# They Can't Find Us: The Search for Informal CS Education

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## ABSTRACT
In this study we found that search terms that would likely be used by parents to find out-of-school computer science (CS) learning opportunities for their children yielded remarkably unproductive results. This is important to the field of CS education because, to date, there is no empirical evidence that demonstrates how a lack of CS vocabulary is a barrier to accessing informal CS learning opportunities. This study focuses on the experience of parents who do not have the privilege of education and technical experience when searching for learning opportunities for their children. The findings presented will demonstrate that issues of access to CS education go beyond technical means, and include ability to conduct suitable searches and identify appropriate computational learning tools. Out-of-school learning is an important factor in who is motivated and prepared to study computer science in college. It is likely that without early access to informal CS learning, fewer students are motivated to explore CS in formal classrooms.

## Categories and Subject Descriptors:
K.3.2 Computer and Information Science Education.

## General Terms
Human Factors

## Keywords
Search, Informal learning, Online education

## 1. INTRODUCTION
The great number of free software and classes that are offered online for CS learning suggest that young people with technical means should be able to access tools for learning computer science (CS) at anytime. Informal learning tools are important in increasing motivation, community and belonging around a given topic [12]. Experience with informal learning in CS - often introduced by parents - is associated with those who choose to pursue computer science as a career [14; 15; 20]. Research suggests that parents are choosing many of the informal learning experiences for their children [6] and parents heavily influence the establishment of an ecology of technology learning [2].


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We sought to understand how a parent with little experience in computing, technology or education would help facilitate the informal learning experience of a child who has an interest in computing. This study looked at common Internet search term low-income parents would likely use for accessing informal CS learning opportunities in different geographic setting across the United States. Each term was used in the Google [8] search engine to compare access to information about online and offline informal learning opportunities including cost, accessibility, and location to determine if informal CS learning opportunities are accessible to parents in the United States (US). We anticipated that the results from the search would not be as productive. However, the complete absence of the rich and free tools for informal CS Learning that are frequently presented at SIGCSE was surprising and troubling.

## 2. BACKGROUND
Recently, there has been an explosion of educational courses offered online. Khan Academy launched a set of CS lessons [9], Coursera recently announced partnership to offer a range of courses including computer science courses and Udacity.com, offers a number of university level CS courses [7]. Virtual instruction is not the only type of online resource for CS learning. Sandbox computing activities, educational games, and the broad expanse of news, blogs and other media provide access to online play and discovery that is an important part in shaping learners for the 21st century. There are many free informal learning tools online that provide resources for learning content and content creation with computing. For example, one can download free drag and drop programming tools, such as Alice [5] and Scratch [13], which encourage sandbox play with computation.

While the above learning resources are frequently free, some question if these resources increase educational inequalities [17; 18]. It is suggested that unequal awareness of online informal learning, coupled with the way they are marketed, cultural values of audiences, and access makes these resources more available to the well-educated and the wealthy, which broadens the gap between the rich and poor in terms of education and income.

Issues of inequality in technology access can be addressed through research on access and use, and design of systems that specifically speak to marginalize communities. In other domains, such as health, targeting parents as users of online resources has proven to be effective in improving information delivery among marginalized communities. Research with mothers has begun to explore how their use of online resources for health information may lead to positive outcomes such as seeking appropriate health care [21]. Beyond health applications, access to online resources has been shown to improve general parenting skills. Na and Chia [16] found that access to online resources increased parents' confidence in their parenting skills, the amount of time they spent with their children, and perceived level of knowledge of their children's development.

To date there has been little research to understand how parents access information about informal learning opportunities. We see a need to address accessing online learning because, while some audiences are able to navigate and critically evaluate online resources, the groups that may be in the greatest need, low-income and low-educational families, have not been addressed. The field of CS education may have particular issues in that the field itself cannot agree on what is "computer science" and what is not. The study presented in this paper is a first step in understanding how a lack of common vocabulary around CS education may be impacting parents' (particularly low-income parents) access to CS education tools.

# 3. DATA COLLECTION METHODS

Internet queries were conducted to find informal CS learning opportunities. We selected three main search terms: *kids computer camp, kids computer classes*, and *kids computer learning*, based upon popularity in Google Analytics. These three terms were paired with the names of twelve cities from four different US regions. These cities were also chosen to represent different populations, including large cities, mid-sized cities, and small cities. To better understand how computing as a subject compared with other discipline specific searches we also conducted searches for *kids math learning*, *kids physics learning and kids animal learning* (seeking natural sciences learning resources)

## 3.1 Selection of Search Engine & Terms

We used two methods in the selection of search terms. First we looked at an analytical tool provided by Google to find the most popular terms associated with computers, learning, and children. Second, we validated these terms in a study with a search task given to parents in a financially depressed neighborhood.

### *3.1.1 Google Search Terms Selection*

Google search was selected as the search engine of choice due to its popularity in the US across regions and socio-economic status [11]. First, we brainstormed a list of possible search terms for finding informal CS learning opportunities for children. This list included:

- Topic search terms such as, *computation*, *computer*, *computer science*, *computing*, *programming*
- Environment search terms, such as *after school*, *camp*, *classes*, *education*, *informal*, *learning, out of school*, *learning*
- Audience search terms, such as *children*, *K-12*, *kids*, *middle school*, *teens*

We then used *Google Insights for Search [1]* to determine the most popular terms among this list. For example, we found that *kids* was used twice as frequently as *children* in searches. We included the term *learning* to be a catch all for other types of informal learning. We recognized that some search terms that were less popular (such as computer science or informal learning), might produce more accurate results for finding informal computer science learning opportunities. However, we determined that it would be more appropriate for this study to select terms that were more popular and more likely to be chosen by parents who are not in a technology field or involved in educational research. We selected our search terms, not to compare terms, but to get the best representation of what we suspected, and *Google Insights for Search* indicated, as terms parents would use in searching for informal computer science learning opportunities.

To compare with other science, technology, engineering and mathematics (STEM) disciplines we conducted searches using the terms *kids learning* paired with *physics*, *math* and *animal*. We chose the terms *math* and *physics* to find results for similar disciplines to CS. We chose the term *animal* to help us understand searches in other disciples that might occur when parents seek learning opportunities based upon their child's interest rather than seeking learning for a specific discipline. We relate parents searching for learning around a child's interest in animals to a parent seeking learning around a child's interest in computing. They may not know the academic name for the STEM fields related to those interests, such as computer science or biology, but they see an opportunity for leveraging that interest into learning.

Two researchers conducted the searches between March and October 2012. All data for each search was collected on one day to limit variations for the search terms. Seasonal variance may have affected search results and is a limitation of the study. For each search, the researchers emptied their cache and cleared their browser history. Based upon prior research that showed 94% of users click only on a first page result, and less than 6% click to the second page we limited our search to the first twenty results as they appeared on the first two pages of default Google results [4].

### *3.1.2 Parents' Search Terms Selection*

Two researchers recruited parents or legal guardians of school age children at a back to school event in a financially depressed neighborhood in Atlanta. Researchers held an information booth at the event providing information about the educational resources available for teens at Georgia Institute of Technology and at the same time asked parents if they were interested in participating in our study. Those who were interested in participating were then asked to search for educational resources for their children on a laptop. Sixteen participants were recruited, however one of them did not complete the study. Out of the sixteen participants, 15 were female while one was male and all identified as African-American. While we did not ask participants age, the range included young mothers in their early 20's to grandmothers in their 50's. Participants were given T-shirts and water bottles at the completion of their participation.

Parents were given a laptop with an open Google Chrome browser and asked to show how they would look for an educational tool or an online resource, if their child expressed interest in computing, via any website or search engine of their choosing. The participants were asked to continue their search until they found a source they identified as related and useful, and recorded their screen as well as their search history and the keywords they used. To avoid affecting the search result, the search history was cleared after each use. Parents were asked about their experience, how they chose which link to open in the search results, and how they identified their final choice as a useful resource for their child.

The analysis of search terms provided some insight into preferences of parents within this demographic. Of the 16 participants only one explicitly expressed preference for use of Bing search engine rather than Google's. Amongst the participants were one illiterate parent, one that did not understand how to go about the task, and one deaf parent. Of all of the parents, only one found a site deemed relevant according to the specifications used for the searches in this overall study (see section 4.1). The site was *Simple Code Works* (simplecodeworks.com). Another important observation is that none of the parents went past the second page of results justifying our resolution to only evaluate the first two pages we received.

## 3.2 Selection of Cities

Our objective was to consider residents across a broad spectrum of the US both by the size of the city they live in and the region they live in. Given these objectives we selected the four largest cities in the US, four mid-size cities, (non-suburban areas with a population between 125,000 and 115,000) and four small cities, (non-suburban areas with a population between 15,000 and 5,000). Cities were also chosen to represent four regions of the US, the Northeast, Midwest, South and West.

**Table 1. Cities Paired with Search Terms**

| Region | Large Cities /Population (in millions) | Mid Cities /Population | Small Cities /Population |
|---|---|---|---|
| Northeast | *New York, NY* /8.2449 | *Allen Town, PA* /119,141 | *Olean, NY* /14,363 |
| Midwest | *Chicago, IL* /2.7071 | *Springfield, IL* /117,076 | *Thief River Falls, MN* /8,660 |
| South | *Houston, TX* /2.1451* | *Gainesville, FL* 125326 | *Crowley, LA* 13,309 |
| West | *Los Angeles, CA* /3.8197 | *Visalia, CA* 126,432 | *Susanville, CA* 17,685 |
| Other | No additional text used with search terms | *Online* used with search terms | |

# 4. ANALYSIS AND RESULTS

After conducting the 42 computer related searches (the 3 search terms independently, then each paired with the term *online*, then each paired with the 12 cities) we had 840 results and classified the results in a number of ways to better understand our data and the implications for access to informal learning. The first step was to combine the duplicate results within each set of search results and then to determine which terms were relevant to CS learning.

## 4.1 Relevance to Children's CS Learning

Search results were considered relevant to children's CS learning if they meet the following criteria:

- *Relevant to computer science* - We only included results that had relevance to learning computer science. In many cases this was easy to determine because the search result was related to something unrelated to computers all together, such as horseback riding, or obviously related to computer science, such as a game programming summer camp. In other cases this was more difficult. For example, the educational goal of some programs was to teach Microsoft Word. We limited the criteria to searches that provide more than teaching Microsoft Office suite, such as those that focused on software applications were more likely to serve as an entry point to more advanced computing skills, such a Photoshop or Illustrator. When in doubt we included the entry as relevant.

- *Relevant to children* – We only included results that had relevance to children, meaning those under the age of 18. In cases such as community colleges, where a child could possibly attend but it was not a welcoming environment for children without special accommodations we did not include the results. In a few cases, it was unclear if a course that was designed for adults was also appropriate for children (For example a library offered classes on HTML for 17 years of age an up). In these cases we included the results as relevant to children.

## 4.2 Duplicate result

A number of relevant results came up multiple times for each search that was conducted... After eliminating the duplicate results from each set of search results, (but not across searches) we had 191 out of 840 sites that were relevant to children's CS learning.

## 4.3 Type of Site / Service

We coded each site by the type of site it was or the service it provided or sold. There were 8 codes that we identified ranging from intensive summer camps to links to books for self-directed learning. Table 2 outlines the criteria used to assign categories.

**Table 2. Codes for Types of Educational Services Offered**

| Code | Name | Description |
|---|---|---|
| A | Camp | Web sites for location-based camps only with informal CS learning. |
| B | Afterschool program | Web sites for location-based afterschool programs only that offered informal CS learning. |
| C | Camp / afterschool | Web sites for location-based programs like camps and afterschool programs. |
| D | Higher Education | Web sites for colleges & technical schools that offer classes for children. |
| E | Online activities | Web sites that offered online tutorials, games or activities to be downloaded in print form or interacted with online. |
| F | Online classes / learning | Web sites that offer CS online courses, distance learning classes for children, or home schooling curriculum |
| G | Directory | Web sites that list children's learning resources for CS |
| H | News, videos, or social networks | Web sites that feature news articles, blogs, videos or Facebook profiles that suggest other resources for encouraging interest in CS. |

## 4.4 Cost

It was difficult to measure cost. Summer camps and after school programs were not comparable in terms of intensity or time. To address this we found the lowest cost option for any camp, after school program, or course and then determine what the daily rate would be. In some cases there were only overnight camp options and in other cases the course only covered two or three hours. We did not reduce this down to an hourly rate because the amount of material coved in a three-hour course may be more equal to the amount of instruction offered at an overnight camp than the hourly rate would reflect. However, we recognize this lack of equable ways to compare cost is a limitation of the study and try to address this in reporting our results.

## 4.5 Camps and Afterschool Programs

The category of camps resulted in the most unique sites. The camp results were dominated by a handful of for-profit nationally run summer camps including Digital Media Academy (appeared for 17 different search terms), Emagination Computer Camps (appeared for 5 different search terms), ID Tech Camp (appeared for 15 different search terms) and Institute for Mathematics and Computer Science (IMACS) (appeared for 5 different search terms). The average lowest daily cost of most of these camps is between $100 - $200. An exception is IMACS, which accredits other learning centers who have a greater range of prices including some lower cost options.

In addition to these national chains there were a handful of camps and after school programs that catered to local populations at much lower cost, such as Camp Katy in Houston, TX, the College of the Sequaoias in Visalia, CA, and Planet Bravo in Los Angeles, CA. These lower cost camps and after school programs were more available in the larger cities and none were found for the four smaller cities (see Table 3).

**Table 3. Unique Search Results by Category & City Size**

| | Big 4 cities | Mid 4 cities | Small 4 cities | Online / no term | Total |
|---|---|---|---|---|---|
| A – Camp | 29 | 13 | 0 | 20 | 62 |
| B – After-school | 3 | 0 | 0 | 2 | 5 |
| C – Camp / afterschool | 6 | 0 | 0 | 5 | 11 |
| D - HigherEd | 3 | 3 | 0 | 1 | 7 |
| E - Online activities | 1 | 0 | 0 | 5 | 6 |
| F – Online classes | 0 | 0 | 0 | 7 | 7 |
| G –Directory | 23 | 14 | 1 | 10 | 48 |
| H – Article/ blog | 29 | 4 | 1 | 11 | 45 |
| Total | 94 | 34 | 2 | 61 | 191 |

## 4.6 Articles, blogs and videos
Of the 45 search results that were article, blogs, or videos, most were lists of summer camps or classes one could enroll their child in to learn more about computer science. Several were news articles about a local resource for computer science education; a few were articles, blogs or videos that emphasized the importance of computer learning.

## 4.7 Online Activities and Courses
To better understand searches for informal learning resources for online or at home we paired the three terms (*kids computer camp, kids computer classes*, and *kids computer learning*) with the word *online* or with no additional term. Among these searches there were seven unique resources for remote CS learning. Three were online or distance learning courses. Four were tutorials or lessons to purchase, print out or view for use at home including: *Kids, Computers and Learning*, *Computer Connections: Inside & Out*, *Kids-Online Click-N-Learn*, *Homeschool Programming Inc.*

In the review of the first page of all of the 191 search result we looked for online educational computer programming tools[1]. There was only one case where one of these tools was mentioned. In this case, the program *Scratch* appeared on the first page of a site in response to a 2011 question posted on a site called Quora.com asking if there are good classes in Los Angeles for kids to learn programming.

[1] CS Learning tools we looked for include Agent Sheets, Alice, BlueJ, CodingBat, E-Slate, Greenfoot, Hackety Hack, JES, Kodu, Logo, Mama, Phrogram, Problets, and Scratch.

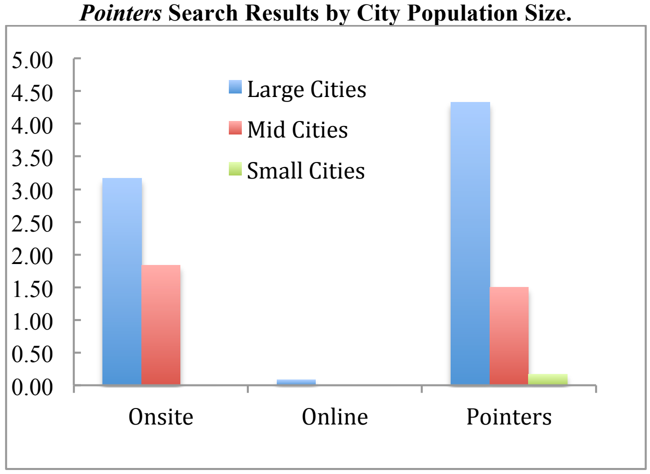
## 4.8 Higher Education & Outreach
Among the search terms there were seven search results for colleges, technical schools or adult community programs that offer classes appropriate for children. These classes were free or lower in price than the camps, around $50 per day. Most of these classes targeted students in junior high through high school.

## 4.9 Location
The most successful searches were those with no location paired with the search terms (*kids computer camp, kids computer classes*, and *kids computer learning)* or with *online* paired with the search terms. These averaged 10.2 unique search results for each of the three terms. In the dispersion of these terms camps were among the leading search results (see Table 3). This may be due to including camp in our search. However, these camps appeared on all searches.

To understand the variations in between the different sized cities and cities in different regions we conducted one-way analysis of variance (ANOVA) for the types of educational services offered (Table 2) among the search results produced for each set of cities by size and by region. To better analyze these findings, we collapsed related types of educational resources into three groups. These three groups consisted of:
1. *Onsite* resources: A. Camps, B. Afterschool programs, C. Camp and afterschool, & D. Higher education classes.
2. *Online* tools: E. Activities, tutorials and games, F. online classes and distance learning
3. *Pointers* to CS learning: G. Directories, H. Articles & blogs

### *4.9.1 City Size*
The one-way between subjects ANOVA was conducted to compare the types of educational services (*Onsite, Online, and Pointer*) among the search results produced for cities with Large, Mid, and Small population sizes (see Figure 1).

**Figure 1. Mean Number of Related *Onsite*, *Online*, and *Pointers* Search Results by City Population Size.**




There was a significant effect of population size on relevant *Onsite* search results at the p<.001 level for the three conditions [$F(2, 33) = 37.66$, $p = 0.000$] (Table 4). Post hoc comparisons using the Tukey HSD test indicated that the mean score for the larger population cities ($M = 3.17$, $SD = 1.34$) was significantly different than the midrange population cities ($M = 1.83$, $SD = 0.79$). Similarly, the small population cities ($M = 0$, $SD = 0$) which had no relevant results, was significantly different than both the large and mid sized cities.

**Table 4. ANOVA of *Onsite* Search Results by City Size.**

| | SS | df | MS | F | p |
|---|---|---|---|---|---|
| Between: | 60.677 | 2 | 30.339 | 37.666 | <0.001 |
| Within: | 26.581 | 33 | 0.805 | | |
| Total: | 87.258 | 35 | | | |

As illustrated in Figure 1, there was only one *online* resources listed. These were insufficient result to have significant differences.

The *Pointer* results were the most frequent occurrences for larger and small city searches. Again we found there was a significant effect of population size on relevant *Pointer* resources search results at the $p<.001$ level for the three conditions [$F(2, 33) = 24.496$, $p = 0.000$]. (Table 5)

**Table 5. ANOVA of *Pointer* Search Results by City Size.**

| | SS | df | MS | F | p |
|---|---|---|---|---|---|
| Between: | 108.633 | 2 | 54.317 | 24.496 | <0.001 |
| Within: | 73.175 | 33 | 2.217 | | |
| Total: | 181.808 | 35 | | | |

Post hoc comparisons using the Tukey HSD test indicated that the mean score for the large cities *Pointer* results ($M = 4.333$ $SD = 2.100$) was significantly different than the searches in mid ($M = 1.500$, $SD = 1.446$) and small cities ($M = 0.167$, $SD = 0.389$). However there was no significant difference between the mid sized and small cities.

### *4.9.2 Regional Differences*

A one-way between subjects ANOVA was conducted to compare the effect of region on the number of relevant Onsite, Online and Pointer search results. Onsite and Pointer results for US cities in the Northeast, Midwest, South and in West showed no statistical differences. The Online results did demonstrate statistical difference between regions. However, because there was only one result among the four regions, this significance is not reliable.

## 4.10 Non-CS Terms

The first two pages from Google engine searches for the three non-CS terms, *kids math learning*, *kids physics learning* and *kids animal learning* resulted in 48 unique results out of the 60 total results. Thirty-one of these results were in the form of online activities, such as games or interactive learning tools. There were also a number searches results that had opportunities for children to take classes at higher education institutions (10 unique search results) or through online classes or distance learning (5 unique search results). This high number of unique resources (an average of 16 per term) can be contrasted to our results from the *kids computer learning* and *kids computer learning online* search terms, which resulted in only 7 unique results (an average of 3.5 per term). Another striking difference is that 46 of these non-CS terms results linked to free learning resources in contrast to 2 free resources provided by the *kids computer learning (online)* searches.

These results may indicate that many more learning resources exist for math, physics and biology. However, the lack of the many pointer sites and irrelevant search results that we found with the CS terms, indicates that the problem, at least in part, is related to the search terms used and how searchers are parsed by the Google search engine.

# DISCUSSION

Not surprisingly the larger, more densely populated cities had more resources for informal CS learning and the type of resources were more varied. Some of this may be a flaw in the search method because residents in mid size or smaller cities may overcome the lack of relevant search results by pairing with better regional terms, such as the county or a near by city. We found no evidence of regional differences in the search results, suggesting this is a national pattern. Across all of the searches the number of unique search results was less than we expected. The amount of repetition, the number of directory sites, articles and blog post (which tended to be less useful as pointers to learning resources than our Google searches) meant that most searches resulted in less than 2 useful results.

While we anticipated that the search results would not be very productive. But the complete absence of the most powerful and free informal learning tools shocked us. The absences of tools such as *Scratch*, *Alice*, or *Greenfoot* in the 840 searches result suggest that if one has little experience with these learning tools or with CS it is unlikely one could find robust CS learning tools.

We were again surprised that free classes and tutorials such as Khan Academy and Udacity never appeared in our searches. There were a few fee based distance-learning programs that target home school audiences as formal classroom equivalents for CS learning. But the fees and formalized structure of these would not appeal to most informal learners. The high percentage of camps that appeared among the small number of useful results was also of concern. The camps were generally over $100 a day, with additional cost of funding students' lunch and aftercare in many cases. For students coming from lower income households this may be too expensive for them to participate in.

The results from our non-CS searches produced a much greater number of unique results that were leading to more free online tools and resources than the computing searches. This could be because there are more relevant learning opportunities to be found for math, physics, and biology than for CS. Yet we know there are a number of useful informal learning tools that are free and easy to access once found and that most of the MOOCs have CS offerings. The findings suggest that in general, informal CS, programing or computational literacy is not accessible to parents with little technical background or financial resources in the same way that other STEM fields are.

# 5. CONCLUSION

Looking through the proceedings of SIGCSE we see a rich array of tools to teach computer science. Some are free tools or programs that one can access online [5; 10; 13]. Others are community outreach programs that target lower income students [13]. And others are tool kits for play [3]. These computational construction kits and others have been available for some time [19]. And the recent influx of free classes and courses would seem to be new opportunities to engage with CS learning at home. Yet none of these opportunities appeared in our search engine results and only one reference among the 840 searches suggested one of them.

Without a background in CS or education one might not be aware that these types of CS education tools exist. This is a lost opportunity for those that cannot afford expensive camps or do not live near to one of the few less expensive informal learning opportunities. It also demonstrated the pattern of open educational resources increasing educational inequalities rather than closing the metaphorical *digital divide* [18].

The solution to these inequity issues lie in the hands of CS educators, researchers, and educational tool developers. Simple steps may make a difference, such as improving search engine optimization by creating metadata that includes more common terms such *kids*, *computers*, and *classes* rather than terms like *educational programming tools* (which turned up a rich list of free CS learning tools). Another opportunity could be found in partnering with camps that appeared repetitively in (and at the top of) our searches. Many of these camps use tools like Scratch or Alice. By encouraging the camps to have links to these free tools on their home page, it could provide new avenues for informal learning among those who cannot afford or who are not yet sure if they want to commit $500 to $1,000 for a camp experience. Finally, these issues are additional motivation for the field of CS education to develop a shared vocabulary, and a vocabulary that parents and non-technical members of the public can use to access CS education.

This study provides baseline data and motivation for future work in CS education that directly address issues of access and equity. This is empirical evidence that our efforts to create free CS learning tools are not reaching marginalized groups who are so often left out of CS education. For future work, we seek to apply our findings in better understanding the role that parents play in selecting and encouraging their children's CS learning experiences. From these further studies we hope to develop community resources of educational technology tools that reach underrepresented and marginalized groups.

For example, we are developing a community based social network for parents in a low-income neighborhood in Atlanta. Using a strong narrative blog structure we hope that parents will communicate about educational issues and interest of their children. Research staff and community members will then create links to informal technology and CS learning opportunities that might be good fits for the families. We anticipate this work will serve as a model for other neighborhoods and seed a database of keywords that are more intuitive for parents and less intuitive for educators and researchers.

## 6. REFERENCES


[1] 2012. Google Insights for Search Google.

[2] Barron, B., 2004. Learning Ecologies for Technologieecal Fluency: Gender and Experience Differences *Journal of Educational Computing Research 31*, 1, 1-36.

[3] Buechley, L., Eisenberg, M., Catchen, J., and Crockett, A., 2008. The LilyPad Arduino: using computational textiles to investigate engagement, aesthetics, and diversity in computer science education. In *SIGCHI Conference on Human Factors in Computing Systems* ACM, Florence, Italy, 423-432.

[4] Chitika, 2010. The Value of Google Results Positioning.

[5] Cooper, S., Dann, W., and Pausch, R., 2000. Alice: a 3-D tool for introductory programming concepts. In *Consortium for Computing Sciences in Colleges*, 107-116.

[6] Crowley, K. and Jacobs, M., 2002. Building islands of expertise in everyday family activity. In *Learning conversations in museums* Citeseer 333-356.

[7] Gee, S., 2012. Sebastian Thrun Resigns from Stanford to Launch Udacity.

[8] Ghemawat, S., Gobioff, H., and Leung, S.T., 2003. The Google file system ACM, 29-43.

[9] Khan Acadamy, 2013. KhanAcademy 226,116,151 lessons delivered. In *Learn almost anything for free*.

[10] Kölling, M., Utting, I., Mccall, D., Brown, N., Stevens, P., and Berry, M., 2011. Greenfoot Programming Education Tools Group, Computing Education Research Group at the School of Computing, University of Kent, Canterbury, UK.

[11] Langville, A.N. and Meyer, C.D., 2006. *Google page rank and beyond*. Princeton Univ Pr.

[12] Lave, J. and Wenger, E., 1991. *Situated learning: Legitimate peripheral participation*. Cambridge Univ Pr.

[13] Maloney, J.H., Peppler, K., Kafai, Y., Resnick, M., and Rusk, N., 2008. Programming by choice: urban youth learning programming with scratch. *SIGCSE Bull. 40*, 1, 367-371.

[14] Margolis, J., 2008. *Stuck in the shallow end: Education, race, and computing*. The MIT Press, Cambridge, MA

[15] Margolis, J. and Fisher, A., 2002. *Unlocking the clubhouse: Women in computing*. MIT Press, Cambridge, MA

[16] Na, J.C. and Chia, S.W., 2008. Impact of online resources on informal learners: Parents' perception of their parenting skills. *Computers & Education 51*, 1, 173-186.

[17] Reardon, S.F., 2011. The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. *Whither opportunity*, 91-116.

[18] Reich, J., 2011. Open Eductional Resources Expand Educational Inequalities. In *Educational Technology Debate*.

[19] Resnick, M., Bruckman, A., and Martin, F., 1996. Pianos not stereos: Creating computational construction kits. *interactions 3*, 5, 40-50.

[20] Schulte, C. and Knobelsdorf, M., 2007. Attitudes towards computer science-computing experiences as a starting point and barrier to computer science. In *Third international workshop on Computing education research* ACM, New York, NY, USA, Atlanta, Georgia, USA.

[21] Ybarra, M.L. and Suman, M., 2006. Help seeking behavior & the Internet: a national survey. *International Journal of Medical Informatics 75*, 1, 29-41.