-formal and formal settings, nor between school-aged and adult samples, so it is unclear whether context or age had any significant effects on the findings.

Timotheou and Ioannou [101] focused on "computationally-enhanced-making" activities (p.219), reporting both the educational settings in which the activities took place (29/57 papers in non-formal settings) and the age range of the samples (40/57 in pre-tertiary education), but not the overlap between these variables. Outcomes from the activities were identified in terms of knowledge gains, changes in attitudes, and the development of 21st century skills. Results of individual papers were provided but were separated from the basic information about setting and sample age, and findings were not summarised in the main text in relation to these variables. However, the clear majority of papers did report positive changes in the three main outcomes, according to the review.

A review by Papavlasopoulou et al. [88] on 'making' activities in formal and non-formal computing education did provide sufficient detail about the studies to identify that 19/43 papers included school-aged samples in non-formal settings. A small number of additional papers were likely to meet these criteria but full information was not provided by the original studies' authors. The paper provided details of the types of methodologies and instruments used in the research, along with the types and focus of the making activities involved in the studies, although these were not summarised in the main text according to setting or sample. The focus of the making activities was mainly programming (17/19) with a broader Science, Technology, Engineering, [Art], and Mathematics (STE[A]M) focus in the two remaining studies. The materials used in the non-formal settings were usually digital, with the most popular being Scratch, although tangible materials (such as LEDs, switches and fabrics) were often also provided. The review provided a useful description of recent studies of making activities in non-formal settings. However, no synthesis across studies was provided concerning the outcomes of the computing education for the young people involved, which is key to helping us understand best practice and to develop future non-formal learning opportunities for computing that are both impactful and engaging.

Five recent reviews and meta-analyses have either focused entirely on non-formal settings, e.g. [20], presented findings split by setting, e.g. [26, 95], or included setting as a moderator variable in assessing the outcomes of computing education [92, 112]. These reviews are summarised in Table 1.

The review by Clarke-Midura et al. [20] was the only paper to focus entirely on non-formal learning activities, although it served as a background to a broader discussion of the development of the authors' own non-formal summer camps. The review highlighted diversity in the activities in terms of settings (e.g. summer camps, workshops, etc.), duration, and content/tools. More specific descriptive statistics were provided for the outcome measures and findings (see Table 1), identifying the number of studies reporting significant or non-significant gains in terms of interest in computing or computing careers. However, the level of detail provided did not allow us to gather a full picture of the non-formal computing education literature, which is the purpose of the current review.

Despite including both formal and non-formal settings, the systematic reviews by Denner et al. [26] and Sharma et al. [95] addressed specific research questions within the computing education literature and provided detailed descriptions of the studies which allowed us to draw out key findings from the studies of non-formal settings only. Both reviews concentrated on game design/play as a method of teaching programming and increasing interest in computing. Like the review by Clarke-Midura et al. [20],

Table 1: Key findings for recent review papers on non-formal computing education for school-aged participants

Authors	No. papers (non-formal /reviewed)	Key findings
Clarke-Midura et al. (2019) [20]	31/31	Brief details provided about studies and outcomes for students. 24 of 31 assessed interest in computing and/or computing careers 6 studies reported gains in one or more interest constructs 7 studies reported non-significant gains in interest
Denner et al. (2019) [26]	21/68	Positive effects reported on programming knowledge (14/21 studies), problem solving and design (7/21), attitudes towards computing (6/21) and computing confidence (5/21). Negative effects reported on attitudes (1 study) and confidence (1 study), and 1 study reported both positive and negative impacts on attitudes.
Sharma et al. (2021) [95]	14/25	Positive effects reported on interest in CS careers (6/14 studies), motivation to take CS courses (3/14), and interest in CS (2/14). None of the 14 relevant studies reported a null effect or decreased interest in CS (3 studies did not report results).
Xu et al. (2019) [112]	3/13	The effects of block-based programming on affective (attitudinal) and cognitive (achievement) student learning outcomes were not moderated by the learning environment (formal vs non-formal).
Scherer et al. (2020) [92]	8/139	A problem-solving instructional approach to programming was more effective within extracurricular activities compared to regular lessons.Educational setting did not impact the effectiveness of any of the other instructional approaches.

both papers identified positive and negative/null effects of a range of game-based interventions on multiple constructs, including attitudes towards computing [26, 95], programming knowledge, and problem-solving and design skills [26]. Both also considered the instructional approaches that were used in the non-formal activities, with Sharma et al. identifying key factors in the success of the game-based interventions and how they were represented across the reviewed studies. Taken together, these two reviews provide an in-depth picture of one specific type of activity within the non-formal computing education research.

The two final studies presented in Table 1 take a meta-analytic approach to computing education research [92, 112]. They mainly focus on studies in formal education, but both include the education setting as a moderating variable in their analyses. Both papers report a very limited impact of setting on their outcomes of interest; indeed only the effectiveness of a problem-solving instructional approach was significantly improved in non-formal compared to formal settings [92]. Given the very small numbers of studies of non-formal computing education included in these analyses, these limited effects are perhaps unsurprising and little can be done to interpret the findings further.

This analysis highlights a need for a systematic review of research focused entirely on non-formal computing education in school-aged samples. The purpose of this paper is to provide a clear and detailed description of both the types of studies being conducted and the impact of the interventions on their targeted participants. This brings together elements of previous reviews and provide a strong basis for the development of future research with young people engaged in non-formal computing education.

3 THE STUDY

The goals of the study were to broadly analyse the research being conducted in non-formal computing education settings in recent years. Specifically, we are interested in the following research questions:

- RQ1: What has been the focus of non-formal computing education research in terms of
  - (a) the learners engaged in the activities?
  - (b) the purpose of the activities and who provides them?
  - (c) the computing topics covered?
  - (d) the outcome measures used to evaluate impact?
- RQ2: What impact does non-formal computing education have on learners according to the research?

We followed the approach of Kitchenham [53], guidance from PRISMA [85] with additional specific guidance for education research from Denner et al. [27] and Newman and Gough [79]. We used Booth's Context-Intervention-Mechanism-Outcome (CIMO) approach [8] to scope our review to give a systematic, manageable and coherent set of studies to consider. This involved narrowing the criteria based on the age of learners and the details of the intervention.

It has been highlighted that searching in educational domains where terminology has not been formalised is difficult [115]. We

Table 2: Search Terms

Category	Search term
Age group	"K-12", K12, school, child*, girl, boy, youth, teen*, young, pupil,grade, adolescent, "pre-college"
Setting	camp, summer, club*, outreach, enrichment, afterschool, "after-school", "out-of-school", "extra-curricular", extracurricular , cocurricular, "co- curricular", "informal education", "informal setting", "non-formal education", "informal learning", "non-formal learning", "non-formal setting"
Computing education	"computing education", "computer science education", "informatics education"

Table 3: Example query for IEEE Xplore database search

Example database query
("All Metadata":"computing education" OR "All Metadata":"computer science education" OR "All Metadata":"informatics education") AND ("All Metadata":camp OR "All Metadata":summer OR "All Metadata":club* OR "All Metadata":outreach OR "All Metadata":enrichment OR "All Metadata":afterschool OR "All Metadata":"after-school" OR "All Metadata":"out-of-school" OR "All Metadata":extracurricular OR "All Metadata":"extra-curricular" OR "All Metadata":cocurricular OR "All Metadata":"co-curricular" OR "All Metadata":"informal education" OR "All Metadata":"non-formal education" OR "All Metadata":"informal learning" OR "All Metadata":"non-formal learning" OR "All Metadata":"informal setting" OR "All Metadata":"non-formal setting") AND ("All Metadata":"K-12" OR "All Metadata":K12 OR "All Metadata":school OR "All Metadata":child* OR "All Metadata":girl OR "All Metadata":boy OR "All Metadata":youth OR "All Metadata":young OR "All Metadata":pupil OR "All Metadata":grade OR "All Metadata":adolescent OR "All Metadata":teen* OR "All Metadata":"pre-college")

therefore adopted the approach of combining terms for computing education and the pre-tertiary age (age 18 and under), group with terms that indicate the presence of a non-formal setting (such as camp or club). A scoping study was conducted to understand the size and nature of the result space and ensured that the synonyms used for computing education and non-formal settings were successful in identifying results that matched the research question.

3.1 Scope

The focus of the systematic review was specifically on pre-tertiary education and on regular or immersive non-formal settings. We define regular settings as taking place with the same target group of learners on four or more occasions (such as an after-school program or a weekend club or a regular session at a youth group), and immersive settings as taking place for at least one whole day, with four or more hours of time spent on educational activities (such as an outreach summer camp). Examples of activities that are not included would be one-off outreach visits to a school, or short workshops (under 5 hours) to test the value of a specific educational tool that is intended for use in formal settings. Our approach therefore excludes short-term interventions, which may be insufficient to detect impact [29].

We also decided to focus on studies that took place in physical settings. Those in online or hybrid settings warrant separate study and we anticipate further studies in this space where programs have moved online due to the pandemic in 2020 and beyond. It is therefore appropriate to allow time for such studies to emerge before reviewing research in non-formal virtual settings.

Given the wide scope of the research questions and the existence of earlier reviews in the area, we chose to focus on research on computing education in non-formal settings from 2015 onwards. Initial scoping of the literature confirmed that over 800 studies would be identified using our search terms within this time period, and would allow us to extend the coverage of previous reviews and minimise overlap with them.

3.2 Method

Searches using our key terms were performed on the included databases in May 2021 for papers published between January 2015 and April 2021. Previous reviews in the field were used to identify search terms; we extended the terms when we found synonyms being used and took care to avoid international bias.

Initial trial searches were conducted with terms such as “robotics”, “coding” and “programming”. We found that this resulted in a large volume of results outside of computing education which we did not have the resource to manually review. The search terms were selected based on the categories used by the chosen databases. Trial searches were undertaken, and the results were compared to the literature reported in previous reviews as detailed in Section 2 showing that the search terms were effective at identifying relevant papers. The search terms used an AND search with synonyms for the target age group (e.g. K-12), setting (e.g. out-of-school) and computing education study context (e.g. informatics education) (see Table 2).

Our search was focused and systematic rather than exhaustive. We focused on computer science education databases and included a general research database to gather research from other disciplines. We included the ACM Digital Library and IEEE Xplore as computer science education databases and ERIC as a general database. In limitations, we will discuss our decision to not include specific learning science or other subject databases (see Section 5.1). To avoid selecting a large number of results with a peripheral mention of the topic, we searched abstract and metadata only rather than full-text.

The initial search resulted in 421 papers (ACM Digital Library: 211, IEEE Xplore: 127, ERIC: 83) being selected for review against our inclusion criteria.

An example search query used on the 17th of May 2021 for the IEEE Xplore database, with a filter start date of 2015, for conference and journal publications is shown in Table 3.

The following criteria were established for inclusion of papers:

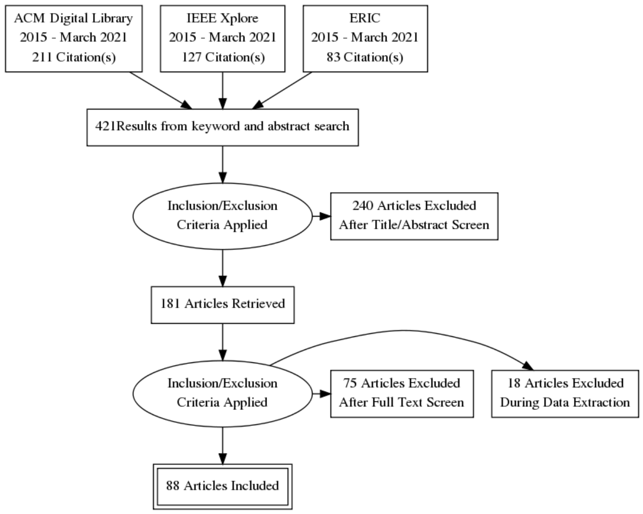

Figure 1: PRISMA Diagram outlining the selection of papers for the current review

(1) Papers should present a study in a non-formal computing setting, or concerning educators or participants in such studies (such as longitudinal impact analysis)
(2) Papers should include learners aged 5-18, or provide separate results to clearly identify this category of participants
(3) Papers should have a specific focus on computing education (including physical computing, cybersecurity, computational thinking and digital making)
(4) Papers should be based on non-formal education in a regular or immersive setting (planned to deliver at least five hours of education to the same group of learners)
(5) Papers should provide substantive qualitative or quantitative data to evaluate the impact of non-formal computing education

Regarding criterion 3, papers focused on education where computing was being used for the purposes of another subject, such as mathematics, were excluded, as were those focused on STEM more broadly. For criterion 5, papers were excluded if they were purely descriptive, theoretical or position papers. The first author agreed criteria with the third and fourth authors and conducted a first pass through the search results removing papers that were clearly out of scope from the title and abstract. Duplicates were also removed. This resulted in 181 papers.

The first author then conducted a second pass based on the full-text of the papers. Any papers identified as borderline for inclusion were discussed with the second or third author and used to refine the criteria. The main reasons for exclusions were: outside of age-range (e.g. college), focus on teachers rather than learners, not focused on computing education, and lack of empirical evidence. This resulted in 106 papers remaining in the sample (see Figure 1).

A quality and relevance pass of the remaining papers was then conducted as the first step of data extraction to ensure that the papers contained sufficient information relevant to the research questions. Two authors separately reviewed the full texts of a sample of the papers (20/106) and met to agree on their inclusion status. The second author then reviewed the remaining full texts in line with the agreed criteria. Any exclusions or uncertainties were flagged and discussed with the first author and consensus was reached concerning their inclusion. Eighteen further papers were removed during the data extraction phase as they were found not to contain sufficient evidence to answer our research questions. This resulted in 88 papers being selected for analysis.

As our field of non-formal learning is an emerging area of study in STEM, guided by Zawacki-Richter et al. [115] and Decker and McGill [23], our approach to data analysis was to start with simple candidate descriptive categories. An analysis team, the first, second and fourth authors, collaboratively agreed the initial set of categories. The three authors came from different computer science, education and research backgrounds, including a very experienced non-formal educator and computer science researcher, an experienced primary educator and education researcher and an experienced secondary teacher and computer science education researcher. The initial categories were

- Country
- Age
- Sample size
- Gender
- Goal of education
- Education provider
- Topic(s)
- Instructional approach
- Outcomes

Using the initial set of codes, the first author read and analysed the full text of a random sample of 12 of the 88 papers (13%) and refined the codes looking for patterns and themes, adding, merging and splitting codes inductively. The percentage of papers in this first pass is in line with recommendations of 10 to 20% for a first pass [54]. The developed categories were reviewed and discussed with the analysis team and included new codes such as an emerging rich set of affective outcomes including interest, intention, engagement and belonging (see Table 11).

Following the first pass and category hierarchy agreement, each remaining paper was read in full and coded by the first author. Again, during the full pass of papers, the analysis team met to discuss coding decisions and example categorisations. Having multiple analysts enabled an emerging interpretation, a rich understanding of the context and increased credibility and dependability of the process [96]. Finally, the first and second authors used the coded text segments to write up the analysis by research question to report on the results. The open-source annotation software hypothesis.is [1] was used for the analysis.

4 RESULTS

The number of studies meeting the criteria increased over the time period studied, 10 in 2015 and 20 in 2020; results from 2021 are partial and proportional to 2020. This suggests that evidence-based research into non-formal computing has not decreased as formal computing education has become more widespread. The 88 studies

[1]https://web.hypothes.is/

Cohort mix	No. of studies
All female	32 (36%)
All male	1 (1%)
Mixed, more female	12 (14%)
Mixed, more male	28 (32%)
Mixed, even	4 (5%)
Unspecified	14 (16%)

Table 4: Reported gender of participants in the studies included in the review. Note: Some studies included multiple cohorts with different mixes

included in the review are shown in the bibliography with a * prefixing the name of the first author.

In this section, we summarise the key aspects of studies in relation to each of the research questions.

4.1 RQ1: What has been the focus of non-formal computing education research?

4.1.1 Learners. As in previous reviews, studies focused mainly on learners from the United States (US), with the next largest cohort being the United Kingdom (UK). The lower secondary school age group (grade 6-8) is the most studied (43 papers). This reflects the importance of this age group in forming identity and establishing interests. There is also a considerable number of studies (n=35) targeting upper high school (grade 9-12) who are close to making decisions about university/college, and who tend to be the focus of outreach programmes from post-18 education providers in order to boost recruitment to computer science programmes. Only 9 studies included in the review focus on primary school (K-5). Given that stereotypes and beliefs are known to form very early in childhood [7], interventions focused on this age range are likely to be important, and future research would benefit from a greater focus on early childhood.

There has been a clear focus on encouraging females into computing, although studies not clearly stating the way they classify gender makes it difficult to compare across the literature. As presented in Table 4 there were 32 female-only cohorts and one male-only cohort. The focus on females has remained steady (around 4-6 per year), although the proportion of these studies within the non-formal computing education literature has declined due to an overall increase in research. In studies where both males and females were included, it was much more likely that they would have more male than female participants, rather than more females than males. One females-only study [68] specifically used an inclusive definition of females and welcomed genderqueer, trans and non-binary youth.

There is also a focus on broadening participation amongst those from different ethnic and socioeconomic backgrounds. While many studies include detailed demographic information, it is often difficult to quantify and compare across studies. This is especially the case when comparing the US and other countries. In the US, there are studies that exclusively include: Black or African American females [32, 99, 100], Latina females [22], Girls of color [93], minority youth [21, 61] and minority boys [30]. Though the numbers are small, the focus on young people from minority ethnic groups appears to be increasing.

Socioeconomic status is less often reported and again difficult to compare across studies and subject to local population biases. Several papers acknowledge that their intake is largely privileged, e.g. [77, 84]; others attempt to address this with targeted recruitment, funding and other measures [10]. One study [4] is situated in refugee camps in Kenya with a highly disadvantaged population of young people who have had little if any prior exposure to computing; another [19] specifically compares a population of lower socioeconomic status with a typical local camp population.

One study [89] concerns a robotics programming workshop for learners with various disabilities. There is little mention of learners with learning or physical disabilities or of neurodivergence in other papers in our review so we do not know how these learners are represented. An intervention in which high-school age interns create lesson plans [13] does consider Universal Design for Learning (UDL) guidelines[2] but the resources are not used within the study. This characteristic of learners does not therefore seem to be well understood in the non-formal computing education literature, yet will be of key importance for future research.

Overall, there is still very inconsistent or incomplete reporting of learner characteristics across the studies included in the review. Different classification systems across countries goes some way to explaining these inconsistencies, but there may also be an impact of the non-formal setting on the type of information deemed to be appropriate to collect about learners compared to a formal education setting. Nevertheless, for the purposes of rigour and replicability, future research in non-formal computing education settings should aim to collect more detailed demographic information about learners and report it in a more consistent way across studies.

4.1.2 Providers and purpose of non-formal computing education. The provider was not always clearly stated in the papers but had to be inferred from the authors' institutions and use of the 'we' pronoun when describing education provision activities. In the vast majority of the studies, education was provided by the same university that was conducting the research: 81 out of 88 studies had a university as an education provider responsible for curriculum and pedagogy (Table 5). There are some examples of education provided by non-profit organisations, tech companies, commercial education providers, libraries and makerspaces, often in collaboration with a university. This reflects what is being researched and may not be indicative of the range of non-formal education that is happening in practice. Large-cohort non-formal programmes such as Girls who Code and CoderDojo are not well-represented in peer-reviewed literature [60]; these programmes are often run outside of higher education without the same motivation for academic publishing.

67 of the studies took place in immersive multi-day settings such as summer camps (Table 6). This reflects social and cultural norms of the US, where summer camps are much more common than in other countries, and where the majority of the research is being conducted. Of the remaining studies, 21 were conducted in regular settings such as after-school and weekend clubs, while only 2 were single-day events. Additionally, 8 of the studies reported

[2]http://udlguidelines.cast.org

Education Provider	Number of Studies
University	81
School or school district	11
Non-profit organisation	9
Educational programme	3
Tech company	4
Commercial education provider	0
Library	1
Makerspace	2
Unclear	3

Table 5: Number of studies included in the review by type of education provider. Note: Where provision of education appears to be a collaboration we have included studies in multiple categories

Duration of intervention	Number of Studies
Immersive	67 (76%)
Regular	21 (24%)
Day	2 (2%)

Table 6: Duration of intervention. Note: Some studies included multiple formats.

repeat attendance at a programme. This is in line with a previous study [20], which found that most interventions in the non-formal computing literature were immersive (one to four weeks) with a smaller number of shorter and longer (regular) programmes.

Understanding the context of the non-formal computing education is extremely important; it may be that young people attending a summer camp run by a university may be very different to those who attend a regular club or one-off workshop and the purpose and outcomes of their participation may also differ. Even within the summer camp approach, different recruitment methods can lead to different samples, and therefore affect results. For example, one study compared groups of young people recruited for computing summer camps from the area local to their university to those from further afield in areas of lower socioeconomic status and higher levels of poverty [19]. Although both groups reported changes in self-efficacy after the intervention, the local group also showed an increased interest in computing that was not evident on average in the outreach group. The outreach group was recruited through teachers, rather than through parents signing up their own child, and they were less likely to have a parent involved in computing careers than their counterparts in the local group. These factors could all have an effect on initial interest and engagement in computing, which will have a subsequent impact on any changes recorded as a result of interventions.

From the education providers' perspectives, we identified a number of different purposes of the non-formal education (Table 7). Broadening participation of under-represented groups was the most common substantive aim. Many studies targeted a specific demographic with a view to increasing participation. Some used culturally-relevant pedagogy to connect with minority youth [21, 113]; others adopted educational practices that were expected

Purpose of education	Number of Studies
Broadening participation	37
Interest development	27
Research	22
Awareness	14
Knowledge development	14
Skills development	8
Recruitment	3
Equity	2
Community benefit	2
Societal	2

Table 7: Substantive goals of education. Note: Some papers stated multiple substantive aims.

to lead to equitable outcomes [68, 76] or to address prior inequity [32]; still others tried to remove barriers to accessing an opportunity [69, 74] or hoped that their topic would appeal to learners from under-represented groups [10, 15]. Interest development was also well represented: these papers used non-formal settings to develop or increase interest in computing with the expectation that fun, positive experiences with peers would increase the likelihood of future participation.

The development of knowledge and/or skills as primary substantive aims is less common across the papers, perhaps indicating that this is seen as the role of formal education. There are studies where non-formal settings are used to fill gaps in formal education, but development of knowledge and skills is more often seen as a secondary goal as part of developing self-efficacy, rather than as the primary goal. As an example Vrieler et al. states *"It was more important that the children left the summer camp with a positive experience with computing and programming rather than achieving all of the learning objectives"* [104, p.3].

Three papers had a primary aim of directly recruiting young people onto specific university computing programmes and measuring the outcome. Recruitment into university computing courses in general is a driver for studies targeting upper secondary learners. Finally, two papers [4, 108] used non-formal education as a setting for improving relationships between culturally diverse communities. These studies both took place outside the US, one with refugees in Kenya and the other in an area of high immigration in Germany. These studies used regular non-formal computing settings to gain benefits beyond improving cognitive and attitudinal outcomes within computing. In the main, the non-formal education opportunities studied are largely local and not part of larger initiatives or programmes.

4.1.3 Computing topics. A wide range of computing topics are being covered in the literature (see Table 8). Most studies focused on general computer programming, and many targeted specific kinds of programming, with games development, mobile app development and robotics/physical computing being popular.

In most cases, the curriculum followed was designed specifically for the intervention which means there is little opportunity for refining instructional materials based on widespread usage. Instructional approaches ranged from direct instruction through to

Topic	Number of Studies
Programming	26 (30%)
Mobile apps	17 (19%)
Making games	15 (17%)
Robotics	12 (14%)
Physical computing	8 (9%)
Creative computing	8 (9%)
Social good	8 (9%)
Cyber security	7 (8%)
Data science	6 (7%)
Computational Thinking	6 (7%)
Culturally relevant topics	3 (3%)
3D printing	3 (3%)
AI	2 (2%)
Augmented reality	2 (2%)
Topics with only 1 study each Digital skills, Society, Poetry, Careers, e-Textiles, Computer graphics, Scientific computing, Humanities Storytelling, Ethics, Lesson planning, Business, Dance, Social justice	1 (1%)

Table 8: Topics covered. Note: Some studies included multiple topic areas.

personal projects supported by mentors. A common approach was to start with direct instruction and gradually reduce scaffolding, leading to a personal project, presentation or showcase. Varying amounts of structure and open activity are found across and within studies. We found 38 examples of direct instruction followed by guided tasks and 20 examples of direct instruction followed by more open activities that could be completed using the skills learned. Personal projects with a strong element of choice featured in 34 of the studies. There were a small number of mentions of specific experiential approaches to learning, including problem-based, project-based, inquiry-based and studio-based learning.

There is a significant focus on programming within the studies, with less focus on other aspects of the software development lifecycle. Three papers used an overall design thinking approach, and 12 were found to have specific focus on requirements gathering and analysis, sometimes with the involvement of external stakeholders. A further 7 explicitly focused on software design, 2 used prototyping, and 3 used playtesting. One paper mentions user experience design as a learning activity.

4.1.4 Measurement instruments and methodologies used. We found a variety of instruments and methodologies in use across the papers included in the review (see Table 9). Most instruments were designed or adapted specifically for a study. Existing instruments were sometimes used but the need to extract specific information to answer research questions or to meet funding needs is perhaps seen as more important than standardising to allow comparison, given the difficulty of standardising outcome measures even between multiple years of the same programme [78]. Accurate categorisation is difficult given that some studies consider attitudes across a combination of questions, whereas others consider multiple attitudinal measures.

Cognitive measures, or evidence of learning, were used in nearly half of the studies, despite knowledge and skill development not being a primary aim of most of the research. We found that learning gains were more likely to be assessed through demonstration of skills. It may be that the formal assessment of knowledge is viewed as unacceptable in what is perceived as a leisure activity. Education providers may rely on other aspects of the programmes (such as interest or engagement) when trying to obtain funding or recruit young people to participate in order to avoid any negative associations with formal schooling, or they may target attitudinal measures due to their aims of broadening participation.

Skill is frequently assessed through manual evaluation of project artefacts against a rubric, with several references to Brennan and Resnick's framework for assessing computational thinking [9] throughout the studies. There is limited application of automated assessment of project outputs, an approach which could save time and support manual assessment. Understanding how to best measure and recognise learning gains within non-formal computing education remains problematic, but should certainly form the basis of discussion and future research.

Affective measures, including interest and intention, were the most common in papers included in the review, reflecting the widespread goal of broadening participation in computing outlined earlier. Affective constructs are largely measured using Likert scales in survey instruments. Within non-formal education, completing surveys and interviews may be viewed as a task that takes time away from the learning activities and the enjoyment of the learners [19]. We saw little evidence of the application of alternative ways to measure these constructs that does not take time away from the main activities. Non-formal computing settings may benefit from ways of measuring outcomes that are perceived as enjoyable or integrated into activities so that they are seen as valuable to the learner.

One of the most common measures of affect was self-efficacy or confidence in computing. In some studies, it seemed that this construct was used as a proxy for the development of knowledge/skills,e.g. [33]. Given that girls tend to underestimate their computing abilities compared to boys with the same level of knowledge/skills [51], using changes in reported self-efficacy as a proxy for learning is likely to be biased and will depend on the samples recruited for the study.

The importance of measuring the long term impact of outreach interventions has been previously emphasised [24]. Only six studies collected longitudinal data to demonstrate the impact of specific interventions on the educational choices of participants (see Table 12). Three considered applications to tertiary education and two (from the same programme) used interviews to gain insight into the future educational decisions made by participants. A further study considered the impact of preparing learners for a high school computing class. Two studies (see Table 12) also highlighted impact outside of educational choices and evaluated the societal impact of regular non-formal computing activities using interviews and journal notes.

In addition to assessing changes to cognitive outcomes at the end of an intervention, many studies also considered how learning developed during the course of the intervention, learning trajectory changes, (see Table 13), including how learners were collaborating,

Table 9: Measurement instruments or methodological approaches

Construct	Type of research	Measurement instrument or methodology
Cognitive	Quantitative	Assessment questions based on content of activity. Often MCQ or T/F [1].
		Time taken to complete tasks, e.g. [107]
		Automated assessment [35].
	Qualitative	Manual evaluation of outputs against a rubric, e.g. [56, 76]
Affective	Quantitative	Likert scale questions
		Georgia Computes!, e.g. [15], STELAR's CT e.g. [105],
		the CS Attitude Survey e.g. [40]
		The Gender and Racial Attitudes Toward Computing inventory [32]
		Papastergiou's self-efficacy scale e.g. [98].
		Show of hands [84]
	Qualitative	Free text responses to surveys
		Short answers to questions, e.g. [102]
		Interviews with subset of survey respondents e.g. [20]
		Interviews as the primary source e.g. [58]
Wider impact	Quantitative	Applications to study computing at tertiary level, e.g. [25]
	Qualitative	Interviews, e.g. [59]
		Field notes, e.g. [4]
Learning Trajectory	Quantitative	Programmatic evaluation of daily project artefacts [34]
		Cognitive load: Paas's 9-point scale [117] and CS CLCS [116]
	Qualitative	Audio/video coding, e.g. [99]
		Field notes [64]
		Evaluation of learners' output against a rubric, e.g. [113]
		Interviews with learners, e.g. [22]

indicating a more holistic assessment approach. These studies often use qualitative data including audio or video recordings, project artefacts, interviews and field notes from researchers. In some cases, this was combined with manual or automated assessment of project artefacts at regular intervals. We also found two studies that used measures of cognitive load during activities.

4.2 RQ2: What is the impact of non-formal computing education on learners?

The 88 papers in our review have been categorised by what outcome is being measured by the respective study, with many papers measuring more than one category. The categories, and their sub-constructs, provide a mechanism for reporting on the impact on learners. Table 10 lists studies measuring cognitive outcomes, Table 11 lists those measuring affective outcomes, Table 12 wider impacts and Table 13 when learning is measured during the intervention.

In line with previous research [26, 101], the outcomes reported by the studies included in this review on the impact of non-formal computing education on learners are broadly positive. The majority of studies focus on demonstrating that an intervention had a positive effect rather than on understanding how particular aspects of the intervention led to success or how learners developed computing knowledge and skill in a non-formal setting. The next sections will identify some of the key impacts that the research into non-formal computing interventions have reported, highlighting particular aspects of interest for future study.

4.2.1 Cognitive Measures. As might be expected, those studies measuring knowledge of specific computing concepts before and after explicit instruction report increases in test scores from pre- to post-test, e.g. [1, 6, 67, 82, 102]. Importantly for non-formal computing education, there was some evidence that regular settings or attending a summer camp multiple times was beneficial for learners [11, 77] perhaps allowing learners to understand and apply more complex concepts over time. Learning gains were similar between males and females [76, 77] although there was some evidence for higher overall scores on tests for males [76].

Moving from knowledge to skills, studies have identified gains in computational thinking, e.g. [55, 56], troubleshooting [117], and independence and productivity [48, 65], as a result of non-formal computing education. In particular, the research seems to suggest that interventions which explicitly taught problem solving [65] or incorporated scaffolded support into self-paced learning [48, 107] had a positive impact on learners' abilities to progress through activities and develop greater independence in tackling difficult tasks. The use of focused case studies in some of this research, e.g. [34, 35, 113] is valuable in understanding an individual's or small group's learning journey over a period of time and how they apply their skills within computational activities. Using their outputs as a measure of both quality and quantity of learning provides insight that cannot always be gained from pre- and post-test scores. More research utilising the rich and detailed data provided by learners as they learn will be important for our future understanding of the impact of non-formal computing education, especially in regular settings that take place over extended periods of time.

Table 10: Cognitive sub-constructs and studies in the review. Note: The number of studies for the each sub-construct (n) is shown.

Sub-construct	(n)	Studies
Knowledge	13	A-Ghamdi et al. (2016) [1], Balaguer Alvarez (2017) [6], Calandra et al. (2021) [11], Jin et al. (2016) [50], Lédeczi et al. (2019) [67], Mouza et al. (2016) [76], Mouza et al. (2020) [77], Nite et al. (2020) [82], Vachovsky et al. (2016) [102], Wolf et al. (2020) [111], Yang et al. (2021) [113], Yett et al. (2020) [114] , Zhi et al. (2019) [116]
Skill	17	Alamer et al. (2015) [3], Cateté et al. (2020) [13], Fields et al. (2016) [34], Fields et al. (2015) [35], Jernigan et al. (2015) [48], Kukul and Çakr (2020) [55], Kwon and Cheon (2019) [56], Litts et al. (2020) [64], Loksa et al. (2016) [65], Mouza et al. (2016) [76], Pantic et al. (2016) [87], Thomas (2018) [99], Wang et al. (2020b) [107], Weibert et al. (2016) [108], Whyte et al. (2019) [109], Yang et al. (2021) [113], Zhong and Li (2020) [117]
Output	7	Al-Khalifa et al. (2019) [2], Kukul and Çakr (2020) [55], MacDowell et al. (2017) [68], Mouza et al. (2020) [77], Ni et al. (2016) [81], Yett et al. (2020) [114] ,Calandra et al. (2021) [11]

4.2.2 Affective Measures. As outlined with respect to RQ1, affective measures were used most often to understand the impact of non-formal education on learners. In terms of perceptions of computing and awareness of what the discipline involves, the majority of papers reported an improvement for those attending non-formal computing sessions.

In particular, the opportunity to address stereotypes of computer science and scientists seems to have an impact on learners' perceptions of computing, especially for girls [41, 60, 86, 98]. Increasing awareness of different aspects of computing may be key to addressing these stereotypes. Non-formal computing education interventions give the opportunity to focus on specific areas of computing, such as artificial intelligence [21, 102] or data science [75], or to give a broader overview of a number of different aspects of computing. This can help to dispel the stereotype that computing is narrowly focused on programming, which many learners may hold from their formal computing education [44].

An important point raised by one study is that improving awareness and perceptions of computing does not necessarily result in continued engagement with the subject or career [59]. Using a detailed qualitative and longitudinal approach, these authors identified those who did and did not go on to study computing after their intervention. Amongst those who did not continue with computing, perceptions had often improved, but increased awareness of the discipline helped them to decide not to pursue computing as a career. This study shows the importance of considering the interaction of different factors on long-term impacts of interventions rather than short-term changes in specific outcomes, which are usually based on averages across all learners.

Several papers measuring interest in computing and future intentions to study or work in the discipline highlight the potential effect of learners' prior interest on the impacts of non-formal interventions. For example, no change/decrease in computing interest amongst learners after an intervention has been linked to high initial levels of interest [98, 102], which may indeed have been the driving force behind them attending the summer camp or other non-formal setting. Others have reported that those who already had high interest or intention to study computing were more likely to show positive changes than those who were not [19, 61]. Again, short-term positive impacts may not always lead to long term change; increased post-intervention interest levels were found to drop again by the following year [84], and even as soon as the following month [6].

Some studies investigate factors that may predict or influence interest, including playfulness, opportunities for personal growth, and a range of social factors [5, 18, 20, 30]. Amongst the studies reviewed, those demonstrating increasing engagement with computing tend to use approaches and topics that are relevant to the young people involved both personally and socially, e.g. [63, 68, 80], and that provide opportunities for creativity or personal choice in the projects undertaken, e.g. [36, 55, 66].

Confidence and/or self-efficacy in computing may also be important contributors to continuing engagement in the discipline [110]. The papers reviewed revealed improvements in these constructs after non-formal computing education interventions. However, an important point to note is that the activities need to be pitched at the right level for learners to avoid the opposite effect: if tasks are too difficult, learners may report decreasing confidence in their abilities [10, 16].

Some papers provide insights into specific aspects of interventions that influence improvements in confidence and self-efficacy [52, 65, 117]. For example it has been reported that explicit instruction in problem solving improved self-efficacy compared to a control group [65] and that all-female groups reported higher self-efficacy than mixed-sex groups [52]. Further research needs to be conducted to better understand the instructional and social factors that influence self-efficacy and confidence outcomes of interventions in non-formal computing education.

Social factors are also found to be important for learners' feelings of belonging to computing and perceived support. Providing role models in non-formal computing education settings, including computer science professors and industry professionals, e.g. [102], and peer mentors, e.g. [18, 32, 61], can help learners understand who can be a computer scientist and increase their identification with the discipline. Taking specific actions towards increasing parental engagement and perceived parental support can also be beneficial, with one study reporting positive outcomes when learners' parents were encouraged to actively engage with content from the intervention [20]. This intentional approach seems to be important to

Table 11: Affective sub-constructs and studies in the review. Note: The number of studies for the each sub-construct (n) is shown

Sub-construct	(n)	Studies
Interest	22	Al-Khalifa et al. (2019) [2], Alamer et al. (2015) [3], Aritajati et al. (2015) [5], Balaguer Alvarez (2017) [6], Clarke-Midura et al. (2016) [17], Clarke-Midura et al. (2020)[19], Clarke-Midura et al. (2018) [18], Clarke-Midura et al. (2019) [20], DeWitt et al. (2017) [28], Dou et al. (2020) [30], Ivancic and Glendowne (2020) [45], Miller et al. (2018) [74], Mobasher et al. (2019) [75], Nesiba et al. (2015) [78], Ni et al. (2016) [81], Nusayr and da Silva (2019) [83], Outlay et al. (2017) [84], Vachovsky et al. (2016) [102], Wang et al. (2019) [106], Wang et al. (2020a) [105], Wolf et al. (2020) [111], Yett et al. (2020) [114]
Intention	18	A-Ghamdi et al. (2016) [1], Al-Khalifa et al. (2019) [2], Alamer et al. (2015) [3], Chipman et al. (2018) [16], Clarke-Midura et al. (2019) [20], DeMatteis et al. (2018) [25], Dou et al. (2020) [30], Escobar et al. (2021) [32], Jin et al. (2018) [49], Kamberi (2017) [52], Lawlor et al. (2020) [60], Lee (2019) [61], McFarlane and Redmiles (2020) [69], McGowan et al. (2017) [72], Pedersen et al. (2020) [90], Sabin et al. (2017) [91], Sullivan et al. (2015) [98], Vachovsky et al. (2016) [102]
Attitude	9	Chen et al. (2019) [15], Escobar et al. (2021) [32], Fowler (2017) [39], Fowler (2019) [40], Fowler and Khosmood (2018) [41], MacDowell et al. (2017) [68], Mouza et al. (2016) [76], Starrett et al. (2015) [97], Wang et al. (2020a) [105]
Perception	14	A-Ghamdi et al. (2016) [1], Alamer et al. (2015) [3], Dou et al. (2020) [30], Fowler and Khosmood (2018) [41], Kamberi (2017) [52], Lakanen and Isomöttönen (2015) [57], Lakanen and Kärkkäinen (2019) [59], Lawlor et al. (2020) [60], McGowan et al. (2017) [72], Nesiba et al. (2015) [78], Ni et al. (2016) [81], Pantic et al. (2018) [86], Paramasivam et al. (2017) [89], Sullivan et al. (2015) [98]
Awareness	8	Chipman et al. (2018) [16], Cummings et al. (2021) [21], Isvik et al. (2020) [44], Jin et al. (2018) [49], Lakanen and Kärkkäinen (2019) [59], Mobasher et al. (2019) [75], Outlay et al. (2017) [84], Vachovsky et al. (2016) [102]
Value	5	Clarke-Midura et al. (2016) [17], Lédeczi et al. (2019) [67], MacDowell et al. (2017) [68], Mouza et al. (2016) [76], Zhong and Li (2020) [117]
Engagement	13	Dahn and DeLiema (2020) [22], Eordanidis et al. (2017) [31], Flesch et al. (2021) [36], Kukul and Çakr (2020) [55], Litts et al. (2020) [64], Lui et al. (2017) [66], MacDowell et al. (2017) [68], Menzies et al. (2015) [73], Mouza et al. (2016) [76], Ni et al. (2017) [80], Pantic et al. (2016) [87], Scott et al. (2017) [93], Wang et al. (2020b) [107],
Enjoyment	1	Zhong and Li (2020) [117]
Self-efficacy	25	Al-Khalifa et al. (2019) [2], Aritajati et al. (2015) [5], Bryant et al. (2019) [10], Chen et al. (2020) [14], Chen et al. (2019) [15], Clarke-Midura et al. (2016) [17], Clarke-Midura et al. (2018) [18], Clarke-Midura et al. (2020)[19], Clarke-Midura et al. (2019) [20], Cummings et al. (2021) [21], DeWitt et al. (2017) [28], Escobar et al. (2021) [32], Feldhausen et al. (2018) [33], Ford et al. (2017) [38], Fowler and Khosmood (2018) [41], Jin et al. (2018) [49], Kamberi (2017) [52], Kukul and Çakr (2020) [55], Lawlor et al. (2020) [60], Lédeczi et al. (2019) [67], Loksa et al. (2016) [65], McFarlane and Redmiles (2020) [69], Mobasher et al. (2019) [75], Sullivan et al. (2015) [98], Wang et al. (2019) [106]
Confidence	14	Chen et al. (2019) [15], Chipman et al. (2018) [16], DeMatteis et al. (2018) [25], Flesch et al. (2021) [36], Ford et al. (2017) [38], Fowler and Khosmood (2018) [41], Kukul and Çakr (2020) [55], Mouza et al. (2016) [76], Ni et al. (2016) [81], Sabin et al. (2017) [91], Sullivan et al. (2015) [98], Vachovsky et al. (2016) [102], Wang et al. (2019) [106], Zhong and Li (2020) [117]
Belonging	6	Aritajati et al. (2015) [5], Escobar et al. (2021) [32], Lee (2019) [61], Mouza et al. (2016) [76], Vachovsky et al. (2016) [102], Yang et al. (2021) [113]
Support	3	Clarke-Midura et al. (2019) [20], Sabin et al. (2017) [91], Vachovsky et al. (2016) [102]
Mentor reliability	1	Clarke-Midura et al. (2018) [18]

Table 12: Wider impact sub-constructs and studies in the review. Note: The number of studies for the each sub-construct (n) is shown.

Sub-construct	(n)	Studies
Further study	6	DeMatteis et al. (2018) [25], Escobar et al. (2021) [32], Kukul and Çakr (2020) [55], Lakanen and Isomöttönen (2018) [58], Lakanen and Kärkkäinen (2019) [59], Weibert et al. (2016) [108]
Societal	2	Arawjo et al. (2019) [4], Weibert et al. (2016) [108]

Table 13: Learning trajectory sub-constructs and studies in the review. Note: The number of studies for the each sub-construct (n) is shown,

Sub-construct	(n)	**Studies**
Trajectory	10	Calandra et al. (2021) [11], Dahn and DeLiema (2020) [22], Fields et al. (2015) [35], Fields et al. (2016) [34], Kukul and Çakr (2020) [55], Litts et al. (2019) [63], Litts et al. (2020) [64], Pantic et al. (2016) [87], Thomas (2018) [99], Whyte et al. (2019) [109]
Collaboration	7	Campe et al. (2020) [12], Jenkins (2017) [47], Kukul and Çakr (2020) [55], Lewis and Shah (2015) [62], Pantic et al. (2016) [87], Thomas (2018) [99], Yang et al. (2021) [113]
Cognitive load	2	Zhi et al. (2019) [116], Zhong and Li (2020) [117]

the success of interventions on feelings of belonging and social support; simply attending a non-formal computing education setting may not be enough to produce a significant impact on learners, e.g. [13, 91].

4.2.3 Wider Impact. As presented in Table 12, two main aspects of the wider impact of non-formal computing education opportunities have been studied: further study in computing courses, and societal integration and collaboration.

Attending summer camps at universities was generally successful in increasing recruitment to computer science courses at those institutions, especially for female students, e.g. [6, 25, 78]. Another study targeting a group that are typically underrepresented in computing reported the success of an intensive summer program and additional support throughout the academic year for Black female students in preparing them to take the Advanced Placement Computer Science Principles (AP CSP) exam in the United States [32]. After participating in the program, the qualifying rate for learners was higher (87.5%) than that for the statewide sample (55.3%) and the national sample (56.9%). Given that there was both a non-formal and a formal element to the program, it is not possible to fully understand the individual effects of the non-formal experiences of the learners' on their outcomes, and it might be that the ongoing support from teachers during the academic year as learners undertook the AP CSP course was more beneficial than other aspects of the program. Attending more of the sessions provided over the course of the year was positively associated with higher scores on the exam.

However, although high scores on AP exams are important, it does not necessarily mean that learners will continue with computing beyond high school. One study found that increasing identification with computer science as a discipline was a key contributor to learners' reported intentions to pursue it as a major at university [32]. This can be linked to the research discussed earlier, which reported that the deeper knowledge and understanding of computing as a discipline as a result of attending a summer school was key to learners' decisions to continue with computer science in the next stage of their education [59]. Intensive or regular non-formal education opportunities could play a key role in supporting learners' computing identities and understanding of the discipline, and it will be important for future research to evaluate how these different elements best work together to support a wide range of learners in their educational journeys.

In terms of societal impact, two studies included in the review focused on how non-formal computing education can be used to foster cross-cultural learning and respect across different ethnic backgrounds and cultural groups [4, 108]. These studies stand out from much of the literature discussed so far, relying on ethnographic methods in which outcomes of non-formal computing education are not measured, but the lived experiences of those involved in the clubs and the researchers are recorded.

In two studies, non-formal computing activities take place in regular clubs over periods of several weeks or months in areas with communities that have high levels of conflict or separation between different groups, e.g. migrants and locals in Germany [108], or refugees from different countries in Kenya [4]. While both sets of clubs focus on teaching programming and computing skills, the authors of the related research studies stress the importance of the clubs in helping students to overcome stereotypes or other barriers between culturally diverse groups. In particular one study reports that working towards a shared goal and overcoming difficulties together may be more useful in broadening participation in computing than direct teaching aimed at identifying differences between groups [4]. This offers an alternative approach to that often seen in the broadening participation efforts in other countries, particularly in the US, and could provide valuable insights into the underrepresentation of different groups in computing if the approach were to be taken in these other contexts.

4.2.4 Learning Trajectories. In addition to measuring knowledge and/or attitudes before and after computing interventions, several of the studies included in the review focused on the processes involved in learning computing over the course of the non-formal learning experience (see Table 13). For two of these papers, the authors considered the cognitive load or mental effort required during learning using standardised measures, but found little difference between working in pairs and working alone [117], or in using worked examples or not [116].

When trying to understand learning, these standardised measures are perhaps not always the most sensitive or nuanced, and qualitative methods may prove more enlightening. Several papers used qualitative methods to understand how young people think about their learning, combined with examination or assessments of the artefacts they produce to provide a rich, detailed picture of the learning journey, e.g. [22, 34, 55, 64, 87, 99, 109]. Understanding of these different learning trajectories and approaches serves to highlight the importance of individualised support and formative assessment, rather than a focus on summative assessment or outcomes.

A focus on collaboration and how it affects learning is also evident in a number of studies, ranging from deliberate paired programming, e.g. [12, 62], to less structured peer interaction and discussion, e.g. [47, 87, 99, 113]. The studies identify key factors that can affect the success of collaborative work, including the levels of experience of each collaborative partner [12, 99], the type of dialogue used by learners and teachers [47, 87], and the task that is being completed [62]. These studies demonstrate how discussion and collaborative work can support learning in computing, which may be a key benefit of non-formal settings, but that care needs to be taken to ensure it is appropriate for the learners and tasks.

5 DISCUSSION

We next consider the limitations of the study, the outcome of the review for each of the research questions, before considering the affordances of non-formal computing education.

5.1 Limitations

This study covers a fairly short time-period (just over 6 years) and is restricted to papers in the English language in three databases that use our keywords in their metadata. This approach has allowed us to give a broad overview without an unmanageable number of studies. The paper selection should be considered to be representative rather than exhaustive. Future literature reviews could narrow the criteria and broaden the search.

The search was applied across key metadata fields rather than full-text to avoid selecting a large number of results with a peripheral mention of the topic rather than a focus on it. The resulting search was focused and systematic rather than exhaustive.

Focus on computing education research databases, rather than other fields such as learning science, engineering or the maker community restrict the coverage of our review. Another review could focus on alternative publication sets to extend and compare to the work covered here.

Importantly, when drawing conclusions from our findings, caution should be urged with respect to making generalisations about non-formal settings per se. It is likely that the studies analysed have been written by researchers investigating outreach activities at their establishments or interventions they have designed rather than studying the work done by external organisations outside of academia. Research about non-formal settings may not be representative of the rich eco-system of non-formal experiences that are available to young people [60].

5.2 What has been the focus of non-formal computing education research?

Broadening participation of groups that are underrepresented in computing is the most common goal across the studies in the review, particularly for females but with some consideration of ethnic minorities and those from low-income areas, with one study focusing on young people with disabilities. There have been attempts to find ways to encourage girls to take an interest in computer science through female-only programmes [25, 60], trying different computing topics [16, 102], changing perspectives [17, 38] and demonstrating the value of computing [28, 81]. A 2020 Google/Gallup report [42] revealed that girls in the US are still much less interested in learning computer science than boys, so this focus would appear to be warranted in that context. However, more work is necessary to understand different contexts across the world.

The systematic review revealed a wide range of computing topics were covered, as well as a number of different teaching approaches, although most studies tended to be fairly programming-heavy. The settings reported in the papers were mainly summer camps involving or led by a university. This finding suggests that research of non-formal settings may not be representative of the entire non-formal computing landscape. It is likely that in some countries, hundreds of thousands of children regularly take part in after-school programs, weekend clubs or a regular sessions at a youth group with computing activities but the extent of such non-formal activity is an open question [60]. In addition, the majority of papers only measured short-term impact of these interventions. More research in regular non-formal settings over longer periods of time will be vital in the future to help us understand more about the affordances and outcomes of non-formal computing education.

Most studies used a quantitative approach to measure changes in cognitive and affective measures. Qualitative evidence such as interviews was frequently used to gain a deeper understanding of quantitative results, often with a subset of study participants. Across the studies there are several cases of deep qualitative research as a primary approach; this is particularly insightful in studies concerning regular settings where we see learners' affective and cognitive development over time. For example, a small number of longitudinal studies have considered the impact of specific interventions on educational choices, with qualitative methods used to understand how the intervention influenced the learners' educational pathways.

5.3 What impact does non-formal computing education have on learners?

In line with previous research in computing education [26, 101], most non-formal computing interventions have a positive short-term impact on the measures they target. This does not mean that all interventions are equal or that the same interventions work equally for different demographic groups. Several studies [19, 31, 93] report different affective outcomes for different demographic groups within the same intervention. Other studies specifically design programmes to be equitable [68, 76, 80] and have success in achieving the same outcomes for females and males. Non-formal computing programmes can have a refining effect on interest and intent, strengthening outcomes for some learners while weakening them for others [59, 69]. It is important to look beyond averages as we would not expect all learners in most interventions to continue to a career in computer science [58].

Negative stereotypes of computing professions may have a negative impact on attitudes and, while efforts to change perceptions have been effective [78, 89, 98], there is some evidence that this is becoming less of an issue [72, 86] with the focus shifting to building a positive understanding of computing. There has been success with developing awareness of what is involved in computing as a subject and as a profession [21, 44]. The need to increase the value and relevance of computing to particular demographics is also recognised [17, 21, 28, 75].

Beyond quantitative changes in outcomes over the course of interventions, the studies in our review also have much to offer in terms of understanding the causes of these changes in outcomes. Qualitative analysis offers insights into the emotional journeys that learners take, the events that shape understanding and connection, and the ways that cognitive and affective changes are linked. For example, we see that some learners become poor collaborators when working in pairs [62], and others become highly motivated to learn new skills through the opportunity to solve local problems [63].

5.4 Affordances of non-formal computing

Non-formal computing is complementary to formal computing education and both offer benefits to learners. The studies in this review have demonstrated a number of affordances offered by non-formal computing:

- **Access and awareness.** Non-formal computing exposes young people to computing topics to which they would not otherwise have access. In parts of the world where computing is not yet mandatory in formal curricula, this could be their first or only exposure to computing [4]. Non-formal computing can also provide access to forward-thinking specialist topics [10, 111] and enable young people to gain awareness [44, 59] of computing education and careers beyond stereotypes and preconceptions.
- **Cultural relevance and equity.** Non-formal computing programmes provide opportunities for young people with common backgrounds to explore what computing means to them [21, 75, 102]. Programmes can be designed specifically to address prior lack of opportunity [32].
- **Practice and personalisation.** Non-formal computing can allow learners to practice and develop their skills over time [55, 99] and incorporate their own interests and values [28, 80, 87] to a greater extent than can be accommodated within the time and curricula constraints of formal education. This is particularly important for learners who may not otherwise have access to hardware or internet outside of school, or who do not see themselves represented in computing.
- **Fun and engagement.** It is clear that the organisers of non-formal computing programmes respect that young people are using their leisure time to participate. Non-formal settings offer the opportunity for mentors and role models to pass on their passion for computing and for young people to experience the personal rewards of creating with technology [20, 36, 63].
- **Community and Identity.** Non-formal settings can connect young people with a shared interest and provide support to develop a sense of belonging [113] and computing identity [22]. Learners can gain access to peers [58], mentors and role models [18], which can help to broaden perspectives of who can be a computer scientist beyond narrow stereotypes.
- **Immediate impact.** Non-formal computing is not just about future potential, it is also about giving young people the skills and opportunities to start making a difference immediately. Non-formal computing can give young people the opportunity to make and share projects and get the experience of launching their creations into the world [68]. There are examples of young people making apps to support their local communities [81] and non-formal computing settings being the site of intercultural collaboration [4].

6 CONCLUSIONS AND FURTHER WORK

The contribution of this paper is to provide a landscape description of recent pre-tertiary non-formal computing education research, including detailing the focus of studies and their outcomes.

This synthesis of the 88 studies provides baseline data for other researchers and ourselves to build upon in investigating computing education both in non-formal and formal settings.

For example, there is evidence that including open tasks is effective for learning and engagement [34, 62, 77, 80, 87], and that active teaching and scaffolding of problem-solving and debugging skills is effective and can lead to independence [48, 65, 107]. As well as valuing open tasks where they can bring their own interests, learners also value the opportunity to produce projects which are culturally relevant [4] or that provide social benefit [28]. Learners value carefully planned, supported but authentic opportunities to develop their computing skills and produce something relevant and meaningful to them. Furthermore, learners can be engaged though participating in the whole software development lifecycle, from discussions with stakeholders through to playtesting and deployment [64]. These findings may be useful for formal education researchers and non-formal researchers to investigate across a broader range of learners or longitudinally.

Further, our review shows a nuanced picture with a indication that there is a need to carefully design programmes to achieve targeted outcomes for specific learners in non-formal setting. Technologies and curricula should be chosen to meet the goals of the intervention and the demographics of the learners; for example, experienced learners with well-established interests have different needs to beginners who may have been volunteered for a programme by their parents [104]. Thought should be given to ensuring that programme and instructional design decisions are made with equity in mind [28, 62, 68].

For future work furthering a non-formal computing education research agenda, based on the evidence in this review, we make the following suggestions:

(1) While there is some improvement in reporting of the characteristics of samples and measures since previous reviews [71], future research would benefit from a more consistent and transparent approach to designing, collecting and reporting these data to enable greater replication of methods and interpretation of results, following [23].
(2) Measuring the impact of both specific interventions and more regular non-formal computing education opportunities is of great importance, as they may attract different types of participants, afford different types of learning experiences and, consequently, have different short-term and long-term impacts. Understanding these differences will help to guide future practice and improve our understanding of causality.
(3) There does appear to be evidence of different outcomes for learners from different backgrounds for some measures, so

disaggregation of data and detailed qualitative analysis is valuable. The path of individuals can be very different from the average path even within specific targeted groups, so future research can investigate the key factors that can lead to significant changes in outcomes.

(4) Finally, more research is required from different contexts around the world, especially building on those studies with young people in difficult circumstances e.g. [4, 108], to broaden the focus of the literature and understand how to support a wider range of learners to become digital creators and innovators.

Over the period of our review, there has been a general increase in evidence-based studies in non-formal computing each year. Continuing research in this area is necessary to broaden and deepen our knowledge concerning young people's development in computing, allowing learners from all backgrounds the best chance to gain the skills, motivation and social support that they need to use computing in their own educational journeys and to contribute to wider society.

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