CITIZEN SCIENCE:
THEORY AND PRACTICE

How Citizen Scientists Learn: Exploring Learning Perceptions Through an International Survey

RESEARCH PAPER

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ABSTRACT

Citizen science (CS) is a growing field of participatory science, bringing together the public, researchers, organizations, and communities to participate in various scientific projects that unfold in different sociomaterial settings known as territories. While research on perceived learning in CS has recently grown, the discussion regarding the different learning approaches, territories, and the overall process as well as their associations with learning factors remains meager. In our study, we unpack three types of learning (formal, informal, and nonformal) and their respective territories in CS, and within this context, review a model of learning to synthesize the project-related and individual factors associated with the perceived learning of citizen scientists engaged in CS activities. We conducted an international survey for adults participating in CS, which was then analyzed using exploratory factor analysis (N = 596). We identified the following five factors regarding CS activities and perceived learning: sociomaterial learning, social learning, reflective learning, situational learning, and material learning. We found that perceived learning was lower for citizen scientists who participated in biology CS projects but higher among citizen scientists who participated in the long term and engaged in a variety of CS activities. Our findings highlight that the learning experiences of citizen scientists can be varied within a CS project because of the varied entanglements of project-related and individual factors, which can be better understood through a model of learning. Our findings contribute to developing further the theories and practices related to CS and CS in education.

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INTRODUCTION

Citizen science (CS) is a research area growing in interest because it is concerned with how certain scientific projects are undertaken by the public and professional scientists to increase overall scientific understanding (Eitzel et al. 2017; Herodotou et al. 2020). CS may be defined and characterized differently by its various stakeholders (e.g., organizations, associations, governments, enthusiast groups, individuals) depending on the degree of participation (i.e., frequency and duration) and the settings of CS (e.g., school, museum, home) (Kloetzer et al. 2021; Vasiliades et al. 2021). Research on learning often begins by looking at the content and design of projects as project participation entails different CS activities or tasks that are done independently and/or collaboratively by participants for the advancement of a project and/or personal gain such as making observations, collaborating with others, or discussing results (Kloetzer et al. 2021).

Researchers have noted that the learning experiences of citizen scientists may shape the overall longevity and fruitfulness of CS projects (e.g., Bruckermann et al. 2020; Peter et al. 2021; Roche et al. 2020; Vasiliades et al. 2021). To improve project sustainability while enhancing output at the project and individual levels, efforts have been made to investigate, for example, the demographics of citizen scientists (Herodotou et al. 2020; Pateman, Dyke and West 2021; Vasiliades et al. 2021), individual learning outcomes (Kloetzer et al. 2021; Phillips et al. 2018; Vasiliades et al. 2021), and the mediums (i.e., online/offline modes) that may support learning (Aristeidou and Herodotou 2020; Bruckermann et al. 2020). However, "research on learning in CS remains under-theori[z]ed" owing to the challenges associated with the creation and evaluation of learning, to the varying degrees of participation in CS projects, and because the paradigms used to examine learning are not explicated sufficiently (Bruckermann et al. 2020, p. 889).

Peter et al. (2021) have taken the initiative by investigating the relevance between project design and the acquisition of knowledge and skills of citizen scientists. Our aim is to continue this discourse with an emphasis on tackling the theoretical foundation of learning and the sociomaterial settings in CS as well as their relevance in understanding the factors for perceived learning. First, we review the different types of learning and their respective sociomaterial settings in CS before discussing the Model for the Design and Evaluation of Learning in CS or MODEL-CS (Bruckermann et al. 2020). Then, we introduce how project-related and individual factors are associated with the perceived learning of citizen scientists engaged in CS activities. Finally, we elucidate these factors by referring to the MODEL-CS.

CITIZEN SCIENCE, LEARNING, AND TERRITORIES

According to the Organisation for Economic Co-operation and Development or OECD (2020) and the European Centre for the Development of Vocational Training or Cedefop (2014), learning can be broadly divided into formal, informal, and nonformal learning. Formal learning refers to learning in an environment that is organized and structured such as a school. It includes learning objectives, learning materials (e.g., textbooks, iPads), and learning resources (e.g., teachers, a tutoring service) that have been allocated to support learning. Learning is intentional from the perspective of the learner, who usually receives certification upon completion such as a diploma. In contrast, informal learning is situational, or experience-based, such as talking with co-workers at the workplace. Learners are not proactively thinking of their own learning in the same way as in formal learning; hence, it is usually unintentional. It does not include learning objectives, and learning materials are not allocated to learning. However, resources such as counseling (if provided) may contribute to learning. Informal learning may sometimes be certified, such as in the completion of a series of online quizzes on, for example, plant species (Cedefop 2014; OECD 2020).

In between formal and informal learning is nonformal learning. Although its definition is debated, nonformal learning generally refers to a semi-structured or semi-organized environment that supports learning, such as a museum. While learning is embedded in the environment, learning objectives are more implicit (i.e., available but not necessarily promoted), learning materials are present (e.g., booklets, diagrams), and learning resources (e.g., workshops) are available but more limited compared with formal learning. Learning is intentional, but it does not usually result in certification (Cedefop 2014; OECD 2020). Overall, much of our learning involves a mixture of informal and nonformal learning in addition to formal learning (National Research Council 2009).

As we can see, each type of learning involves a varied use of materials and resources in conjunction with opportunities for interaction (i.e., communication between people), which is known as sociomateriality (Orlikowski 2007). The types of learning and their sociomaterial counterpart in CS can be understood through the discussion of territories. According to Kloetzer et al. (2021), territories "indicate different sociomaterial contexts and resources, cultural and institutional values, and, sometimes, the various groups who may take part in citizen science projects (p. 286)." In other words, the territories for learning in CS are constructed through the varying combinations of project characteristics (e.g., values or aims, goals, the research area), individuals (e.g., citizen scientists, policymakers, project stakeholders), resources (e.g., training and support), and materials (e.g., smartphones, sound recorders). Kloetzer et al. (2021) list six different territories about which we explain next in relation to the three types of learning.

Formal learning primarily includes the formal education territory (i.e., schools). CS can occur in schools through its integration with curricula so that learning objectives are defined and learning materials as well as resources are provided. As students (who also act as citizen scientists) are already enrolled in the school, learning is intentional; however, it is not clear whether certification from the school includes a direct connection to CS because competing interests such as ensuring resources (e.g., lesson plans) are applicable to school curricula and CS activities. Informal learning primarily takes place within the family territory. Here, CS projects aim to encourage exploratory learning through interaction (e.g., discussion with others) in everyday situations without the need for acquiring or utilizing certain materials (e.g., measuring devices). Depending on the project, learning resources such as tutoring may be available. Learning itself is not proactively pursued nor established in this territory; hence, learning is meagerly perceived (Kloetzer et al. 2021).

Nonformal learning takes place mainly in the territories of out-of-school education, museums, and local and global communities. Learning remains intentional for out-of-school education programs and museums as both typically support learning through, for example, workshops or courses, which include hands-on materials such as a water sampling kit, even though specific learning objectives are not always explicit. Interestingly, some out-of-school education programs may allow citizen scientists to operate independently from professional scientists during participation while others include apprenticeship, which may pave the way for certification.

For the local and global communities territory, CS projects are flexibly structured, and learning is part self-directed and part collaborative. A community or out-of-school program may provide the necessary materials (e.g., iPads) and resources (e.g., training) to learn, and some may directly collaborate with citizen scientists; however, sometimes the learning materials provided are not used for the learning that is intended. While certification for skills and knowledge obtained are not necessarily commonplace, dialogue between citizen scientists, the community, and project stakeholders may be enhanced and thus lay the foundation for future CS projects (Kloetzer et al. 2021). Overall, CS project initiators seem to find a stronger launchpad in this territory since learning is not compelled, and scientific literacy is not explicitly emphasized as the primary goal or purpose (National Research Council 2009).

The online territory is more difficult to categorize as it includes characteristics from formal, informal, and nonformal learning. Online CS projects such as Grass Gazers may serve as a substitute for when in-class, formal learning is not possible because of, for example, the outbreak of a disease (see Van Haeften et al. 2021). Online CS projects may also provide online materials (e.g., e-books, videos) for self-study as well as resources (e.g., forums, webinars) that allow citizen scientists to connect with other citizen scientists, researchers, policymakers, teachers, and formal education providers such as universities (Aristeidou and Herodotou 2020; Bruckermann et al. 2020; Kloetzer et al. 2021; Roche et al. 2020). Learning can be intentional when enrolling in substitute study programs such as Grass Gazers or unintentional when troubleshooting technical issues during, e.g., data collection (Kloetzer et al. 2021).

Citizen scientists in the online territory are typically self-directed, whether learning objectives are explicitly present or not (Aristeidou and Herodotou 2020), reflecting a more constructivist approach to learning, in which learners autonomously manage their own learning (Packer and Goicoechea 2000). Like the family territory, when learning is not perceived, participation is difficult to sustain (Kloetzer et al. 2021). Learning in online CS is not typically certified, but there have been efforts to address this such as the European Guidelines for Validating Non-Formal and Informal Learning (Cedefop 2016) or the Informal Learning in Citizen Science (ILICS) model by Kloetzer et al. (2013) as mentioned by Aristeidou and Herodotou (2020, p. 2).

A MODEL FOR INTERPRETING THE PROCESS OF LEARNING IN CITIZEN SCIENCE

Recently, researchers have developed different models to better capture and understand learning in CS. For instance, Phillips et al. (2018) developed a framework to capture and evaluate perceived learning through six categories: "interest, self-efficacy, motivation content, process and nature of science knowledge, skills of science inquiry, and behavior and stewardship (p. 7)." Kloetzer et al. (2021) took a different approach and created a comprehensive "thematic map of volunteers' learning" in CS by combining prior research from Citizen Cyberlab (Jennett et al. 2016) to focus on how and what is learned as well as the barriers for learning (p. 300). Bruckermann et al. (2020) note that project initiators typically do not focus on the design and evaluation of learning and thus developed the Model for the Design and Evaluation of Learning in CS projects or MODEL-CS. The model functions as a heuristic tool for analyzing CS projects and learning through identifying and connecting the stages of a project: inputs, CS activities, outputs, and outcomes.

At the input stage of a project, professional scientists form learning opportunities based on their goals and motivation as well as those of citizen scientists. Next, citizen scientists utilize the learning opportunities by engaging in one or more CS activities. Sufficient use of CS activities via participation generates measurable and observable outputs for professional scientists to examine. Finally, outputs are then transformed into scientific outcomes or individual learning outcomes (which we refer to as perceived learning), which may (not) correspond with one another. However, it is important to note that the outcomes at the end of a project feedback to professional scientists and citizen scientists and thus shape their current and even future goals and motivations for other projects (Bruckermann et al. 2020, p. 890).

RESEARCH QUESTIONS

In this study, we investigate the following research questions:

1. What kind of project-related and individual factors can be identified?
2. How are the project-related and individual factors associated with the perceived learning of citizen scientists engaged in CS activities?

DATA AND METHODS

OVERVIEW

Our study is based on a survey (see Supplemental File 1: Survey instrument, for relevant survey questions) that addressed adult citizen scientists (over the age of 16) in Europe. An adaptation of Lohman's (2005) informal learning survey and research conducted by Jennett et al. (2016) about learning in CS were used as the basis for creating answer choices. We define citizen scientist as any person who has participated in scientific projects in collaboration with professional scientists by voluntarily, contributing to, for example, data collection, analysis, and/or dissemination of a scientific project or observational campaign, even if the term CS was not explicitly used (Haklay 2013). During its development, we piloted the survey with 11 citizen scientists who provided feedback. Overall, our survey focused on Europe because it was created within the context of the EU Horizon 2020 CS Track project.

DISSEMINATION AND APPROACH

The survey (available in 10 languages) was disseminated systematically in Europe via universities and other research institutions, environmental organizations, civil societies, policy makers, volunteering organizations, etc. from January 2021 until July 2021. We also sent direct emails to projects and institutes conducting CS, inviting them to respond to the survey and/or distribute it throughout their networks; hence, principles of snowball sampling were used (see Goodman 1961). The survey was promoted on social media channels and CS-related forums. We also asked the platforms of national and international CS associations for support and promotion of the survey. Throughout the survey dissemination, we were actively searching for best practices of similar survey distribution strategies (e.g., Ganzevoort and Van den Born 2020). We also sent follow-up emails and reminders to encourage more citizen scientists to answer.

Altogether, we focused on 11 CS activities (e.g., asking questions, searching information from the internet, trial and error) and their relationship with one another. We then examined the following project-related factors: initiators, research areas, and goals. For individual factors, we examined participation in CS (in years), regularity of participation, number of projects in which respondents participated, and CS activities in which respondents were engaged in learning. Regarding the project-related factors, it was possible to choose more than one option (i.e., one CS project could relate to many research areas).

SAMPLE CHARACTERISTICS OF SURVEY RESPONDENTS

A total of 1,083 respondents from 38 countries and 5 continents responded to the survey. To detect possible attrition bias, a logistic regression was implemented using the following demographic characteristics obtained from our survey: gender, age, education level, yearly income level, and participation in CS (in years) (see Supplemental File 2: Survey data, Tables A1 and A2). We found that respondents who had been engaged in CS from 6 to 10 years ($p < 0.04$) or for more than 10 years ($p < 0.001$) as well as those who identified themselves as male ($p < 0.03$) were more likely to respond. Those who had a post-secondary non-tertiary education ($p < 0.04$) were less likely to respond. However, according to the Wald Chi-Squared test, the only demographic characteristic that was significant was how long the respondent had engaged in CS ($X^2 = 26.0$ df = 3, $p < 0.001$). The data analysis for the subsample was based on data with no missing values in considered CS activities ($N = 596$).

DATA ANALYSIS

Regarding relevant CS activities, we referred to those from the survey question: *"In your experience, to what extent do you feel you have learned something while doing the* *following activities?"* (see Survey instrument, item 21). This Likert-based question listed values from one (not at all) to five (a great deal). The value of six meant that the CS activity was not relevant or possible in the project and was thus considered as missing information. Exploratory factor analysis (EFA) was conducted to determine the relationship and correlation between CS activities as well as to reduce the dimension of response variables. The answer choice of "Other, please specify" covers multiple different CS activities and was also excluded from EFA.

Our subsample size of N = 596 is suitable for factor analysis (Guadagnoli and Velicer 1988). The univariate and multivariate normality within the data set was examined before initiating EFA. Since the data set cannot be considered normally distributed (see Survey data, Table A3), EFA was initiated using Spearman's rank correlation (see Survey data, Table A4). The suitability of the data set was examined using Kaiser-Meyer-Olkin criterion (Kaiser and Rice 1974). A value close to one indicates high suitability for factor analysis and our value is 0.91.

Figure 1 represents a scree plot of eigenvalues that can be used to determine the extraction of factors (Cattell 1966). The curve drops after the first factor, with another, smaller drop after the fifth factor.

Another criterion for factor extraction is discovering the cumulative percentage of the variance explained. Depending on the discipline, the factors with cumulative percentage from 60 to 80 of the total variances explained are considered usable (Hair et al. 2010, Streiner 1994). In this study, 75% of the total variances were explained after determining five factors. Table 1 shows all the factor components that are extracted.

Factors were not statistically significantly correlated (see Survey data, Table A5), so the loadings of factors were rotated using the Varimax rotation (Kaiser 1958). In this study, the component loadings of 0.35 or higher are included when interpreting the factors. The communality (h^2) provides the percent of variance in a variable explained by all common factors. The original CS activities from the survey, rotated factor loadings, and the communalities are presented in Table 2 below. Based on the factor loadings and the earlier discussion on territories (Kloetzer et al. 2021), which is based on sociomateriality (Orlikowski 2007), factor 1 was named sociomaterial learning, factor 2 was named social learning, factor 3 was named reflective learning, factor 4 was named situational learning, and factor 5 was named material learning.

Factor scores were then determined by calculating the matrix production of the factor loading presented in Table 2 and observations were centered. The factor scores were not normally distributed (Shapiro-Wilk normality test: Factor 1 scores $W = 0.96$, $p < 0.001$; Factor 2 scores $W = 0.96$, $p < 0.001$; Factor 3 scores $W = 0.95$, $p < 0.001$; Factor 4 scores $W = 0.97$, $p < 0.001$; Factor 5 scores $W = 0.95$, $p < 0.001$). We used the non-parametric Kruskal-Wallis test to compare the factor scores between the different groups. We calculated the eta-squared measure (Tomczak and Tomczak 2014) as an effect size for the Kruskal-Wallis test and interpreted it with the thresholds 0.01, 0.06, and 0.14 for small, medium, and large effects respectively (Morse 1999). Initial to the comparisons, we grouped the data based on the project-related factors (e.g., research area of the project) and individual factors (e.g., number of participated projects). The Dunn's A test (1961) was used for pairwise comparisons (see Survey data, Table A6). A

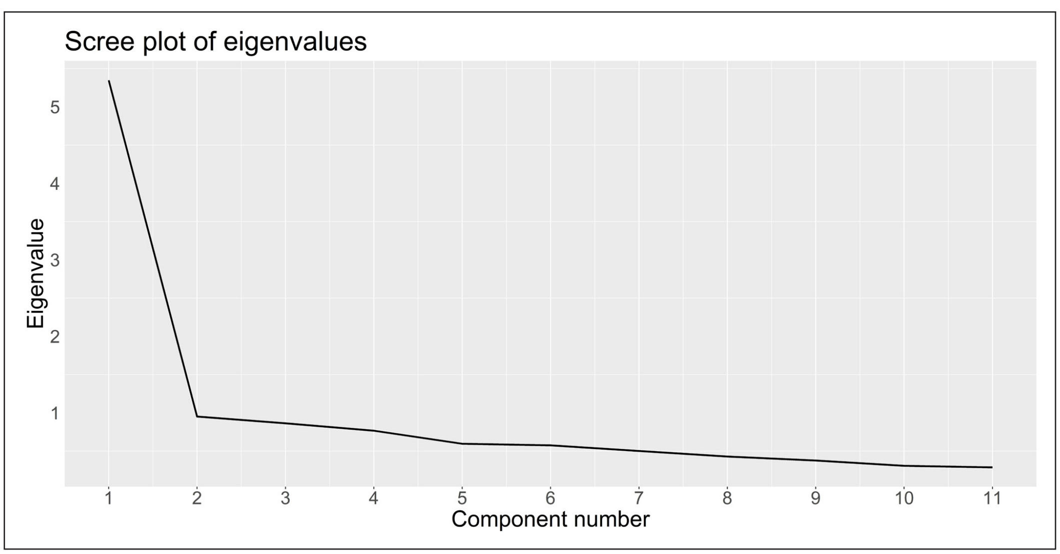

Figure 1 Scree plot of eigenvalues.

COMPONENT	INITIAL EIGENVALUES		EXTRACTION SUMS OF SQUARED LOADINGS		ROTATION SUMS OF SQUARED LOADINGS				
	TOTAL	% OF VARIANCE	CUMULATIVE %	TOTAL	% OF VARIANCE	CUMULATIVE %	TOTAL	% OF VARIANCE	CUMULATIVE %
1	5.35	48.6	48.6	3.57	32.4	32.4	1.63	14.8	14.8
2	0.95	8.7	57.3	1.90	17.3	49.7	1.47	13.4	28.2
3	0.86	7.8	65.1	0.49	4.5	54.2	1.28	11.6	39.8
4	0.77	7.0	72.0	0.44	4.0	58.2	1.27	11.5	51.3
5	0.60	5.4	77.5	0.35	3.1	61.3	1.10	10.0	61.3

Table 1 Extracted factor components.

Extraction method: Maximum likelihood estimation.

Rotation method: Varimax.

VARIABLE (CS ACTIVITY)	FACTOR 1 (SOCIOMATERIAL LEARNING)	FACTOR 2 (SOCIAL LEARNING)	FACTOR 3 (REFLECTIVE LEARNING)	FACTOR 4 (SITUATIONAL LEARNING)	FACTOR 5 (MATERIAL LEARNING)	h^2
Talking and interacting with others (face to face or in online communities)		0.67				0.67
Observing others		0.72				0.69
Searching information from the internet				0.40		0.39
Trial and error			0.68			0.58
Reflecting on your previous knowledge or actions			0.56	0.35		0.54
Reading professional magazines and journals				0.72		0.65
Asking questions	0.46					0.52
Attending a training program or studying the material provided by the project (guides, manuals, etc.)				0.39		0.42
Sharing materials and resources with others	0.41				0.83	1.00
Collaborating with others to do tasks	0.74					0.77
Creating something new (e.g., innovations, art)	0.61					0.52

Table 2 Varimax-rotated factor scores using Spearman correlation matrix.

Note: Factor loadings <.35 are suppressed.

p-value of less than 0.05 was considered as the limit for a statistically significant result.

Since it was possible to select more than one initiator, research area, or goal for a project in the survey (see Survey instrument, items 12, 13, and 14), respondents were first manually grouped based on the project's research area so that each project, along with their initiator and goal, belonged to one of four project groups: biology, history, other natural sciences, and other research areas.

Next, respondents were clustered using K-modes clustering (Chaturvedi, Green, and Caroll 2001) based on individual factors related to experience in CS (i.e., participation in years, regularity of participation, number of projects in which respondents participated, and CS activities in which respondents were engaged in learning). The number of clusters was selected using the elbow method, in which you identify the point where eigenvalues level off. Since the procedure can yield results in locally optimal solutions (Chaturvedi, Green, and Caroll 2001), we repeated it 200 times to obtain stable clustering.

RESULTS

PROJECT-RELATED AND INDIVIDUAL FACTORS: GROUPS AND CLUSTERS

Concerning the first research question (What kind of project-related and individual factors can be identified?), we first manually grouped the respondents based on project-related factors and then clustered respondents based on individual factors. Table 3 presents the project groups and project initiators, in which the project groups are listed vertically (e.g., biology, history, etc.) and the project initiators are listed horizontally (e.g., an association/a non-governmental agency, scientific institution, etc.).

Next, Table 4 presents the project groups and project goals. Like Table 3, the project groups are listed vertically (e.g., biology, history, etc.) and the project goals are listed horizontally (e.g., data/research, education/outreach, etc.).

Regarding participation clusters, we found a four-cluster K-modes solution (Table 5). The descriptive statistics of participation clusters is presented in Table A7 in the Survey data. The four clusters are listed vertically and their corresponding participation characteristics (e.g., participation in CS (years), regularity of participation, etc.) are listed horizontally.

PROJECT-RELATED AND INDIVIDUAL FACTORS ASSOCIATED WITH PERCEIVED LEARNING

For our second research question (How are the project-related and individual factors associated with the perceived learning of citizen scientists engaged in CS activities?), we addressed how the project groups and participation clusters were associated with perceived learning in CS activities. First, we examined the learning factor scores between the project groups (Table 6).

The highest median in sociomaterial learning was in the other research areas group (median = 1.24). The history (0.76) and other natural sciences groups (0.43) had positive median scores, indicating an above-average perceived learning. The sociomaterial learning score median was negative within the biology group (–0.54), indicating a below average perceived learning. The differences between the groups were statistically significant (Kruskal-Wallis test, Table 6), yet the effect size was small (eta squared = 0.05). A Dunn's test (1961) for paired comparisons revealed that the most significant differences were between biology and other research areas groups ($Z = -4.79$, Holm-adjusted $p < 0.001$), and between the biology and history groups ($Z = -3.97$, Holm-adjusted $p < 0.001$).

PROJECT GROUP/ INITIATOR	AN ASSOCIATION/A NON-GOVERNMENTAL AGENCY	SCIENTIFIC INSTITUTION	GOVERNMENTAL AGENCY	INDIVIDUAL OR GROUP OF INDIVIDUALS	OTHER INITIATORS (E.G., OTHER INSTITUTION, BUSINESS, MEDIA)
Biology	127 (44%)	119 (42%)	32 (11%)	27 (9%)	27 (9%)
History	36 (38%)	13 (14%)	9 (9%)	40 (42%)	27 (27%)
Other natural sciences	24 (38%)	21 (33%)	1 (2%)	15 (24%)	6 (10%)
Other research areas	21 (28%)	31 (41%)	8 (11%)	12 (16%)	17 (23%)

Table 3 Project groups and initiators (% of projects in group).

Note: Respondents may have selected multiple project initiators; hence, the percentages do not add up to a 100%.

PROJECT GROUP/GOAL OF THE PROJECT	DATA/RESEARCH	EDUCATION/ OUTREACH	DEVELOPMENT/ INNOVATION	POLICY INITIATIVES/ POLITICAL DECISION-MAKING	OTHER
Biology	197 (90%)	62 (28%)	15 (7%)	14 (6%)	5 (2%)
History	67 (80%)	31 (37%)	7 (8%)	4 (5%)	3 (4%)
Other natural sciences	38 (75%)	18 (35%)	2 (4%)	1 (2%)	1 (2%)
Other research areas	36 (60%)	30 (50%)	16 (27%)	19 (32%)	3 (5%)

Table 4 Project groups and goals (% of projects in group).

Note: Respondents may have selected multiple project goals; hence, the percentages do not add up to a 100%.

CLUSTER	N	PARTICIPATION IN CS (YEARS)	REGULARITY OF PARTICIPATION	NUMBER OF PARTICIPATED PROJECTS	ENGAGED CS ACTIVITIES
1	183	10+	Weekly	2–5	Data collection Discussing results Disseminating results Public outreach for the project
2	200	10+	Weekly	2–5	All CS activities* except providing resources
3	79	10+	Weekly	10+ projects	All CS activities*
4	134	2–5	Once every few months	Just one	Data collection

Table 5 A four-cluster K-modes solution.

* The relevant CS activities are listed in under item 18 (Survey instrument).

PROJECT GROUP/ FACTOR	BIOLOGY	HISTORY	OTHER NATURAL SCIENCES	OTHER RESEARCH AREAS	KRUSKAL-WALLIS TEST p-VALUE (CHI SQUARED, df = 3)
	FACTOR SCORE MEDIAN (INTERQUARTILE RANGE)				
Sociomaterial learning	–0.54 (–2.47, 1.24)	0.76 (–1.01, 2.16)	0.43 (–1.06, 1.98)	1.24 (–0.60, 2.60)	<0.001* (33.21)
Social learning	0.41 (–1.03, 1.08)	0.41 (–0.98, 1.08)	0.36 (–0.98, 1.79)	0.41 (–0.31, 1.79)	0.054 (7.63)
Reflective learning	–0.23 (–0.91, 0.57)	0.39 (–0.19, 1.01)	0.45 (–0.79, 1.13)	0.45 (–0.79, 1.13)	0.01* (11.13)
Situational learning	0.05 (–1.40, 1.13)	0.53 (–0.65, 1.55)	0.04 (–0.71, 1.41)	0.12 (–1.16, 1.91)	0.06 (7.30)
Material learning	–0.27 (–1.33, 0.70)	0.33 (–0.50, 1.09)	0.24 (–0.50, 0.80)	0.38 (–0.50, 1.90)	<0.001* (20.66)

Table 6 Perceived learning scores in project groups.

* Differences between groups are statistically significant.

Social learning score medians were very similar within project groups (Biology, median = 0.41, history, median = 0.41, other research areas, median = 0.41, other natural sciences, median = 0.36). The Kruskal-Wallis test did not indicate differences between project groups (Table 6) and the effect size was small (eta squared = 0.008).

Reflective learning scores were similar within the other natural sciences group (median = 0.45), the other research areas group (median = 0.45), and the history group (median = 0.39). Like the sociomaterial learning score, the reflective learning score median was below zero in the biology group (–0.23). This indicates that perceived reflective learning is below average in this group. According to the Kruskal-Wallis test, the differences between project groups were statistically significant (Table 6), but the effect size was small (eta squared = 0.01). Pairwise comparisons with Dunn's tests (1961) revealed that the statistically significant difference was between the biology and other natural sciences groups (Z = –2.77, Holm-adjusted p = 0.03).

The situational learning medians were quite similar within project groups (History, median = 0.53, other research areas, median = 0.12, biology, median = 0.05, other natural sciences, median = 0.04). According to the Kruskal-Wallis test, the differences in situational learning scores were not statistically significantly different within project groups (Table 6) and the effect size was small (eta squared = 0.007).

Looking at the perceived learning for material learning, the groups other research areas (median = 0.38), history (0.33) and other natural sciences (0.24) had similar medians. The biology group is the only group presented with a negative median (–0.27), indicating a below average perceived learning for material learning. The differences were statistically significant (Table 6), but the effect size was small (eta squared = 0.03). According to Dunn's test (1961), the statistically significant differences were between the biology and history groups (Z = –3.35, Holm-adjusted P = 0.004), and between the biology and other research areas groups (Z = –3.69, Holm-adjusted P = 0.001).

PARTICIPATION CLUSTER / FACTOR	1	2	3	4	KRUSKAL-WALLIS TEST p-VALUE (CHI-SQUARED, df = 3)
	FACTOR SCORE MEDIAN (INTERQUARTILE RANGE)				
Sociomaterial learning	−0.89 (−2.46, 1.02)	1.24 (−0.26, 2.31)	2.03 (0.46, 3.46)	−0.85 (−3.16, 0.63)	<0.001* (127.31)
Social learning	−0.26 (−1.08, 1.08)	0.41 (−0.31, 1.79)	1.08 (0.41, 1.79)	−0.95 (−2.17, 0.41)	<0.001* (86.15)
Reflective learning	−0.23 (−0.91, 0.51)	0.45 (0.26, 1.13)	1.01 (−0.23, 1.69)	−0.67 (−1.47, 0.45)	<0.001* (63.46)
Situational learning	−0.23 (−1.39, 0.87)	0.81 (−0.29, 1.62)	1.10 (0.03, 1.91)	−1.05 (−2.86, 0.09)	<0.001* (83.13)
Material learning	−0.40 (−1.33, 0.70)	0.70 (−0.43, 1.53)	0.70 (−0.13, 1.90)	−0.50 (−1.77, 0.33)	<0.001* (80.93)

Table 7 Perceived learning score medians in participation clusters.

* Differences between clusters are statistically significant.

Next, we examined the perceived learning score medians in participation clusters (Table 7).

The results in Table 7 indicate that diverse participation in CS activities was associated with higher scores in sociomaterial learning, since clusters two and three have the highest medians (1.24, 2.03). In these clusters, citizen scientists participated in CS often and diversely (see Survey data, Table A7). According to the Kruskal-Wallis test, the differences between clusters were statistically significant (Table 7) and the effect was large (eta squared = 0.21). Further examinations reveal that differences were statistically significant between all the clusters except between clusters one and four, which had the lowest score medians in sociomaterial learning (see Survey data, Table A6).

Similar observations can be seen in other learning factors. For all factors, the third cluster of citizen scientists with long experience in CS, and who participated frequently in multiple CS projects, had the highest perceived learning (social learning median = 1.08, reflective learning median = 1.01, situational learning median = 1.10, material learning median = 0.70). Correspondingly, perceived learning was lower in the clusters that had fewer participated CS projects and a few engaged CS activities. For all factors, the effect size was either medium or large (social learning, eta squared = 0.14; reflective learning, eta squared = 0.10; situational learning, eta squared = 0.14; material learning, eta squared = 0.13). The pairwise differences between factors are statistically significant in all comparisons except between clusters two and three (see Survey data, Table A6). When comparing scores for material learning, the difference between the first and the fourth participation clusters is not statistically significant.

DISCUSSION

Our aim was to understand project-related and individual factors so that we could investigate how they are associated with the perceived learning of citizen scientists engaged in CS activities. We initially focused on the relationship between 11 different CS activities for perceived learning and were able to identify the following five factors: sociomaterial learning, social learning, reflective learning, situational learning, and material learning. These factors highlight the different relationships that exist between CS activities and perceived learning. In sociomaterial learning (factor 1), citizen scientists perceived learning through sociomateriality, i.e., when interacting with others to perform group work or inquiry in combination with creating and distributing material or resources. In social learning (factor 2), citizen scientists perceived learning primarily through social interaction that involved observation of and discussion with others. In contrast, in reflective learning (factor 3), citizen scientists perceived learning through the self by means of personal reflection and experimentation. Next, in situational learning (factor 4), citizen scientists perceived learning through the sociomaterial combination of unstructured situations (e.g., reading magazines, searching for information on the internet) and structured situations (e.g., attending a training session). Finally, in material learning (factor 5), citizen scientists perceived learning through the distribution of materials and resources to others.

Project-related factors were manually grouped based on research area, which included their corresponding initiator and goal. We found that perceived learning was lower for citizen scientists who participated in biology CS projects, especially regarding sociomaterial learning, reflective learning, and material learning, and the difference with other projects, initially, seemed to be significant. However, the effect size was small, which means it is difficult to say to what degree biology CS projects in our survey lacked CS activities that were sociomaterial-based (e.g., group work along with sharing resources), self-directed (e.g., trial and error), or material-based (e.g., sharing materials). In a similar study, Peter et al. (2021) found that the training offered to citizen scientists in biodiversity CS projects does not typically incorporate enough opportunities for practice or reflection. Also, most citizen scientists collected data alone, and collaborative work, such as material sharing or group work, was uncommon (Peter et al. 2021). In their systematic study of environmental and nature-based CS projects, Vasiliades et al. (2021) found that 80% of citizen scientists primarily engaged in data collection that did not require "physical or intellectual effort" and that project leaders mainly focused on discussing the project data when communicating with citizen scientists (p. 10).

However, perceived learning for citizen scientists who participated in biology CS projects seemed to be on par with other CS projects regarding social learning, and then similar to other CS projects regarding situational learning. While this suggests that CS activities for social interaction (e.g., talking with others) as well as structured situations (e.g., attending a training session) and unstructured situations (e.g., searching for information on the internet) are present, it is important to note that the effect size was, yet again, small. Regarding biology CS projects, Peter et al. (2021) also found that perceived learning was positively associated when citizen scientists could interact with other citizen scientists, project staff, and professional scientists, receive information regarding the project, attend training, and receive feedback or recognition for their participation. Vasiliades et al. (2021) discovered that "aspects related to training and recruiting" were the next two frequent topics in communication within projects (p. 10), and that the primary science goal of projects was to provide citizen scientists with an "understanding of scientific content and knowledge" (p. 9). Interestingly, although it was possible to select multiple project goals in our survey, we noticed that the most common goal indicated by citizen scientists for biology CS projects was data or research, which may suggest that the scientific component of a project (e.g., data collection and analysis) takes precedence over education. Comprehensive training sessions that include clear learning goals and equip citizen scientists with the necessary knowledge or tools for tackling potential epistemological and ethical challenges arising during participation can promote the sustainability and thus eventual completion of CS projects (Roche et al. 2020; Vallabh et al. 2016).

Regarding individual factors, they were clustered based on participation in CS (in years), regularity of participation, number of projects in which citizen scientists participated, and CS activities in which citizen scientists were engaged in learning. We found that citizen scientists who engaged in a variety of CS activities perceived greater learning regarding sociomaterial learning. We also noticed that citizen scientists who participated in CS for a longer duration (i.e., 10 or more years) and engaged in a variety of CS activities had the highest perceived learning. On the one hand, prior experience such as education may be relevant as it can enhance the ability to, for example, search for information on the internet and read professional literature, leading to an increase in perceived learning during these CS activities. While researchers disagree on the demographics of citizen scientists (e.g., Hart et al. 2022), it has been found that training and similar support is crucial for citizen scientists who have a lower secondary education background (Bruckermann et al. 2020; Roche et al. 2020).

On the other hand, while exploring motivation is a challenging topic in CS research, CS shares similarities with volunteerism, which Finkelstien (2009) argues to be intrinsic. As citizen scientists continue to participate in CS projects, their motivation tends to shift over time from egoism (extrinsic) to collectivism (intrinsic) (Land-Zandstra et al. 2021). Smith et al. (2021) underscore that citizen scientists "with intrinsic motivations have greater participation frequency and duration" in CS projects (p. 14). Data collection is often the primary role of citizen scientists, and in fields such as biology, it is commonly done alone, even though citizen scientists have other important personal motivations such as contribution to science and/or society, social engagement, personal rewards, or growth. Some citizen scientists may be motivated to begin or continue their participation because they have identified a connection between the project's characteristics and their own identity and values (Roche et al. 2020; Vasiliades et al. 2021; West, Dyke, and Pateman 2021). To better understand the connection between the project and citizen scientists, we turn to the MODEL-CS.

The MODEL-CS underscores how the goals and motivations of professional scientists and citizen scientists converge during the foundation of a project. However, at the end of the project, they are likely to diverge as citizen scientists and professional scientists focus on the relevant outcomes, which may affirm or alter future goals and/or motivation. In addition, the roles of professional scientists and citizen scientists shift as the project unfolds. While professional scientists offer certain learning opportunities, it is the citizen scientists who provide the input or labor through engaging in various CS activities. However, CS activities can occur in different territories and thus have their own affordances and limitations for perceived learning through, for example, the allocation of resources and materials, the explication of learning goals, instructions, and feedback, or the infrastructure for supporting collaboration (Bruckermann et al. 2020).

According to Vasiliades et al. (2021), nearly half (48%) of environmental and nature-based CS projects were launched in local communities (p. 8). As explained earlier, since learning is usually semi-structured in this territory, CS projects do not always make learning goals explicit, supply learning materials and resources, or provide recognition, even though citizen scientists participate to learn in addition to their other goals and motivations such as taking practical actions in solving local issues (Roche et al. 2020; West, Dyke, and Pateman 2021). This may generate a conflict of interest as discussed by Roche et al. (2020) and thus discourage participation. There were citizen scientists from our survey who strongly perceived learning through participating long-term and frequently in different projects and thus had engaged in a variety of CS activities. Stepping into different territories may allow citizen scientists to supplement any previous gaps experienced on, for example, learning, as well as to discover CS projects that are more personally relevant.

It is important to note that there were magnitude differences between the effect sizes for project-related and individual factors. Overall, the effect size for individual factors was larger than for project-related factors, suggesting that the characteristics of citizen scientists may be more important regarding differences in perceived learning than the characteristics of projects. To better grasp the characteristics of citizen scientists and, potentially, address issues regarding, for example, training, experience, or recognition, project initiators could consider the idea of accreditation, or the systematizing of skills, competences, and experiences (West and Pateman 2016). The research by Herodotou et al. (2020) and the online CS platform SciStarter (https://scistarter.org/) may provide possible approaches in developing accreditive practices.

In their analysis of young citizen scientists (ages 16 to 19 years old) participating in Zooniverse projects, Herodotou et al. (2020) generated five engagement profiles, which revealed the degree of engagement and contribution to a project as well as project preference. Next, SciStarter hosts training modules that address not only general knowledge of citizen science, but also the topics related to projects. Citizen scientists can improve or review their understanding as well as earn badges that can be linked to their profile through completing modules. Project initiators on SciStarter can discern certain skillsets or knowledge by badge type and experience through badge variety. On the one hand, the creation of profiles may enable an organized understanding on the behavior of citizen scientists, which could be used to address issues relating to participation frequency and activity preference. On the other hand, the learning modules and badges on SciStarter could represent a potential method for tackling issues relating to training and recognition.

LIMITATIONS

Regarding limitations in our research data, the survey was disseminated via public social media campaigns, projects that could be on the internet, and direct personal contact. The use of snowball sampling (Goodman 1961) may have influenced the structure of the survey data. Therefore, there may have been CS projects unknown to researchers and thus excluded from receiving the survey. Finally, the size and visibility of a CS project may have affected its accessibility.

Additionally, many citizen scientists do not identify themselves as such (Haklay 2013), and it should be acknowledged that some audiences might find the term “citizen” problematic and want to avoid it altogether (Eitzel et al. 2017). Instead, many citizen scientists identify themselves as volunteers or hobbyists. Although we provided a popularized description of citizen scientists’ CS activities, some may have felt that they did not belong to the target group.

Furthermore, the survey was not uniformly distributed across the world. There was an uneven distribution as 89% of respondents are European. The effects of the skewed geographical nature of the survey data will be further examined in future publications. In addition, a dropout analysis revealed that more experienced citizen scientists were more likely to complete the survey, which means there is likely an attrition bias in our subsample. Despite these limitations, our study sheds more light on the current practices of CS. Even though there are studies on learning in CS, many of them focus on learning within individual projects and/or disciplines. Our study addresses the European-level challenge to observe and analyze the current state-of-art across various projects and disciplines, and we were able to reach a large group of active citizen scientists who were able to provide insights on learning in CS activities.

CONCLUSION

In our study, we discussed how CS occurs in different sociomaterial settings known as territories, which entail formal, informal, or nonformal learning, and we reviewed a model for learning to identify and investigate the project-related and individual factors associated with the perceived learning of citizen scientists engaged in CS activities. While each CS activity may foster learning, when considering the relationship of those listed in our survey using EFA, sociomaterial learning, social learning, reflective learning, situational learning, and material learning emerge. We found that the differences and similarities in perceived learning regarding sociomaterial learning, social learning, reflective learning, situational learning, and material learning may relate to the research area of a CS project (e.g., biology), or the citizen scientist's experience in CS (i.e., participation in CS (in years), regularity of participation, number of projects in which citizen scientists participated, and CS activities in which citizen scientists were engaged in learning). When considering effect sizes, it seems that individual characteristics relating to experience in CS are more significant to perceived learning than project characteristics such as research area, but this finding could have been partly related to the subsample used in this study. Overall, our study builds on the work by Peter et al. (2021) through the incorporation of the MODEL-CS, which allowed us to not only unravel the intertwined relationship between project-related and individual factors, but also highlight the overall cycle of learning for citizen scientists.

DATA ACCESSIBILITY STATEMENT

The CS Track survey data is not publicly available. Requests for human subject educational research data can be made by email to Raija Hämäläinen (raija.h.hamalainen@jyu.fi).

NOTES

Our survey is designed for adults and no parental consent is needed from those who are 16 years old or older. All survey participants provided their informed consent to be surveyed. The survey does not include ethically sensitive or problematic topics as well as providing a "prefer not to answer" choice to certain questions such as gender.

SUPPLEMENTAL FILES

The supplemental files for this article can be found as follows:

- **Supplemental File 1.** Survey instrument. DOI: https://doi.org/10.5334/cstp.485.s1
- **Supplemental File 2.** Survey data. DOI: https://doi.org/10.5334/cstp.485.s2

ETHICS AND CONSENT

This research was carried out with the University of Jyväskylä (JYU), which follows the guidelines of the Finnish National Board on Research Integrity. JYU provides researchers with assessments of and consultation on ethical questions in the form of the Human Sciences Ethics Committee, which aims to promote the development of ethical and responsible research.

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COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the study as follows: study conception and design: all authors; data collection: Lampi, E., Sabel, O.; Hämäläinen, R.; analysis and interpretation of results: Peltoniemi, A.J., Kauppinen, H., Lämsä, J., Sabel, O., Hämäläinen, R.; draft manuscript preparation: all authors, but led by Peltoniemi, A.J. and Kauppinen, H. All authors reviewed the results and approved the final version of the manuscript.

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