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Predictors of creative computing participation and profiles of experience in two Silicon Valley middle schools

Brigid Barron *, Sarah E. Walter, Caitlin Kennedy Martin, Colin Schatz

Stanford University School of Education, United States

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ABSTRACT

Examination of the "digital divide" has increasingly gone beyond the study of differences in physical access to computers to focus on individuals' use of technological tools for empowered and generative uses. In this research study, we investigated the relationship between access to tools and experience with creative production activities. Our participants included 160 8th grade learners from two public middle schools. The local communities represented by the two schools differed in parent education levels, proportion of recent immigrants, and average family income. Findings indicated substantial variability in students' history of creative production experiences within both communities. Three sets of analyses were completed. First, the two school populations were compared with respect to average levels of student creative production experience, access to tools at home, use of learning resources, frequency of technology use, and access to computing outside of their home. Second, correlates of variability in individuals' breadth of experience with creative production activities were explored across both schools through a regression analysis. The resulting model indicated that students' experience was best predicted by the number of technology tools available at home, number of learning resources used, frequency of computer use at home, and non-home access network size. In a third analysis, profiles of experience were created based on *both* breadth and depth of experience; the resulting four groups of students were compared. More experienced students utilized a broader range of learning resources, had access to more tools at home, taught a wider range of people, and were more confident in their computing skills. The groups did not differ in their self-reports of interest in learning more about technology.

1. Introduction

Design-oriented activities are believed to play a special role in learning to adapt computing tools for one's own purposes (Ber, 2006; Kafai, 1995; Papert, 1980). Projects that involve the production of a personally meaningful artifact can offer the motivation that drives persistence and the setting of learning goals, as designers work to create what they imagine (Barron, 2006). Within such projects learners frequently encounter implementation challenges that provide opportunities to develop the knowledge, skills, and intellectual capabilities that underlie what has been called technological fluency (National Research Council, 1999). Web design, game making, robotics, programming, animation, and movie making are all examples of projects that are likely to be fluency-building and that youth find compelling (Barron, 2006; Resnick, Rusk, & Cooke, 1998; Walter, Forssell, Barron, & Martin, 2007).

It is not clear that opportunities for these types of creative production activities are equally distributed across more and less affluent communities, raising concern that the benefits of computing resources will accrue for those who are already most economically advantaged. Individual differences in computing experience are one manifestation of what has been called the digital divide (Hargittai, 2003). Initially the term "digital divide" was defined with respect to computer ownership or basic access to the Internet. More recent definitions have reflected a multidimensional construct capturing inequities in how people use computing tools and how skilled they are (DiMaggio, Hargittai, Celeste, & Shafer, 2004; Hargittai, 2008). Use and skill can vary as a function of income, age, ethnicity, gender, education level, or geographic location, as these variables frequently reflect differences in access to tools and learning resources (Barron, 2004; Hargittai & Hinnant, 2008; Warschauer, 2000).

* Corresponding author. Address: 485 Lasuen Mall, Stanford, CA 94305, United States. Tel.: +1 650 725 0194; fax: +1 650 725 7412.
E-mail address: Barronbj@stanford.edu (B. Barron).

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In this paper we report on a study designed to contribute data on the relationship between experience with creative production activities and access to tools and resources. Our research is guided by a learning ecology framework grounded in the assumption that learning takes place across the life spaces of home, school, and community (Barron, 2004) and that the proper unit of analysis is the individual learner and the multiple settings in which the learner spends time. The learning ecology framework draws on ecological perspectives from psychology as well as constructs developed from sociocultural and activity theory. Ecological perspectives emerged from a desire to better articulate the interdependencies between variables at the child and environment levels, and acknowledge the tight intertwining of person and context in producing developmental change (Bronfenbrenner, 1979; Cole, 1996; Lerner, 1991; Lewin, 1951; Rogoff, 2003). Sociocultural, activity, and situative learning theorists (Cole, 1996, 2000; Engeström, 1987; Greeno, 1989; Lave & Wenger, 1991; Pea, 1993; Rogoff, 2003; Vygotsky, 1978) foreground the role of tools that have been created by prior generations as critical mediators of cognitive and social practices such as language, writing, and other representational systems.

Ecological metaphors have recently been applied to other studies of technologically rich environments (Brown, 2000; Looi, 1999). For example, Nardi and O'Day (1999) introduced the idea of an information ecology. In their view, "an information ecology is a system of people, practices, technologies and values in a local environment. Like their biological counterparts, information ecologies are diverse, continually evolving, and complex." The current learning ecology definition shares with the definition of information ecologies the idea that both relational and material resources are important in any socio-technical ecology (Brown, 2000; Nardi & O'Day, 1999) and it implies a dynamic learning system open to multiple influences. In line with this perspective, it is key to understand learning as made possible by configurations of resources in the forms of social relationships, tools, informational resources, and activities. Consequently for this study we designed metrics and analyses that would provide information about an individual's access to computing tools and learning resources at home, in school, in the community or on the Internet. In addition to examining correlations between experience and access to resources, we investigated variables such as confidence, interest, and knowledge sharing, which are likely influenced by experience with creative production activities.

Below we summarize some of the empirical literature that documents correlations between a number of demographic variables and measures of use, access, and skill.

1.1. Demographics, access and use

Despite narrowing gaps in access to computing tools at home and at school as a function of demographic variables, there is growing concern that new information technologies may contribute to further inequalities along economic, cultural, or gender lines because of differential use, attitudes, or skill (DiMaggio et al., 2004; Hargittai, 2008). This concern is fueled by recent studies that suggest that differential use of computing tools is related to demographic variables, including gender and socioeconomic status (SES). In a socioeconomically and ethnically diverse college freshman sample, positive correlations between parent education levels and creative contributions were found and males were more likely to post original artwork online (Hargittai & Walejko, 2008). Similarly, analysis of the 2003 US census data showed that students whose parents have any graduate education or whose family income is $75,000 or greater are approximately twice as likely as their peers to use the Internet to complete school assignments and find information (DeBell & Chapman, 2006).

1.2. Mediators of individual differences in experience

Differences in types of technology use associated with demographic variables are mediated by access to learning opportunities, both those provided in formal settings such as schools or after-school clubs, and informally in peer networks or home settings. Both quantitative survey data and qualitative comparative studies have found that while students with low-SES use school computers more frequently than do their high-SES counterparts in math and English courses (which often use drills), high-SES students are the main users of technology in science courses where computers are often used for more sophisticated tasks, such as simulation and research (Becker, 2000; Margolis et al., 2008; Warschauer, 2000). Additionally, previous work has found that even when children have similar levels of home access to computers, those from higher socioeconomic backgrounds are more likely to experience educational gains from the resource than children from lower SES backgrounds (Livingstone & Helsper, 2007). Other comparative case studies have shown that lower SES schools had more problems keeping computers working and spent less money on professional development that would help teachers learn to incorporate technology with instruction in meaningful ways (Warschauer, 2000).

Studies of technology-related course offerings have shown differential rates of high level computing electives between low-SES and high-SES schools. While courses offering computer science or programming are offered in 10–14% of schools in the top three SES-based quartiles, these courses are taught in only 5% of the bottom SES-based quartile (Becker, Ravitz, & Wong, 1999). Goode, Estrella, and Margolis (2006) noted that in Los Angeles, the College Board certified Advanced Placement computer science course was disproportionately offered in schools serving more affluent districts. Even within groups that have high access to technology, experience with creative production activities is linked to use of learning resources such as courses in or out of school, reading material, or tutorials (Barron, 2004).

Family practices also influence interest and learning. Studies of middle class families have shown that the amount of parent–child coactivity around computing predicts a child's interest and engagement in computing (Simpkins, Davis-Kean, & Eccles, 2005). Similarly, a qualitative study of parent roles in learning in an affluent sample identified a variety of ways that parents nurtured creative production projects through collaboration, lending or buying learning resources such as books, by brokering opportunities such as summer camps, and by directly explaining concepts to their child (Barron, Martin, Takeuchi, & Fithian, 2009).

Finally, design experiments, a form of research that first develops innovative environments and then studies how learning occurs within them (Brown, 1992), provide evidence that divides can be bridged through intentional interventions. Projects that create opportunities for youth in community-based computing clubs or schools show that even when home access is low, resources in the forms of tools and mentors can lead to increased engagement in programming, music creation, graphic design, and other creative production activities (Barron, 2006; Barron, Martin, & Roberts, 2006; Peppler & Kafai, 2007; Resnick et al., 1998). Together, the studies reviewed in this section support the claim that although mean differences as a function of demographic groups are frequently observed, there is also variability within demographic groups that needs to be better understood.

1.3. Social networks and learning ecologies

Research done by Hank Becker suggests that technological divides along economic lines are worsened by ‘‘community effects”. He argues that because of residential segregation by SES, children living in low-SES families tend to live in neighborhoods where they are less likely than children living in more affluent communities to have access to a computer through a neighbor or friend (Becker, 2000). This line of reasoning can be extended to consider the importance of social learning networks (National Research Council & Institute of Medicine, 2000). Access to peers and adults who have experience, interest, and expertise is likely to be as important or more important than access to tools. Given the documented spread of technical knowledge in co-located communities, it is important to consider the nature of school or neighborhood communities in terms of how widely expertise is distributed. Peer groups at school are often the source of inspiration for the development of production-oriented hobbies such as web design, animation production, or robotics (Barron, 2006; Chandler-Olcott, & Mahar, 2003). The likelihood of finding a classmate with such interests will be related to the proportion of experienced peers in a school. At this point, we know of no studies that have provided data comparatively examining distributions of experience profiles with creative production activities across schools. While co-located communities are important to understand, from a learning ecology perspective it is important to consider learning opportunities as distributed across life settings (Barron, 2004, 2006). Accordingly, in this research we examined access to learning resources that may be found at home, school, in the community, or on the Internet.

2. Research questions and analytical approach

The above review makes a convincing case that demographic variables are a significant predictor of the use of computing technologies for particular kinds of activities. However, there is a need to know more about how the form and extent of participation in creative production activities varies among adolescents and what mediates differences within and across groups. It has been argued that there is currently ‘‘an imbalance between speculation and evidence” with respect to the implications of new technologies for communicative and expressive agency (Sefton-Green, 2006). In order to better design environments that support learning for all students, it would be helpful to understand how individual differences in experience relate to access to tools at home and to broader learning resources across the life spaces of home, school, neighborhood, and Internet community.

To address these gaps in the literature, the present study investigates patterns of experience with creative production activity in a diverse sample of 8th grade students residing in Silicon Valley region of Northern California and attending one of two schools whose populations differ in economic profile. Silicon Valley is considered a hub of technological innovation due to the high density of semiconductor and technology companies, engineers, venture capitalists, and entrepreneurs tied to research advances at local universities. Our measure of creative production experience asks students to report on their opportunity to engage in 16 types of design related activities (e.g. robotics, game design, movie making, and website creation). We calculate both their breadth of experience (the total number of activities) and their depth of experience (the number of activities they have repeatedly engaged in). We addressed three questions, and for each we used a unique analytic approach.

(1) *Do students differ in their prior creative production experiences or access to computing tools and learning resources as a function of the school they attend?* In this analysis we sought to understand if the populations attending our two schools differed in their average levels of experience or access to learning resources. Differences were expected because the socioeconomic profiles of the two schools varied with one school having a higher proportion of families qualifying for free or reduced price lunch and lower average parent education levels.

(2) *What factors predict 8th grade students' breadth of creative production experience?* Given the importance of design-oriented projects for building knowledge, confidence and interest, it is important to understand sources of variation in middle school students' breadth of experience. Based on prior literature we predicted that school, gender, access to learning resources, frequency of use, and tools at home might be related to breadth of experience. We did not have a refined theory about the relative importance of these variables and consequently used a stepwise regression model to address this question. This exploratory analytical approach allows us to identify the set of variables that accounts for the most variance in breadth of experience and to order the variables with respect to how much variance they explain.

(3) *How do students with different profiles of creative production experience vary in their access to resources and their confidence, interest, and knowledge sharing?* We complemented the variable-focused approach described above with a person-centered approach (Roeser, Eccles, & Sameroff, 2000). By considering both breadth and depth of experience we created four profiles of student experience: high breadth/high depth, high breadth/low depth, low breadth/high depth, and low breadth/low depth. We examined whether these four groups differ in their access to tools at home, learning resources, and access to parents who use computers in their jobs. We also examined whether the four groups differ in confidence, interest and knowledge sharing.

3. Methods

Sample. One hundred and sixty 8th grade students from two public middle schools in Silicon Valley, ‘‘Juniper” and ‘‘Maple”, participated. Forty-eight percent of the sample attended Juniper ($N = 77$) and 52% attended Maple ($N = 83$). Of the total sample, 79 were male and 81 were female. Juniper is located in a primarily upper middle class community. According to school data provided online by the California Department of Education (2003) for the year of the study, less than 5% of students were eligible for free or reduced lunch and less than 1% of students were classified as socioeconomically disadvantaged. The school was diverse with respect to student backgrounds: 42% White, 35% Asian/Pacific Islander, 7% Hispanic, 4% African–American and 12% of other backgrounds or who did not respond. Maple is located in an economically diverse district. At Maple, 52% of students were eligible for free or reduced price lunch, 60% were classified as socioeconomically disadvantaged, and many were bilingual or English-language learners. The student population was also diverse, with 67% Hispanic students, 24% White, 4% African–American, 4% Asian/Pacific Islander; less than 1% fell into any other group or did not answer.

3.1. Procedures

A pencil and paper survey, described below, took approximately 30 minutes to complete. It was administered during a regular class period by researchers while the classroom teacher remained in the room.

3.2. Instruments

Access, interest, and experience survey. Questions focused on five areas: (1) students' access to technology at home and school; (2) students' history of technology use across communicative, entertainment, learning and creative production activities; (3) students' use of formal and informal learning resources; (4) motivational aspects of learning about technology including interest, confidence, and valuing technology as a subject and potential career; (5) knowledge sharing about technology with others. This survey was adapted from one developed for use with high school students in previous research studies (Barron, 2004; Barron, Martin, & Roberts, 2002; Barron et al., 2006).

3.3. Measures

We did not have access to individual students' family income or parental education levels and thus were unable to link SES directly to experience with creative production activities. We instead have several measures of access and use of computing tools. These are described below.

Frequency of home use. Students indicated their frequency of computer use at home from the following options: never, less than once a week, about once a week, several times a week, and almost every day. We created a binary score to indicate whether they were a regular home user or an infrequent user. Regular home use was defined as a response of, "several times a week" or "almost every day". Across the entire sample ($N = 157$), 77.1% of the students are frequent users of technology at home.

Non-home access network. Using the same scale, students were asked how frequently they used technology in each of several out-of-home contexts. These included a friend's house, a relative's house, a community center, and classes in school. For each location we created a binary score to indicate whether they were a regular or infrequent user, with regular use defined as at least "several times a week." We then summed the binary scores for each location to create a total score reflecting the number of places where students regularly used a computer (non-home access network size). Across the sample ($N = 137$), the scores ranged from 0 to 5 ($M = 0.93$, SD = 0.99).

Number of technology tools at home. Using a checklist format, students were asked to indicate their access to specific tools at home: Internet access, a printer, a video camera, a digital camera, a handheld device such as a PDA, and a scanner. Using a multiple-choice format, students were also asked to indicate whether they had 0, 1, 2, or 3 or more computers at home. A tools at home measure was computed by summing the number of computers and the number of other tools indicated with a total possible score of 9. Across the sample ($N = 157$), the numbers ranged from 0 to 9 ($M = 5.59$, SD = 2.47).

Learning resources. Using a checklist format, students were asked to indicate the specific places (e.g., class in school, community center, after-school club), people (e.g., mother, father, friends) and distributed resources (e.g., books, online material) that helped them learn about computing. A total score was computed across places, people, and resources with a total possible score of 16. Scores across the sample ($N = 152$) ranged from 1 to 16 ($M = 5.84$, SD = 2.82).

Knowledge sharing. Students were asked to indicate whom they were teaching about computing from a list of relational categories: mother, father, brothers, sisters, grandparents, other relatives, teachers, and people they work with at school or in a job. A total score was computed, with a highest possible score of 10. Across the sample ($N = 148$), the scores ranged from 0 to 8 ($M = 2.04$, SD = 2.14).

Confidence scale. Confidence was measured by asking students to rate their agreement with three statements reflecting their subjective feelings of competence with computers. These included statements like, "I am good with computers". These items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). In the current sample the alpha was 0.89 reflecting a good level of reliability. Across the sample ($N = 146$), the scores ranged from 1.33 to 5 ($M = 3.92$, SD = 0.89).

Interest scale. The interest in learning about computing technologies scale was based on a factor analysis that yielded a five item scale that reflected engagement in learning (e.g. "I would like to learn more about computers"), positive affective reaction to learning (e.g. "Learning about what computers can do is fun"), and the importance of being knowledgeable (e.g. "It is important to me that I am knowledgeable about computers"). In the current sample the alpha was 0.82 reflecting an adequate level of reliability. Across the sample ($N = 145$), the scores ranged from 1.8 to 5 ($M = 3.95$, SD = 0.82).

Creative production experience scale. Students' depth and breadth of experience were derived from students' responses to a set of questions about their experience with 16 creative production activities. Although there are many kinds of experiences that build fluency, we focused on those that were more likely to involve some aspect of design, personal expression and/or require more advanced concepts related to computing: creation of multimedia, programming, creation of art, publication generation using a desktop publishing program, starting a newsgroup, building robots or other technological inventions, coding web sites using HTML, generating web sites using an application, publishing a web site, using a computer to simulate or model phenomena, designing with a CAD program, developing a database, creating a digital movie, creating an animation, creating a computer game, and creating a piece of music. Activities were presented as descriptions of possible products and/or software, such as "Made a publication such as a brochure or newspaper using a desktop publishing program like Pagemaker or Word" and "Created a piece of art using an authoring tool like Photoshop or Paint Shop". Students were asked to indicate the number of times they had participated in each activity from a choice of: never, once or twice, three to six times, and more than six times. This set of items was used to create two summary scores: breadth of experience and depth of experience, used together to create the four profiles of experience in our third analysis.

(a) Breadth of experience. We counted the number of activities each student had participated in at least once. This served as the measure of students' *breadth* of experience. Across the sample ($N = 147$), the scores ranged from 1 to 16 ($M = 7.51$, SD = 3.65). A median split was used to define "high breadth" and "low breadth" groups, with eight or more activities constituting "high breadth".

(b) Depth of experience. We counted the number of activities each student had participated in more than six times. This served as the measure of students' *depth* of experience. Across the sample ($N = 147$), this measure ranged from 0 to 15 ($M = 2.27$, SD = 2.57). A median split defined "high depth" and "low depth" groups, with two or more activities constituting "high depth".

4. Results

We report our results in three sections that correspond to our three research questions. In the first section we provide a comparison of the two school communities, in the second section we present our regression analysis, and in the third we report on our person-centered analysis using profiles of student experience.

4.1. School-based analysis

A series of *t*-tests was carried out to assess whether on average, students from Juniper (higher SES) differed from students at Maple (lower SES) on measures of access and experience. Results are shown in Table 1. On average, students at Juniper had access to more tools at home, had greater breadth scores, and had greater depth scores. There were no significant differences in the average number of learning resources they reported using. Students at Maple on average had a larger non-home access network. These average differences are clearly important. However, the descriptive statistics also indicate that within each school there is substantial variability on each measure. In order to more deeply understand what other factors in addition to school make a difference for students' history of experience, we use a stepwise regression in our next analyses that allows us to determine the relative contributions of a set of variables to explaining variability across the two schools. We chose breadth of experience as our dependent measure rather than depth since the range was restricted on our depth of experience metric.

4.2. Variable-centered analysis

Regression analysis was used to explore the relative contribution of factors that were correlated with students' breadth of experience. Once again, the breadth of experience score was calculated by summing the number of creative production activities that students had ever engaged in. Following our review of literature, we hypothesized that the following factors would vary with a student's breadth score: whether or not the student was a regular computer user at home, school attended, gender, number of technology tools at home, number of learning resources, and the size of the student's non-home access network. Because we did not have a theoretical rationale for their relative importance, we used these variables in a stepwise regression, using the breadth score as the dependent variable. Due to missing data from participants, the total n for this analysis was 127. Assumptions were met for multicollinearity, independent errors, collinearity, and heteroscedasticity.

We first offer descriptive statistics about the variables used in our analyses. In this sample, 77% of students were regular users of a computer at home, reporting that they used it at least several times a week. Descriptives for total number of tools, size of access network, access to learning resources, and breadth of experience are shown in Table 2.

The final model ($R^2 = 0.39$) is shown in Table 3. Neither gender nor school accounted for significant variance in breadth. Instead the number of tools at home, students' regular use of a computer at home, the number of learning resources they accessed, and the number of places that they regularly accessed a computer predicted breadth.

Tools at home accounted for most of the variance ($r^2 = 0.25$, b = 0.38, $p < 0.01$) followed by frequency of computer use at home, non-home access network size, and number of learning resources used. Table 4 shows bivariate relationships between breadth of experience and the significant predictors.

This regression shows the importance of access to tools and time with the computer at home as well as access to learning resources and tools across a child's life settings. In the next section, we use breadth and depth scores to create four profiles of experience. This allows us to classify individual children and compare the experience groups with respect to their access to tools at home, frequency of use, number of learning resources, and the like.

4.3. Profile-centered approach based on experience profiles

Descriptives. We created creative production experience profiles within our overall sample based on both breadth and depth: *beginner* (low breadth, low depth), *explorer* (high breadth, low depth), *specialist* (low breadth, high depth) and *generalist* (high breadth, high depth). Table 5 illustrates our classification criteria for the four groups.

Table 1
Access and experience as a function of school.

	Maple		Juniper		*T*	*P*
	Mean	SD	Mean	SD		
Tools at home	4.56	2.64	6.72	1.64	6.08	0.001
Non-home access network	1.14	0.83	0.64	1.11	2.99	0.03
Learning sources	5.80	2.95	5.87	2.69	0.15	NS
Breadth score	6.76	3.59	8.38	3.56	2.75	0.007
Depth score	1.85	1.83	2.76	3.16	2.11	0.001

Table 2
Descriptive statistics of variables used in the regression analyses.

	N	Mean	SD	Median	Minimum	Maximum
Tools at home	157	5.59	2.47	6	0	9
Non-home access network	137	0.93	0.99	1	0	5
Learning sources	152	5.84	2.82	6	1	16
Breadth score	147	7.51	3.66	7	1	16

Table 3
Intercorrelations between regression variables.

	1	2	3	4	5
1. Tools at home	–	0.50**	0.13	0.20*	0.66**
2. Breadth score		–	0.33**	0.33**	0.49**
3. Non-home access network			–	0.39**	0.13
4. Learning sources				–	0.12
5. Regular use at home					–

* $p < 0.05$.
** $p < 0.01$.

Table 4
Regression model for predicting breadth of experience.

	B	SE *B*	*β*
Constant	1.77	0.73	
Tools at home	0.38	0.13	0.27**
Non-home access network	0.67	0.27	0.19*
Regular use at home	2.20	0.76	0.24**
Learning sources	0.22	0.10	0.18*

* $p < 0.05$.
** $p < 0.01$.

The labels for these groups were chosen to reflect patterns of experience with the creative production activities as we do not have data to show that they correspond to differences in knowledge or skill. A summary of these profiles and their corresponding mean breadth and depth values is show in Table 6.

On average, the generalists in our sample had tried 11 of the 16 activities at least once and had engaged with four or five of the activities more than six times. The explorers in our sample on average had tried 10 of the 16 activities but were unlikely to have engaged in any of them more than six times. The specialists in our sample on average had only tried out six of the 16 activities but they had repeatedly engaged in two or three of them. Finally, the beginners in our sample on average had only tried four of the 16 activities and like the explorers had not pursued any of them repeatedly. In the following analyses, we contrast students who fall into our four experience profiles according to our variables of interest.

Number of technology tools at home. Table 7 shows the mean number of technology tools available at home, for each profile group. A one-way ANOVA indicated significant differences between profile groups, $F(3) = 11.84$, $p < 0.01$. Post-hoc analyses revealed differences between beginners and explorers ($p < 0.05$), and between beginners and generalists ($p < 0.01$). All post-hoc analyses used the Games–Howell method, recommended when there are unequal cell sizes or variances (Hilton & Armstrong, 2006).

Table 5
Classification of experience groups.

		Breadth (# of activities experienced at least once)	
		Low (0–7 activities)	High (8–16 activities)
Depth (# of activities experienced more than six times)	Low (0–1 activities)	Beginner	Explorer
	High (2–15 activities)	Specialist	Generalist

Table 6
Mean breadth and depth scores, by profile group.

	Breadth		Depth		*N*
	Mean	SD	Mean	SD	
Beginner	4.18	1.79	0.43	0.50	61
Specialist	6.22	1.22	2.94	1.39	18
Explorer	10.00	1.82	0.61	0.50	18
Generalist	11.14	2.02	4.88	2.49	50

Table 7
Mean number of technology tools at home by experience profile.

	Mean (SD)	*N*
Beginner	4.40 (2.69)	63
Specialist	5.68 (1.92)	19
Explorer	6.28 (2.35)	18
Generalist	6.83 (1.68)	53

Table 8 shows the percentage of each group that has each technology peripheral tool at home. Chi-squared analysis indicates that beginners were less likely than generalists to have handheld devices and digital movie cameras at home. Differences in digital camera access approached significance, with beginners having lower rates of access than generalists.

Home and non-home computer access. Table 9 summarizes the mean number of locations other than home at which the student is a regular user of computers (non-home access network), for each profile group. A one-way ANOVA indicated differences between profile groups, $F(3) = 3.84$, $p < 0.05$. Post-hoc analyses revealed that generalists regularly access significantly more non-home locations than beginners.

Fig. 1 shows the percentage of each profile group that reported regular use of a computer at home, school, a friend's house, a relative's house, and a community center. Because the assumption of an expected frequency of at least five observations per cell was frequently violated, we were only able to use the chi-squared test of association to test the significance of association between profile group and regular use for "home" and "in school during class time." Chi-squared analyses indicated significant relationships between profile group and home frequency group ($X^2 = 26.34$, $df = 3$, $p < 0.01$). The proportion of students who used a computer regularly at home was higher for the generalists than for the beginners. The difference as a function of profile group for use at school during a class was not significant ($X^2 = 5.28$, $df = 3$, $p < 0.15$).

Students' use of learning resources. Table 10 shows the mean number of learning resources reported by students in each of the four profile groups. A one-way ANOVA indicated significant differences between profile groups, $F(3) = 5.85$, $p < 0.01$. Post-hoc analyses revealed differences between beginners and generalists ($p < 0.01$).

The sixteen learning resources fit into three main categories: people, places, and distributed resources. One-way ANOVAs indicated that only the distributed learning resources differed by experience group. Because of a violation in equality of variances the data were transformed by taking the square root of each value and rerunning the ANOVA. The results were maintained, $F(3) = 5.65$, $p < 0.01$. Post-hoc analyses indicated that generalists were more likely to use distributed resources than were beginners. The proportions of students within each profile group accessing each of the distributed learning resources are detailed in Fig. 2. Two additional learning resources, "playing games" and "on my own," were queried but were not included in the total score since they did not fit easily into our schemes of people, places, or distributed resources. In Fig. 2 we include the percentage of students reporting that they learn on their own for descriptive purposes as it was the most commonly reported learning resource for all groups.

Table 8
Percentage of profile groups-reporting each tool at home.

	Beginner (%)	Specialist (%)	Explorer (%)	Generalist (%)	X^2	*P*	*N*
Internet	74.60	100.00	100.00	100.00	–	–	153
Printer	68.25	89.47	94.44	98.11	–	–	154
Scanner	53.97	68.42	72.22	77.78	2.00	0.572	154
Handheld	53.97	47.37	50.00	62.96	17.77	0.000	154
Digital camera	17.46	26.32	38.89	53.70	7.79	0.051	154
Video camera	19.05	36.84	50.00	53.70	16.48	0.001	154

Table 9
Mean number of locations where computers are regularly accessed (access network) by experience profile group.

	Mean	SD	*N*
Beginner	0.63	0.68	56
Specialist	0.87	0.92	15
Explorer	1.00	1.18	14
Generalist	1.27	1.19	49

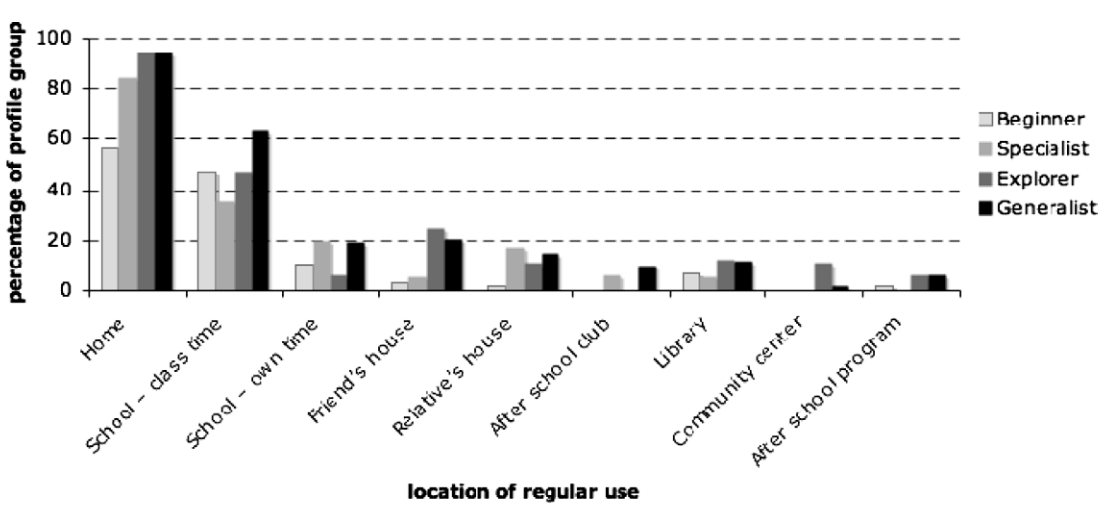

Fig. 1. Percentage of each profile group who regularly use the computer in each setting.

Table 10
Mean number of learning resources by experience profile.

	Mean number of learning resources (SD)	*N*
Beginner	4.95 (2.63)	58
Specialist	5.21 (2.51)	19
Explorer	6.94 (3.10)	18
Generalist	6.83 (2.67)	53

Parent jobs. The learning resources data suggested that parents are an important learning resource. In another item we asked students to indicate whether their mother and father used a computer in their job. Although this may be a crude indicator of parent expertise, we analyzed this variable to see if there would be differences by profile group. Generalists were more likely to have a parent who used technology in their job (93.8%) than were beginners (63%), $X^2 = 14.3$, $df = 3$, ($p < 0.01$). The percentage of students who had a parent that used technology in their job was 87.5% for explorers and 82.4% for specialists, respectively.

Knowledge sharing. Recall that students were asked to indicate, from a list of relational categories, whom they were teaching about computing: mother, father, brothers, sisters, grandparents, other relatives, teachers, people they work with at school or in a job. To examine the association of experience profile with the likelihood of teaching others we used a median split based on the number of relational categories they marked and then used a chi-squared analysis to test the significance of association. The low level knowledge sharing group ranged from zero to one relational category, and the high level included two or more categories (the range for the high level group was 2–8). According to chi-squared analysis, the distributions of level of knowledge sharing differed as a function of the experience profile ($X^2 = 24.65$, $df = 3$, $p < 0.01$). Examination of the residuals indicated that the generalists were more likely to be high knowledge sharers than the other three profiles. The percentage of high knowledge sharers represented 77%, 47%, 32%, and 32% of the generalists, explorers, specialists, and beginner experience profile groups, respectively.

Confidence. A one-way ANOVA indicated significant differences between profile groups on our measure of confidence, $F(3) = 8.21$, $p < 0.01$. The means were 3.59 (SD = 0.89), 3.73 (SD = 0.91), 4.31 (SD = 0.63), 4.30 (SD = 0.78) for the beginners, explorers, specialists, and generalists, respectively. The post-hoc analysis indicated differences between beginners and specialists, and between beginners and generalists ($p < 0.01$). In contrast to the variables relating to access to tools and learning resources, in this analysis the specialists rated themselves as highly on confidence as did the generalists.

Interest. A one-way ANOVA indicated no differences between profile groups on our measure of interest, $F(3) = 1.58$, NS. However, a Levene test for equality of variances was significant. A non-parametric procedure, the Kruskal–Wallis test confirmed the non-significant differences between profile groups ($H(3) = 6.42$, NS). The means were 3.91 (SD = 0.94), 3.66 (SD = 0.59), 3.94 (SD = 0.56), 4.13 (SD = 0.74) for the beginners, explorers, specialists, and generalists, respectively, and reflect a high level of interest for all groups.

4.4. Distribution of experience profiles by school

School. Although school was not a significant predictor of breadth of experience once our other metrics of use and access to tools were taken into account, we were interested in understanding how many students in each school fell into our different experience profiles that were based on both breadth and depth. From a social network perspective, having a greater number of classmates with high levels of experience may be advantageous as interests and expertise might be shared informally. According to chi-squared analysis of school versus profile groups, the distribution of profiles differed significantly between schools ($X^2 = 7.86$, $df = 3$, $p < 0.05$). Follow-up pair-wise comparisons indicated that a greater percentage of students were generalists at Juniper than Maple, while the reverse was true for beginners. At Juniper, 44% of students fell into the generalist group, 7% fell into the specialist profile, 14% were classified as explorers, and 36% were classified as beginners. At Maple only 27% of the students were classified as generalists, 17% were classified as specialists, 10% were classified as explorers, and more than 46% of students fell into the beginner category. These patterns indicate that although in both schools we found highly experienced students, they were more likely to be found at Juniper. In combination with the data on the association between knowledge

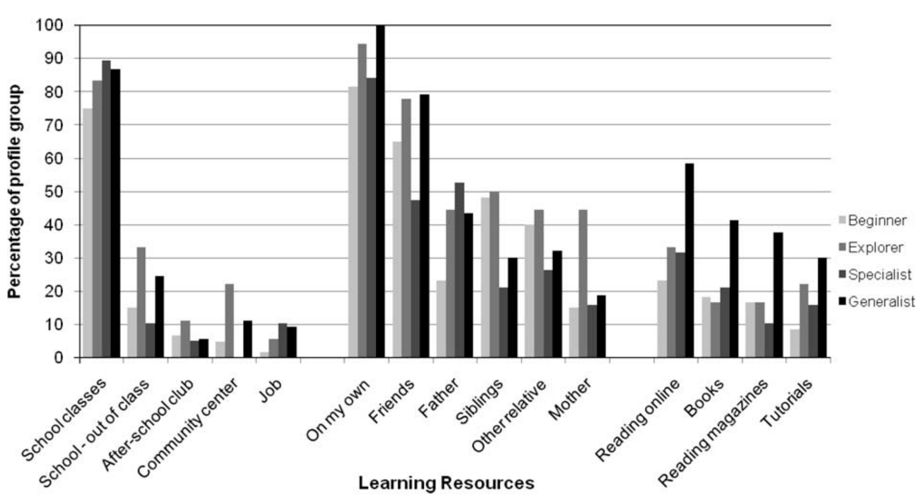

Fig. 2. Learning sources accessed by experience profile.

sharing and experience, these data suggest we should expand our unit of analysis from the individual to include the social groups with whom they come into contact on a regular basis.

5. General discussion

This study examined individual differences in a diverse group of 8th grade students' histories of experiences with creative production activities and related these differences to students' learning ecologies. Our learning ecology metrics included self-reported access to learning resources found at home, school, in the community, and through digitally mediated contexts such as the Internet. Across the analyses we found strong evidence that there are wide experience gaps with respect to participation in creative production activities and that these gaps are linked to issues of access. Below we discuss our results with respect to four key take-away points: (1) the home setting is a key aspect of a learner's learning ecology; (2) variability in experience with creative production activity is significant and inconsistent with the image of the digital native; (3) the most experienced students are learning from a distributed set of resources; (4) greater experience is associated with more confidence and the sharing of one's expertise with friends and family.

5.1. Home access matters

The first analysis showed that on average there were differences between students attending the two Silicon Valley schools on measures of access to tools at home and on measures of experience. As expected, the students from the more affluent school community were more experienced and benefited from more tools at home. The variable-centered analysis confirmed the relationship between home access and experience with creative production activity. It showed that regardless of school, students with greater breadth of experience had more tools at home, and were more likely to use the computer frequently at home. Additionally, they regularly utilized a greater number of non-home access points, and reported learning from a broader range of resources. Neither gender nor the school they attended explained a significant amount of the variance in experience after all of the other variables were simultaneously taken into account. These findings point to the importance of analyses that go beyond comparisons of averages. The number of tools at home in fact accounted for the most variance in our model.

These findings are consistent with other studies that demonstrate the significance of home access. Home computer use correlates positively with measures of school readiness and cognitive development (Li & Atkins, 2004), as well as reading and mathematics test scores, after controlling for family SES level (Attewell & Battle, 1999). Home Internet use has been shown to correlate positively to standardized reading achievement scores and grade point averages (Jackson et al., 2006), as well as higher-level Internet user skills (Hargittai & Hinnant, 2008).

Our findings expand this list of correlates of home access and use to include participation in creative fluency-building activities, lending credence to concerns that youth's varying levels of engagement in computing activities may lead to new forms of inequity because of differential opportunity to develop skills. Our person-based analysis that compared youth with different profiles of production experience also confirmed the importance of home. When we compared students with different profiles of experience, we found that access to resources distinguished the four groups. In fact, on almost every variable, beginners differed from their more experienced peers. Our person-centered analysis indicated that students classified as beginners had fewer computing tools at home overall than the generalists or the explorers. They were less likely to have home access to the Internet, access to a printer, a scanner, a digital still camera or a video camera. Beginners were also less likely to use a computer at home on a regular basis and reported significantly fewer regular access points beyond the home. Beginners were also less likely than generalists to have a parent who used technology in their jobs.

5.2. The myth of the digital native

Contrary to popular images of all youth as uniformly immersed in sophisticated technological activity, we found that the learners in this sample differed widely in their breadth and depth of experience. Some students had the opportunity to explore most of the 16 creative production activities we queried, while others had only explored one or two. Similarly, some students reported they had engaged in at least some of the activities more than six times, which presumably allowed them to develop significant levels of competence. Others had no depth of experience in any of the activities. To take into account both breadth and depth we created four profiles of experience. Beginners had low breadth and low depth, specialists had low breadth but had found a few activities that they pursued repeatedly, explorers had dabbled in many of the activities but rarely more than once, and generalists had both a broad range of experience and depth with several of the activities.

Examining the specific types of activities that students had experienced revealed that some activities were more equally accessed than others. When we collapsed our 16 activities into three main genres, we found that publication or art projects were much more equally experienced than were activities that were more likely to require computational thinking (Wing, 2006) such as programming, simulation, or game design. In fact, only 50% of beginners or explorers had ever done any of the computational activities we asked them about. Differences in opportunities for uses such as simulation or programming are particularly troubling because it is these activities that are most likely to build the kinds of technological fluencies (National Research Council, 1999) that nurture creative agency (Monroy-Hernandez & Resnick, 2008). Our specialists were also unlikely to have developed depth in a computational activity; in fact, fewer than 20% of them had repeatedly engaged in one of these activities. They were most likely to have depth of experience with multimedia or using a software program to develop a website. Multimedia and website production also provide important opportunities for the development of what has been called new media literacy (Lankshear & Knobel, 2007) – and they may be more commonly accessed because the tools of production have been made more accessible and online communities of learning offer multiple supports for newcomers who want to learn.

5.3. Experience is associated with the use of distributed learning resources

In general, beginners reported learning from fewer resources than the generalists, explorers or specialists. When we categorized the learning resources as people, places, or distributed resources, we found that the beginners learned from fewer distributed resources than our generalists. They were less likely to use tutorials or read books or online materials to learn. This may be because they have less access to materials or it may be because more experienced learners have had the opportunity to develop an interest that leads them to seek out information (Hidi & Renninger, 2006). We do not have the type of data that would allow us to distinguish these possibilities. Regardless, this pattern suggests that to study the learning ecologies of youth it is important to have metrics that index a variety of learning resources including ones that can be accessed online or through libraries.

5.4. Experience is associated with knowledge sharing and confidence

Differences between the experience profile groups extended to knowledge sharing. It has been well documented that adolescents teach as well as learn from others in their local communities (Kiesler, Zdaniuk, Lundmark, & Kraut, 2000; Rogoff, 1998; Tudge & Rogoff, 1989). This is particularly true for new technologies where the traditional knowledge/age relationships have been reversed. Our profile groups differed in their reports of teaching others to use computing technologies. We found that beginners shared their knowledge of computing with a smaller range of possible learners than did the generalists. The capacity to teach others often represents an opportunity to learn; we also know that providing explanations often results in clarification and elaboration of one's knowledge, resulting in benefits to the explainer as well as the listener (Webb, 1989). In fact, some recent designs for computer based pedagogical agents take advantage of this phenomenon (Biswas, Schwartz, Leelawong, Vye, & The Teachable Agents Group at Vanderbilt, 2005).

As Becker (2000) has pointed out, divides along economic lines can be worsened by community effects. Becker's research, along with popular conceptions of the "digital divide", focuses on physical access to tools and to the Internet, but it is important to expand the conception of differential access to include knowledge networks (Frank, Zhao, & Borman, 2004). Our data suggest that more experienced adolescents are more likely to report teaching others; this is significant given other research findings that informal learning among peers is a key way that technical knowledge spreads through a community. Ethnographic studies highlight the fact that friendships can be the source of the development of interest in particular hobbies and pastimes and that activities like moviemaking or robotics are often joint productions (Barron, 2006; Barron, Martin, Takeuchi, & Fithian, 2009; Chandler-Olcott & Mahar, 2003). Students also support teachers in their attempts to incorporate technology into classroom lessons. Case study research with students at Juniper schools revealed that some experienced students were being employed by teachers as teaching assistants and occasionally as in-home technical consultants (Barron, Martin, Takeuchi, & Fithian, 2009). These highly experienced middle school students are examples of an emerging category of teens referred to as "pro-ams", amateur experts or hobbyists who have developed specialized knowledge about topics of interest using digital media (Anderson, 2006; Gee, 2008; Leadbeater & Miller, 2004). All of these data suggest the importance of extending the unit of analysis beyond the individual to examine the learning ecologies as constituted through sustained relationships.

Teaching others may also have implications for one's self-perception as someone who is competent with new technologies (Mercier, Barron, & O'Conner, 2006). Consistent with this conjecture, and with theories of self-efficacy that target mastery experiences as critical for developing confidence (Bandura, 1986), we found that beginners were less confident in their computing skills than were either the generalists or the specialists.

Our findings on interest suggest that in general, despite differences in histories of experience, interest in and valuing of learning about technological topics was high for all students in the study. Interest can have high payoffs for learning and is thus a potential resource to be drawn upon by teachers and others who have opportunities to support it through provision of material resources and ideas for projects (Hidi & Renninger, 2006).

5.5. Limitations and directions for future research

Scholarship on the topic of equity and computing benefits from a broad range of methodological approaches as every method of research has both strengths and limitations. The conclusions that can be drawn from our research are limited, firstly, by its reliance on eighth graders' self-report. It is possible that students were under- or overestimating their experience. It is also limited because we did not have an individual metric of family socioeconomic status. Finally, because the data were all correlational we cannot warrant causal inferences about the links we observed between experience, tools, confidence, and learning resources. However, overall the portraits of experience provided a consistent pattern of differential participation. Generalization to other communities significantly dissimilar from Silicon Valley, in which fewer parents work in computing fields, should be made with caution. It may be that the rates of participation in creative production activities for our generalists are higher than would be found in less technologically saturated communities. If anything, this suggests that students elsewhere may be even less engaged in certain creative pursuits that involve technologies.

Future studies might extend the current research in a number of ways. First, it would be useful to validate knowledge and practice differences as a function of experience profiles. While we are fairly confident that experience builds knowledge and new communicative skills, the development of independent metrics would be useful. In particular, it would be powerful to assess whether and how production activities lead to new preferences for communicative contexts, repertoires of collaborative practices, and approaches to learning. Case study, ethnographic methods, and quantitative metrics such as the ones described in this study could be usefully combined to do this work. Multiple methodologies are in order if we hope to understand new forms of learning and their outcomes (Sefton-Green, 2006).

Second, experimental or quasi-experimental work providing intentionally designed learning environments, mentors, and projects would help warrant causal arguments about the roles of learning resources and tools in the development of interest, confidence, and experience. Developmental case study research would also help provide process accounts of what factors drive interest and participation in production activities. Our four profiles of experience might be productively applied to longitudinal studies in order to begin to trace typical pathways of media production expertise development.

Finally, extending the unit of analysis to peer groups, schools, and broader knowledge or learning networks is critical. Research on teacher knowledge networks has found that colleagues with hybrid expertise including technical expertise and pedagogical content knowledge were called on most frequently for support, and they, in turn, had their own external networks that helped them keep up to date (Ryymin, Palonen, & Hakkarainen, 2008). There is much to be learned about the dynamics of knowledge sharing in informal and school based communities and how to create communities with high densities of relational ties that support their learning. It would be productive to identify conditions under which learners spontaneously collaborate to learn and create. Social network tools might in fact be used to assess the generativity of environments intentionally designed to bridge divides and create equitable learning opportunities.

6. Conclusions

The experience differences we found in this sample of students, all living in the Silicon Valley region, suggest that despite increasing levels of physical access, opportunities to participate in creative fluency-building activities are unequally distributed. Differences were tied to home access to tools, size of the non-home access network, as well as use of broader learning resources. It would seem that the original concerns that sparked research on a possible digital divide are still valid. While access to some computing tools was common for all of our students, there were differences in the number of computers at home, the types of digital accessories found there, and whether or not parents used computers in their jobs. New conceptualizations of learning go beyond the expansion of content knowledge to include development of a sense of oneself as a legitimate participant in the practices, activities, and ways of communicating associated with a domain (Lave & Wenger, 1991; Nasir & Saxe, 2003). While access to tools is important, it may be just as important to provide resources for learning in the form of an engaged social network of teachers, parents, and peers. As we move towards solutions that bridge these divides, we need to attend to the broader learning ecologies that students access and develop, and find ways to make these more diverse, generative, and interconnected.

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