PREPRINT

Author-formatted, not peer-reviewed document posted on 18/03/2022

DOI: https://doi.org/10.3897/arphapreprints.e83854

People-Powered Research and Experiential Learning: Unraveling Hidden Biodiversity

Melanie Pivarski, Matt von Konrat, Thomas Campbell, Ayesha Qazi-Lampert, Laura Trouille, Aimee Davis, Selma Aburahmeh, Joseph Aguilar, Cosmin Alb, Ken Alferes, Ella Barker, Kelli Boulware, Sicong Cao, Christine Christian, Arturo Corona Jr., Kaltra Demiri, Daniel Evans, Connor Flavin, Victoria Gogol, Elizabeth Heublein, Edward Huang, Jake Hutchinson, Cyrus Jackson, Odaliz Jackson, Michi Kirihara, Annette Kowalczyk, Alex Labontu, Briajia Levi, Sylvie Martin-Eberhardt, Joann Martinec, Pansy Nguyen, Sarah Nolimal, Victoria Reese, Joannie Rodriguez, Yarency Rodriguez, Jacob Shuler, Jasmine Silvestre, Glenn Simpson, Gabriel Somarriba, Rogers Ssozi, Tomomi Suwa, Cheyenne Syring, Keith Thompson, Caitlin Vaughn, Mario Viramontes, Chak Shing Wong

ARPHA Preprints Author-formatted, not peer-reviewed document posted on 18/03/2022. DOI: https://doi.org/10.3897/arphapreprints.e83854

People-Powered Research and Experiential Learning: Unraveling Hidden Biodiversity

Melanie Pivarski[‡], Matt von Konrat[§], Thomas Campbell[|], Ayesha T. Qazi-Lampert[§], Laura Trouille[¶], Aimee Davis[#], Selma Aburahmeh[|], Joseph Aguilar[‡], Cosmin Alb[‡], Ken Alferes[‡], Ella Barker[‡], Kelli J. Boulware[‡], Sicong Cao[‡], Christine Christian[‡], Arturo Corona Jr.[‡], Kaltra Demiri[‡], Daniel Evans[‡], Connor Flavin[‡], Victoria Gogol[‡], Elizabeth Heublein[‡], Edward Huang[¤], Jake Hutchinson[‡], Cyrus Jackson[§], Odaliz Rubee Jackson[‡], Michi Kirihara[‡], Annette Kowalczyk[‡], Alex Labontu[‡], Briajia Levi[¤], Sylvie Martin-Eberhardt[«], Joann Lacey Martinec[§], Pansy Nguyen[»], Sarah Nolimal[˄], Victoria Reese[#], Joannie Rodriguez[‡], Yarency Rodriguez[§], Jacob Shuler[˅], Jasmine Silvestre[‡], Glenn Simpson[|], Gabriel Somarriba[¦], Rogers Ssozi[‡], Tomomi Suwa[ˀ], Cheyenne Syring[‡], Keith Thompson[˅], Caitlin Vaughn[§], Mario R Viramontes[‡], Chak Shing Wong[‡]

‡ Roosevelt University, Chicago, United States of America
§ Field Museum, Gantz Family Collections Center, Chicago, United States of America
| Northeastern Illinois University, Chicago, United States of America
¶ The Adler Planetarium, Chicago, United States of America
# Field Museum, Learning Center, Chicago, United States of America
¤ University of Illinois at Urbana-Champaign, Champaign County, United States of America
« Michigan State University, East Lansing, United States of America
» Connecticut College, New London, United States of America
˄ DePaul University, Chicago, United States of America
˅ Field Museum, Visitor Services & Analytics, Chicago, United States of America
¦ University of Florida, Gainsville, United States of America
ˀ Field Museum, Keller Science Action Center, Chicago, United States of America

Corresponding author: Matt von Konrat (mvonkonrat@fieldmuseum.org)

Reviewable v 1

Abstract

Globally, thousands of institutions house nearly three billion scientific collections offering unparalleled resources that contribute to both science and society. For herbaria alone - facilities housing dried plant collections - there are over 3,000 herbaria worldwide with an estimated 350 million specimens that have been collected over the past four centuries. Digitization has greatly enhanced the use of herbarium data in scientific research, impacting diverse research areas, including biodiversity informatics, global climate change, analyses using next-generation sequencing technologies, and many others. Despite the entrance of herbaria into a new era with enhanced scientific, educational, and societal relevance, museum specimens remain underused. Natural history museums can enhance learning and engagement in science, particularly for school-age and undergraduate students. Here we outline a novel approach of a natural history museum using touchscreen technology that formed part of an interactive kiosk in a temporary museum exhibit on biological specimens. We provide some preliminary analysis investigating the efficacy of the tool, based on the Zooniverse platform, in an exhibit environment to engage patrons in the collection of biological data. We conclude there is great potential in using crowd-sourced science coupled with online technology to unlock data and information from digital images of natural history specimens themselves. Sixty percent of the records generated by community scientists (citizen scientists) were of high enough quality to be utilized by researchers. All age groups produced valid, high quality data that could be used by researchers, including children (10 and under), teens, and adults. Significantly, the paper outlines the implementation of experiential learning through an undergraduate mathematics course that focuses on projects with actual data to gain a deep, practical knowledge of the subject, including observations, the collection of data, analysis, and problem solving. We here promote an intergenerational model including children, high school students, undergraduate students, early career scientists and senior scientists, combining experiential learning, museum patrons, researchers, and data derived from natural history collections. Natural history museums with their dual remit of education and collections-based research can play a significant role in the field of community engagement and people-powered research. There also remains much to investigate on the use of interactive displays to help learners interpret and appreciate authentic research.

Keywords

analysis, biodiversity, bryophytes, citizen science, crowd-courced science, community science, experiential learning, families, interdisplinary research, intergenerational participation, K-12, museum, people-powered research, taxonomy, undergraduate students

Introduction

Globally, thousands of institutions house nearly three billion scientific collections, each of which can have multiple layers of associated metadata (Holmes et al. 2016, Sweeney et al. 2018). Extensive, professionally managed natural history collections, with their broad taxonomic, geographic, and temporal scope, offer unparalleled resources that contribute to both science and society (e.g. Graham et al. 2004, Berendsohn and Seltmann 2010, Hedrick et al. 2019). Digitization has greatly enhanced the use of herbarium data in scientific research, impacting diverse research areas, including biodiversity informatics, global change biology, analyses using next-generation sequencing technologies, and many others (Bebber et al. 2010, Heberling and Isaac 2017, James et al. 2018, Lang et al. 2019, Soltis et al. 2018). Digitization of specimen records and their associated data will provide unparalleled educational resources that can be tailored to diverse audiences (e.g., professional scientists, students- biology majors and non-majors, and the general public; (Cook et al. 2014). Natural history museums can enhance learning and engagement in science, particularly for school-age students. Recently, we reported the use of an online web-based tool using a crowd-sourced model that produces quality taxonomic data sets and enriches engagement through real contributions to science (von Konrat et al. 2018). Here we outline a novel approach of a natural history museum using touchscreen technology that formed part of an interactive kiosk in the temporary museum exhibit *Specimens: Unlocking the Secrets of Life* (*Field Museum 2016*). Participation in authentic research experiences is an important component in moving youth toward engaging in meaningful scientific thinking and preparing them to enter a modern workforce where STEM plays a central role (National Research Council 2010). We provide some preliminary analysis investigating the efficacy of the tool in an exhibit environment to engage patrons in the collection of biological data. Significantly, we demonstrate the collaborative role that experiential learning played in this process for university students. From 2020 through 2021, a group of mathematics, actuarial science, data analytics, and computer science students from Roosevelt University, Chicago, U.S.A. worked on data cleaning, processing, and analysis for this project. This was completed during the course, Industrial Applications of Mathematics at Roosevelt University; this course was developed in conjunction with the Preparing for Industrial Careers in Math (PICMath) program (MAA 2021). Both this course and the PICMath program seek to give students an authentic experiential learning experience involving real problems in order to prepare them for future careers in mathematics, actuarial science, and data analysis. Experiential learning consists of contextually rich concrete experience, critical reflective observation, contextual-specific abstract conceptualization, and pragmatic active experimentation (Morris 2019). Working with real data introduces a variety of technical challenges; overcoming these provides a firm grounding for students in their future careers (Dorff and Weekes 2019). Much like a direct experience analyzing real specimens gives an enhanced learning experience to museum patrons, experiential learning courses involving community partners are a high impact educational practice (Kuh 2008). By engaging the public in measuring the specimens, having biology interns observe and report on the measuring process, and having university students perform the data analysis on these, the project ceases to be simply a scientific analysis and instead becomes a true community endeavor. There was broad participation across a range of ages, career stages/paths, and disciplines. We conclude there is great potential in using crowd-sourced science coupled with online technology to unlock data and information from digital images of natural history specimens themselves. Significantly, this provides an ongoing opportunity for student growth through experiential learning. Throughout this project we recognize the valuable contributions of all participants to both the data and the analysis. Large projects that involve crowd-sourced science or participatory science are often referred to as 'citizen science' (Eitzel et al. 2017). Recently there has been a lot of discussion and debate that this term is not inclusive (e.g., Heigl et al. (2019), Auerbach et al. (2019)). Throughout the manuscript we use the words 'people-powered research' and 'community science' interchangeably in order to emphasize the key role of the community - including students, museum patrons, faculty, and scientists. We also use the phrases 'community scientist' and participants to refer to the museum patrons who generated data. Defining these terms and indicating alternative terms to 'citizen science' follows recommendations and strategies promoted by Eitzel et al. (2017) in order to avoid confusion. We acknowledge that this differs from many uses of the phrase 'community science' which instead emphasize scientific questions which originate in the community itself (Pandya 2019).

Objectives

We wanted to apply and develop the statistical and computational expertise of college students to determine the scientific quality of data generated by museum patrons.

Specifically, our objectives are to determine the following:

1. Are the general public able to provide usable real data?
2. To what scale is real usable data generated (i.e. over 70% for example)?
3. To what scale can different age groups (demographics) generate usable data?
4. Is there a difference in the setting of the kiosk - i.e., one where a facilitator is available (in the Science Hub) versus non-facilitated (in the *Specimens* exhibit)?
5. To explore the effectiveness of public participation in a museum setting.

We also seek to demonstrate how this exercise was driven by student work in a formal class setting. Although this was part of an industrial mathematics course at Roosevelt University, this type of university and museum collaboration could be replicated by partnerships between educators and museums seeking to work with community generated data on a large scale. An underlying goal, as demonstrated below, was for students to develop a series of publicly accessible computational tools for data curation, validation, and analysis.

History of the collaboration

Herbaria are reservoirs of both well-documented specimens and undescribed diversity (Bebber et al. 2010). New species are described each year from specimens that have been housed in collections for decades, if not centuries. However, the pace of such discovery is slow, especially for non-angiosperms, and accelerating the process of discovery is expensive (Soltis et al. 2018). In order to help overcome this, Field Museum began partnering with educational institutions in the greater Chicago area in 2012, developing the MicroPlants project where students and the general public would generate data as community scientists aiding taxonomists (von Konrat 2012). There were many benefits, especially connecting natural history collections to education. Students, in particular, would have a hands-on experience where they could contribute to scientific discovery in a way that could be used in introductory biology courses as well as K-12 settings. Teachers who were not experts in botany or the life sciences could easily incorporate this into their courses. Our group provided an outline describing a model of a crowd-sourced data collection project that produces quality taxonomic data sets and empowers community scientists through real contributions to science (von Konrat et al. 2018). The project is an ongoing collaboration between taxonomists, community science experts, teachers, and students from both universities and K–12. Scientists, who have more specimens than taxonomists can measure or observe, in this case, could use these student measurements to accelerate the pace of discovery. As a result of meetings between Field Museum scientists, faculty from many institutions, students, and community scientist experts, an online web-based version was developed for the Zooniverse platform (Zooniverse 2021b). Classes could meet in a computer lab at their home institutions and generate measurement data contributing to authentic research. The project became surprisingly popular receiving media attention, (e.g., Cimons (2018), Ruppenthal (2018)) and in 2017 had over 11,000 participants who generated almost 100,000 measurements. As data was collected, it became clear that due to the size and complexity of a real unculled dataset it would need to be cleaned and analyzed using more advanced techniques and semi-automated tools, and so collaborations with mathematics faculty occurred. An analysis of the web data showed excellent results (von Konrat et al. 2018), and an updated version of the project involving new images was created for a touchscreen kiosk for the Field Museum. This kiosk differed from the classroom setting not only because there was no instructor assistance for data collection, only an explanatory walk through via an optional onscreen tutorial, but also in its physical setting. The question of whether this new interface would lead to a usable data set remained.

Materials and methods

Outlined below are the process and methodology including development of the kiosk, data collection, data analysis, and data validation. All data was taken in units of pixels and for simplicity of presentation we present results in units of pixels; however, the images were consistently scaled so that pixels can be converted into microns via the conversion 1 pixel= 1.05 microns.

Experiential learning and interdisciplinary science

Experiential learning foregrounds the crucial role experience takes in the learning process (Kolb et al. 2014). According to Kolb (1984), learning involves four cyclical stages; concrete experience, reflective observation, abstract conceptualization, and active experimentation. A strong experiential learning experience in data analysis involves a set of real data, questions of interest to the partner, and domain knowledge for the data. All of these elements require an ongoing communication between the mathematics students and scientists. Interactions between biologists and math students occurred in the 2020 and 2021 Industrial Applications of Mathematics class at Roosevelt University. Biologists visited the class, at the start of the semester in person and regularly on Zoom, to present the overarching project, raw datasets of both measurements and demographics, the discoveries so far, and background information. Students problem solved to determine how to process the data, validate and improve upon initial processing and cleaning, and analyze the data. The biologists joined the class every few weeks to both pose and answer questions about the data, kiosk set up, and the biological underpinnings. Complimenting the experiential learning model, the students engaged in interdisciplinary collaborative community science experience where they worked along with the scientists to unpack raw data, reflect on the data, think about the data, and act on how to apply this data in a meaningful way for stakeholders. For over a decade, the need to accelerate the adoption of interdisciplinary approaches has been recognized in an era of vast data sets (Derrick et al. 2011). The biologists were also able to help focus the research in a direction that was most meaningful for their needs. In a typical semester, students would visit the museum, interact with scientists, and gain exposure to scientific natural history collections in order to put the science and industrial questions into context. However, due to the global pandemic, this was achieved remotely and virtually. An earlier web version of the Zooniverse MicroPlant project allowed youth participation where high school students engaged in making leaf measurements remotely on their own devices which was an experience similar to the kiosk. This helped the students to understand the experimental set up and to pose relevant data questions. At the end of the spring 2020 section of the course, many questions about selected images were answered, but others about the large-scale dataset remained. There was some student work on the project over the summer, and then in spring 2021 the second group of mathematics students worked intensively with this dataset and biologists to expand upon the previous student work and complete the data analysis.

Research organism and biological context

The MicroPlants project focuses on a group of early land plants often referred to as bryophytes. Bryophytes, including mosses, liverworts, and hornworts, are the second largest group of land plants after flowering plants and are pivotal in our understanding of early land plant evolution (e.g., Ligrone et al. (2012), Zhang et al. (2020)). Bryophytes play a significant ecological role including CO_2 exchange (DeLucia et al. 2003), plant succession (Cremer and A.B.. 1965), production and phytomass (Frahm 2008), nutrient cycling (Coxson 1991), and water retention (Pócs 1980). Bryophytes, together with lichens, serve as the “macrophytes,” providing a matrix where many microscopic organisms live, including tardigrades, mites, rotifers, micro-mollusks, microalgae, microfungi, and prokaryotes (Gerson 1982, Huttunen et al. 2017). For the MicroPlants project we focused on the liverwort genus *Frullania* (Fig. 1). This genus has a worldwide distribution and is one of the largest and taxonomically most complex genera of leafy liverworts with more than 2,000 published names (Hentschel et al. 2015). Specifically, participants were asked to measure a modified leaf, or lobule (Fig. 1), from digitally rendered images.

Development and description of the kiosk

Given the success of the web based MicroPlant project on Zooniverse, the Field Museum adapted the measurement tool to a touchscreen kiosk which was first used in the exhibit *Specimens: Unlocking the Secrets of Life* of the Field Museum. This was a special exhibit which ran from March 10, 2017, through January 7, 2018 showcasing the museum's collection of over 30 million specimens and their ongoing scientific potential. Museum patrons, who had just viewed many of the typically hidden scientific specimens, were able to interact with digitized versions of liverwort specimens on the kiosk so that they too could contribute to scientific discovery (Fig. 2).

After the *Specimens* exhibit closed, the kiosk was updated to include a survey question about the participant's age group. The kiosk then became one of the rotating exhibits in the Grainger Science Hub (Field Museum 2021) where it was used in 2018. After it was retired from the Science Hub, it made appearances at Field Museum Member Nights and at ad hoc events.

Data collection from kiosk

Initially, the kiosk was located in the *Specimens: Unlocking the Secrets of Life* exhibit at the Field Museum. For this phase of data collection, the general public interacted with the kiosk, viewing a brief instructional demonstration which was programmed into the kiosk that showed them an animation of how to measure the length and width of lobules along with the need for these line segments to be perpendicular. They then viewed a randomly displayed MicroPlant image. The image contained a stem of the plant with a various number of lobules, typically between 1 and 10 lobules (Fig. 1), which participants would measure using the touchscreen (Fig. 2). During the course of 24 days in 2017, staff, students, and volunteers unobtrusively observed and collected demographics on who was using the touchscreen. Later, these were matched with the corresponding kiosk measurements in the data processing phase.

Because these demographic observations were labor intensive, there was a desire for participants to self-classify their demographics; this would also increase accuracy. When the kiosk moved to the Science Hub in 2018, it included a brief demographic survey for participants to fill out. This survey allowed participants to pick one category or to skip the question. However, the survey did not automatically reset between each participant. Demographic information was collected over a 48 day period in 2018. The demographic results were saved separately from the kiosk lobule measurements, and these files were matched in the data processing phase (Table 1).

Initial data processing

Students in the 2020 and 2021 Industrial Applications of Mathematics course at Roosevelt University were tasked to clean and analyze data generated by museum participants and demographic data collected by interns (Fig. 3).

Pre-processing of crowd-sourced data

Any time a person presses the submit button on the kiosk, the kiosk records the data and transfers the image measurements to a comma separated variable (csv) file. Each image was labeled with a unique subject identification number for ease of analysis. In the csv file, each submission receives its own line whether it has measurements or not. The csv file includes the image ID, x and y coordinates, timestamp, degree of angles, and other information, in a json format. There will be multiple measurements for each image because the kiosk displays each image on multiple occasions. If a particular image was measured ten times, the csv file will add a new line per new measurement for a total of ten separate lines. Using the language PowerShell, we performed an initial extraction and cleaning of the data which removed unnecessary notation and made a clean csv file which could be used for data analysis.

There was a second set of demographic information for data collected in the Science Hub in 2018 and data collected in the *Specimens* exhibit in 2017. For the 2018 data, these demographic records were recorded on the kiosk itself by museum patrons. For the 2017 data, these records were recorded by a set of interns who observed museum patrons using the kiosk. Each of these was matched to the line segment data from the kiosk using timestamps via Excel VBA. This matching process was verified for samples of the data to guarantee computational accuracy. The initial matched data set, without cleaning, will be considered *all data*. All data includes anything that was submitted through the kiosk by pressing the submit button along with the associated demographic information.

Data cleaning

Once the measurement and demographic data were aligned into a single file, it was important to extract the measurements involving intersecting pairs of line segments. Missing data is data missing one or two lines of measurements. For example, someone could have pressed the submit button without taking any measurements. Another scenario, someone could have tapped the screen leaving only one line as a measurement and then pressed the submit button. Invalid data is data with any measurements of two or more lines that do not intersect. Potentially valid data is any data with an intersecting pair of lines regardless of location on screen. Once this initial data parsing process was done and the data was cleaned so that all invalid data was removed, we performed some manual checks to verify the accuracy of the initial cleaning process. This stage of the data processing is objective; there are no judgements that needed to be made about the quality. It resulted in an excel file where each row in the excel file corresponded to a pair of intersecting line measurements along with the corresponding image and demographic information. We also kept a record of the submitted measurements that had only invalid measurements in order to determine the percentages of high quality data that came from each demographic category.

Advanced data cleaning

Once the data was split into a csv file where each row corresponded to a unique pair of intersecting lines, it was necessary to determine which data was of sufficiently high quality to use. Because the kiosk specified that pairs of line segments should intersect at 90 degree angles, an initial cut was made to all data based on the angle measured. *Good data* is any data with an intersecting pair of lines that have an angle 80 degrees or above. After an analysis comparing to an expert was performed, a second set of cuts using the interquartile range (IQR) independently for each axis was made to remove outliers (Zwillinger and Kokoska 2000). To calculate the IQR cut for each axis, we first split the dataset into quartiles (Q_0=min ,Q_1, Q_2=median, Q_3, Q_4=max) and set IQR = Q_3-Q_1. We keep all data that is in the range from Q_1-1.5*IQR to Q_3+1.5*IQR (Table 2).

Determining an appropriate cutting schema using expert measurements

The images were measured by experts in order to test the validity and quality of data. In order to determine the best way to find accurate lobule measurements from the data, we plotted data gathered from the public from one of these images (ID No. 8735482) along with expert measurements of the same image to see how accurate the angle cuts were. We used this first image to guide our cleaning process, and then after we determined the process, we verified it with a second image. Our goal is to have a set of cuts that leaves us with public data that gives the same axis lengths as the expert data does. We assumed that images that contained multiple lobules from the same specimen would have near identical sizes for those lobules; this meant we would be able to average over them.

Comparing the expert data with the public data from the first image, we can say that (17/119) = 14.3% of all good data had both small and large axis lengths within the expert's min and max measurements. Similarly, (47/119) = 39.5% of all good data had small and large axes within 10 pixels of the expert's average measurements. There were many outliers. The angle cuts alone didn't remove data where people measured background leaves or partial lobules, and the background leaves and partial lobules had a noticeably different size than the intended lobules. The outliers from the background leaves skewed the averages--using just the angle cuts, the resulting averages differed from the expert by a large amount and the standard deviations in the public measurements were large. Because we wanted a way to cut outliers that didn't rely on the expert data, we decided to use IQR cuts to remove these outliers (Table 3), and we plotted the result for the individual endpoints of the line segments that were measured by the public. When these points are far from the lobule's edge, it indicates an inaccurate measurement. Although this technique kept one set of measurements from a partially obscured lobule, it produced a more accurate set of measurements which was strongly clustered on the image as well as a more accurate pair of averages (Fig. 4,Fig. 5).

Validation via a second expert image measurement

In order to verify that our process of cleaning and cutting the data leads to measurements which are close to expert measurements, we applied the process to a second image. This image (ID. No. 25352420) had not been used to determine the data cleaning procedure, so it is a useful way to check that our procedure was not biased by the image used to create it. For this image (ID. No. 25352420), the expert predicted the smaller axis length to be 96.49 pixels with standard deviation of 3.99, and the larger axis to be 193.79 pixels with a standard deviation of 2.92. When the general public measured it, they found (after cutting for angle and outliers using IQR) that the smaller axis length to be 97.34 pixels with standard deviation of 8.34, and the larger axis to be 187.83 pixels with standard deviation of 6.17. These are statistically the same. This is evidence that removing faulty data using the IQR bounds leads to a dataset which can produce a good measurement (Table 4).

Processing the IQR range for the full dataset

For each image, an image-specific interquartile range (IQR) was found for both the major and minor axes in the remaining good data. One can determine statistical outliers by considering only data that is within 1.5*IQR of the middle quartiles. This was used to remove data that was an outlier for one or both axes. For the two sample images, we computed these manually in Excel. In order to extend this to all of the different images, these calculations were done both in Python and using Excel pivot tables. By comparing the two programming solutions with the manual ones, we were able to verify their correctness. Note that unlike an angle cut, this type of cut depends on all of the data that has been collected for an image. Because of this, there may be variations in whether a particular set of measurements is cut when new data is added to the analysis.

Examples of measurements on the kiosk

Fig. 6 is an example of a pair of lines that do not intersect, known as invalid data. The image is an example of a data entry that would not meet our qualifications for good data, or IQR range data. However, this is the kind of data that will be under the category of all data because all data accepts any data entry regardless of quality.

Fig. 7 passes the qualifications for potentially valid data, a pair of intersecting lines. This is an example of a pair of lines that intersect with an angle of 33 degrees. This image is an example of a data entry that would not meet our qualifications for good data or IQR range data. However, this is the kind of data that will be under the category of all data and valid data.

Fig. 8 passes the qualifications for good data, a pair of lines that intersect and form an angle of at least 80 degrees. This is an example of a pair of lines that intersect with an angle of 88.6 degrees. This is an example of a data entry that has the potential to pass the qualifications of the IQR range data. This is also the kind of data that will be under the category of all data, good data, and potentially IQR range data.

Results

Overall, measurements were of high quality. Significantly, all age groups produced data that could be used by researchers, including children (10 and under), teens, and adults. The clustering of measurements obtained by these groups with the expert measurements can be visualized in Fig. 5. Regarding measurement retention, our initial predictions were that around 50% of measurements would make it through the IQR cut process and that the older the age group the more measurements would be retained. It was thought that children 10 and under would have more inconsistent measurements than the other age groups simply due to their young age. After our statistical data cleaning, 60% of the initial measurements were retained, higher than originally anticipated (Fig. 9, Fig. 10, Table 5). We felt that the most notable of these was that in the Science Hub the youngest age group of kids under 10 had just over 50% measurement retention and in the *Specimens* exhibit children (who were not being helped by older friends or relatives) had a 41% measurement retention, which was contrary to our initial thoughts. This means that children did a remarkable job following instructions and taking the MicroPlant measurements seriously. Unsurprisingly the lowest retention within a self-identified age group at 43% were those that skipped giving their age; this was the case for 627 measurements. A general assumption is that this group took the kiosk experience less seriously or were pressed to engage in other museum activities.

Comparing the Science Hub data with the *Specimens* exhibit data

While the initial data analysis was performed on a 2018 dataset collected from the Science Hub, a secondary analysis was done on a dataset collected in the *Specimens* exhibit. This exhibit was focused on the large collection of scientific specimens at the museum, and so the kiosk was only a small part of the larger exhibit. This differed from the Science Hub, which is a dedicated space where visitors can interact with scientists as well as specimens from the Museum's collection. The fact that there was a smaller time frame where interns collected demographic data from the *Specimens* exhibit (24 versus 48 days), meant that the amount of data collected from the *Specimens* exhibit was smaller. Because some of the images had a very small amount of data associated with them, we combined the two datasets to perform the IQR cuts. Note that because the IQR cuts depend on the specific dataset used, the results may change when additional data is added in. This happened here; the IQR cut for the 2018 data alone had 3,125 pass the cuts. When we added in the 2017 data there were 3,126 data out of the 2018 set within the IQR ranges. This suggests that combining the two is robust. When these combined cuts were used to examine the 2017 exhibits data, we found that although there was a smaller amount of 2017 data collected, the quality was similar and the majority of data collected was usable based on completeness, angle, and IQR cuts. Because the quality of data was good, the majority of images in the 2017 dataset had sufficient data to determine the lobule lengths and widths (Table 6).

Image clarity for observers

To gain more insight into the image measurement data, an analysis was conducted on the images themselves. The classification of the MicroPlant images was based on the number of lobules present, complexity, and clarity of the image. Standard deviations of the axis length measurements were used to determine the clustering of the axis measurements. The lower the standard deviation the closer together the measurements are clustered. The image classifications were then compared to the standard deviations of the axis measurements, post IQR cut for each image. There were no notable trends present between the complexity of the images and the standard deviations of the measurements.

We then looked at images with large standard deviations, meaning the measurements were not very clustered together. Out of the 78 distinct subjects, we found only three subject id’s with very large standard deviations, one of them from the 2017 dataset. This was only 4% of the total images displayed on the kiosk. One similarity between these three different subject id's is the number of observations counted, with each having between 6-14 observations total. This can be one possible explanation about the low quality of data collected since such data was very limited. For the image with only six measurements, there was confusion between the lobule and the leaf behind the lobule. The shading of the pictures can leave room for confusion as well; it might become unclear what is considered part of the lobule and what is not.

Comparison of participant and expert measurements

With the goal of comparing the accuracy between participant measurements and expert scientist measurements, students conducted the same statistical test used in von Konrat et al. 2018 on the IQR cut data for image ID. No. 8735435. This was the third distinct image which had expert measurements associated to it. The statistical test used was a t-test which measures the difference between two data sets and determines if they are significantly different. After performing the angle and IQR cuts 45% of the original 855 participant measurements remained. After calculating the t-values for the minimum and maximum axis data with a confidence interval of 95%, we were able to conclude that the participant measurements after IQR cuts were not significantly different from expert measurements.

Community engagement with kiosk

Though literally hundreds of citizen or community science platforms exist, to our knowledge this was one of the first to be featured in a live interactive museum exhibit. Commonly, people-powered research projects engage participants online via platfoms like Zooniverse (Zooniverse 2022) or via targeting specific interests of their users- iNaturalist (California Academy of Sciences and National Geographic Society 2022) or WeDigBio (WeDigBio 2022). We wanted to know what impact placing an exploratory and unguided community science platform within a museum setting would have. What percentage of people who pass through the exhibit would stop to engage with the kiosk platform? (Table 7). Rough calculations based both on our observations, ticketing information, and data set timestamps tell us that about 14-20% of individuals who passed through the *Specimens* exhibit interacted with the kiosk in some manner. We were able to tabulate kiosk interactions by occasionally placing interns who observed and recorded from a distance who was interacting with the exhibit following standard protocols for observing people in exhibitions. These observers noted approximate age and perceived gender of participants as well engagement levels.

The Science Hub is designed for hands-on interactions and discussion with scientists. During the time that the kiosk was present in that location, 23,549 people visited the Science Hub, and 1,014 groups of people interacted with the kiosk. We estimate that between 4.3% and 12% of the visitors to the Science Hub interacted with the kiosk; if the group sizes were similar to those directly observed in the *Specimens* Exhibit, approximately 8% of the Science Hub patrons interacted with the kiosk. Because the kiosk was a stand-alone exhibit in the Science Hub, it is likely that museum patrons were more inclined to interact with the scientists present rather than a stand-alone computer exhibit.

Data resources

GitHub houses all of our data and scripts (Labontu 2022). Scripts were used to take raw data (Raw 2018 Data , 2017 data with intern observations) and parse it into the "All Data" and "Good Data" formats.

Initial IQR cuts and comparisons to expert data were done by hand. Systematic IQR cuts were performed in Excel Pivot Tables for IQR. Results from IQR cuts in Python are in Processed 2017 and 2018 data, which includes totals of the 2017 and 2018 data broken down by demographics, average lengths and standard deviation for each image after IQR cuts, and also the All Data sets for both 2017 and 2018. For the third image with expert measurements, t-test results were performed in Excel.

Discussion

All age groups produced valid, high quality data that could be used by researchers, including children (10 and under), teens, and adults. Significantly, the paper outlines the implementation of experiential learning through an undergraduate mathematics course that focuses on projects with actual data to gain a deep, practical knowledge of the subject, including observations, the collection of data, analysis, and problem solving. We here promote an intergenerational model including children, high school students, undergraduate students, early career scientists, and senior scientists, combining experiential learning, people-powered research, and data derived from natural history collections.

Data precision

From this study, the public is capable of producing a usable set of measurements. But there are two limitations to the precision of these measurements. One is the touchscreen technology. Because the smallest unit was a pixel, the difference of just a couple of pixels in the measurement corresponded to a 1% difference in length. This level of precision could not be improved upon with the technology used. The second is the variation in public measurements. Scientists who want to distinguish between species whose size differences are large (such as 10% difference) would be able to use work from the public; however, if the difference is very subtle (such as a 1% difference in length), it wouldn't be possible.

For cases where multiple types of species may exist in an individual image, there could be multiple sizes of measurements in an individual image. This would make the IQR analysis ineffective at finding outliers, and so more subtle methods would need to be employed. But if one found clusters of different sizes, it may be possible to create a machine learning algorithm to use for the data processing portion.

Experiential learning and interdisciplinary science

Interdisciplinary science entails the collaboration of scientists with largely non-overlapping training and core expertise to solve a problem that lies outside the grasp of the individual scientists (Cech and Rubin 2004). Yet interdisciplinary research (IDR) is more than collaboration: it is also applying concepts or methods from other fields or writing to make your research accessible to other types of scientists (Brigandt 2013). IDR is better suited for addressing critical "big picture problems" such as sustainability and conservation (Palmer 2001, Carayol 2005, Campbell 2005). Early IDR exposure aids cross discipline communication (Bridle et al. 2013) and makes students more likely to pursue STEM careers (Daugherty and Carter 2017).

This was an authentic interdisciplinary experience in experiential learning. Students from various backgrounds, specialties, and ages were involved in all aspects of this project from inception to completion. While this report focuses on the data analysis, prior collaborations with both college and high school students led to the development of the project. Thus, all involved students participated in a rich, real world learning experience to generate and later analyze a real and meaningful data set answering questions that were previously unanswered. Students involved in the data analysis found the skills that they acquired through the project to be highly applicable to their post-graduation jobs, commenting, "I've used a lot of the VBA skills from your classes with the Field Museum." This indicates that this project was good preparation for both research work and industry jobs. As this course was originally developed as part of the PICMath program, it is a way to both fulfill the goals of the program and to increase scientific knowledge. Future endeavors could implement student evaluation prior to, during, and post course, as student feedback on their learning journey is effective in improving both student satisfaction and learning (Mandal 2018).

Despite the critical role of experiential learning in building student research skills and capacity, few have explored social interaction mechanisms used to facilitate student experiential learning in an interdisciplinary research team (Ryser et al. 2008). This has great potential in future reiterations that could be investigated.

Exploring motivation and testing between audiences

There remain many interesting education and learning questions that could be investigated using the current data set as well as future studies embarking on similar large scale projects. For example: How many measures must be taken by each kind of user group? Are there significant differences in measurement facility among children, adolescents, and adults? Are there significant differences between a facilitated audience and a purely online audience? Limited work has investigated the arc of engagement from secondary to post-secondary education and into adulthood. Examining a cross-sectional population set will allow us to study reasons and motivations of learner engagement moving from a formal to an informal setting. The potential also exists to use this project to explore how authentic research experiences can both develop student interest in STEM and STEM careers (Boyer 2017) as well as promote learning of biodiversity concepts (Gunckel et al. 2012).

Although it is possible to use this dataset to compare kiosk locations, in the future, having a consistent set of self-described demographic categories would allow for a consistent comparison of how different demographics interact in the the different kiosk locations. However, given that the desire to collect demographic information was realized after some data was collected, the addition of a brief demographic survey to the kiosk was a natural course correction. In addition, collection of demographic information before starting the activity interrupts the activity and presents other challenges when switching between participants.

Our experience with this project yielded insight into how to plan for future projects. For other taxonomic projects, the most robust measurements will involve images where the public can easily identify the object to be measured. As noted in the conclusions, the distinction between smaller lobules and the larger underlying leaves led to a number of inaccurate measurements. Because this is a large, multi-year project, students who are involved in it will graduate before it is completed. Faculty and museum leaders are the ones maintaining continuity of the project; they need to make sure that the student data work is documented and stored in a way that is both carefully labeled and accessible. This allows multiple years of students to collaborate and make significant continual progress in a robust manner. In terms of project management, the most challenging aspect was maintaining contact and retaining connections between student cohorts. It is critical to plan for this from the very start of development when pursuing such projects.

Community Science in a museum setting

Though we are able to tabulate a certain interaction level by patrons with the kiosk (Table 10), it is worth noting that we also have sets of observational notes about how individuals and groups interacted with the kiosk display. Because we did not have questionnaires and surveys always linked to the activity, engagement levels and observations were noted by onlookers for a portion of the time that the kiosk was in the *Specimens* exhibit. From observer notes, we were able to compile a word map demonstrating the true inclusive nature of the activity and summarize interactions with the kiosk (Fig. 11). Because museums are often visited by families and groups, the kiosk was a place where people gathered to interact and engage not only in science, but with each other. We were able to note many examples of parents, children, and peers working together in a truly collaborative manner as is core to community science. Our anecdotal observations of patrons interacting with the kiosk support the supposition that there is a growing body of evidence suggesting that such digital technology can create engaging learning opportunities in museums (Roberts et al. 2018). There is great potential in implementing community science activities in a natural history museum environment using digital technology to help foster curiosity and engagement with scientific collections. Unobtrusive video recording and patron surveys would be invaluable in providing deeper insight.

Conclusions

A project which involves the public, high school interns, and university students, can allow for the entire community to create scientific discoveries. It allows for scientists to analyze large collections of specimens, and it helps to give students an in-depth experience of what it is like to be a professional scientist or data analyst. This occurred at all levels. Given a sufficient number of community members measuring leaves, we were able to get high quality measurements, which were comparable to expert measurements, using methods that can be automated. This bodes well for crowd-sourcing taxonomic data collection from images. Mathematics alumni reported that the process of developing and creating these automated data processors was educationally beneficial for them as they were able to apply their skill set to internships and post-graduation jobs working with data. Students of some cohorts of both the Industrial Applications of Mathematics course and museum interns have continued to pursue graduate degrees.

Due to the success in measuring lobules, an extension of the MicroPlants project, *Unfolding of MicroPlant Mysteries* (Zooniverse 2021a), is currently under way where other attributes of liverwort images are identified by participants using an online tool. Data on branching patterns and reproductive structures is being collected from participants and then analyzed by students to advance further discoveries. We are currently working on mapping content to Next Generation Science Standards (NGSS) and using these connections to develop lessons and activities to populate a new Zooniverse classroom (https://classroom.zooniverse.org/). This has the potential for future contributions and learning through a platform and with technology that is accessible to a large demographic of learners. We hope this continues to drive connections between universities, museums, students, researchers, and community scientists.

Acknowledgements

The Student Center for Science Engagement at Northeastern Illinois University helped provide funding for student interns. Financial support was provided by the National Science Foundation (Award No. 0949136, 1145898, 1458300, 1541545, 2001509 to M.v.K.). Support is also acknowledged from C. Moreau (PI) and T. Lumbsch (co-PI) - Research Experience for Undergraduates (REU) Site: Evolution of Biodiversity across the Tree of Life (Award No. 1559779). The Grainger Bioinformatics Center, Field Museum, is also acknowledged for support with digital infrastructure. This publication uses data generated via the Zooniverse.org platform, development of which is funded by generous support, including a Global Impact Award from Google, and by a grant from the Alfred P. Sloan Foundation. We would like to thank the following individuals for their support imaging specimens: Jonathan Scheffel and Steve Schulze (Field Museum), Anthony Carmona and Stephanie Maxwell (Northeastern Illinois University), and Ed Gluzman and Vishal Patel (DePaul University, Chicago, Illinois). We are grateful to Brendon Reidy, Xenia Alava, Dara Arabsheibani, Alex Vizzone, and Zak Zillen (all Northeastern Illinois University); Kavita

Elliott (The Ohio State University); and Pedro Rebollar (DePaul University) for their support with guest interactions. Ramsey Millison and Ariel Wagner (both DePaul University) provided imaging and guest interaction support.

We thank the following individuals for technical and administrative support, consultancy, and general assistance throughout the project: Lauren Hasan and Beth Crownover (both Field Museum); Kristina Lugo (Roosevelt University and Field Museum); Anthony Flores, Maha Khan, Alexandra Lopez, Lisa Murata, and Oana Vadineanu (all Northeastern Illinois University); Gabriel Somarriba (University of Florida); Mariam Nasser (Elgin Academy, Elgin, Illinois); Joey T Rene Shelley (University of Illinois, Chicago); Audrey Aronowsky (Department of Ecology and Evolution, University of Illinois at Chicago); Beth Sanzenbacher (Bernard Zell Anshe Emet Day School, Chicago, Illinois); Jennifer Campagna (Blaine Elementary School, Chicago, Illinois); Christine LaPointe (Hillcrest Elementary School) (Green Ambassador, Field Museum); Laura Briscoe (New York Botanical Garden); Jordan Newson (Albion College); and Taylor Walker (Hollins University). We acknowledge Jose Hernandez Lopez (Northeastern Illinois University) and Allison Chen (University of California) for their early efforts investigating Google Analytics as part of the demographic survey.

We would like to acknowledge previous cohorts of Roosevelt University students whose quantitative work was influential for this analysis. The following performed analyses on subsets of the kiosk data under the direction of Prof. Steve Cohen: Jonathan Aird, Estevan Carrillo, Esther Fiala, Ian Fluhler, Nathan Gregory, Martin Hayford, Breanna Ivery, Jonathan Kasongo, Brian Keyser, Andrew Moskwa, Vingie Ng, Mary Strickler, Eric Synajie, and Haki Wright. Thanks also to Cuong Pham (pictured) for demonstrating the kiosk at the museum.

The following Roosevelt University students performed large scale processing of data from the web platform; this type of parsing and processing work was essential for the current authors to learn how to work with a similarly formatted dataset: Julia Buczek, Matt Caraher, James Crigler (pictured), Davaadulam Ganzorig, Kyler Gillespie, Robert Hennecy, Thomas Hill, Chengjian Li, Ashlyn Liu, Marcos Mercado, Ali Myhelic, Nupur Patel, Rebecca Plata, Jacob Rubinstein, Michael Sassaman, Luke Swanson, and Joshua Torres (pictured).

Finally, we would like to give a huge thank you to all of the children, families, teens, and adults who visited the museum and took time to engage with the kiosk. Without them, none of this would be possible.

References

- Auerbach J, Barthelmess E, Cavalier D, Cooper C, Fenyk H, Haklay M, Hulbert J, Kyba CM, Larson L, Lewandowski E, Shanley L (2019) The problem with delineating narrow criteria for citizen science. Proceedings of the National Academy of Sciences 116 (31): 15336-15337. https://doi.org/10.1073/pnas.1909278116

- Bebber DP, Carine MA, Wood JRI, Wortley AH, Harris DJ, Prance GT, Davidse G, Paige J, Pennington TD, Robson NKB, Scotland RW (2010) Herbaria are a major frontier for species discovery. Proceedings of the National Academy of Sciences 107 (51): 22169-22171. https://doi.org/10.1073/pnas.1011841108
- Berendsohn W, Seltmann P (2010) Using geographical and taxonomic metadata to set priorities ilasyn specimen digitization. Biodiversity Informatics 7 (2). https://doi.org/10.17161/bi.v7i2.3988
- Boyer N (2017) Inspiring the Next Generation of Scientists and Engineers: K-12 and Beyond. Computer 50 (7): 17-19. https://doi.org/10.1109/mc.2017.204
- Bridle H, Vrieling A, Cardillo M, Araya Y, Hinojosa L (2013) Preparing for an interdisciplinary future: A perspective from early-career researchers. Futures 53: 22-32. https://doi.org/10.1016/j.futures.2013.09.003
- Brigandt I (2013) Systems biology and the integration of mechanistic explanation and mathematical explanation. Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences 44 (4): 477-492. https://doi.org/10.1016/j.shpsc.2013.06.002
- California Academy of Sciences, National Geographic Society (2022) iNaturalist. https://www.inaturalist.org
- Campbell L (2005) Overcoming Obstacles to Interdisciplinary Research. Conservation Biology 19 (2): 574-577. https://doi.org/10.1111/j.1523-1739.2005.00058.x
- Carayol N (2005) Why do academic scientists engage in interdisciplinary research? Research Evaluation 14 (1): 70-79. https://doi.org/10.3152/147154405781776355
- Cech TR, Rubin GM (2004) Nurturing interdisciplinary research. Nature Structural & Molecular Biology 11 (12): 1166-1169. https://doi.org/10.1038/nsmb1204-1166
- Cimons M (2018) Scientists want YOU to help them study amphibious lil plants. Popular Science. URL: https://www.popsci.com/liverwort-plant-citizen-science/
- Cook J, Edwards S, Lacey E, Guralnick R, Soltis P, Soltis D, Welch C, Bell K, Galbreath K, Himes C, Allen J, Heath T, Carnaval A, Cooper K, Liu M, Hanken J, Ickert-Bond S (2014) Natural History Collections as Emerging Resources for Innovative Education. BioScience 64 (8): 725-734. https://doi.org/10.1093/biosci/biu096
- Coxson D (1991) Nutrient release from epiphytic bryophytes in tropical montane rain forest (Guadeloupe). Canadian Journal of Botany 69 (10): 2122-2129. https://doi.org/10.1139/b91-266
- Cremer K, A.B.. M (1965) Early stages of plant succession following the complete felling and burning of Eucalyptus regnans forest in the Florentine Valley, Tasmania. Australian Journal of Botany 13 (2). https://doi.org/10.1071/bt9650303
- Daugherty M, Carter V (2017) The Nature of Interdisciplinary STEM Education. Springer International Handbooks of Education159-171. https://doi.org/10.1007/978-3-319-44687-5_12
- DeLucia E, Turnbull M, Walcroft A, Griffin K, Tissue D, Glenny D, McSeveny T, Whitehead D (2003) The contribution of bryophytes to the carbon exchange for a temperate rainforest. Global Change Biology 9 (8): 1158-1170. https://doi.org/10.1046/j.1365-2486.2003.00650.x
- Derrick EG, Falk-Krzesinski HJ, Roberts MR, Olson S (2011) Facilitating interdisciplinary research and education: A practical guide. In: American Association for the Advancement of Science (Ed.) Science on FIRE: Facilitating Interdisciplinary Research and Education.

- Dorff M, Weekes S (2019) A Student Research Course on Data Analysis Problems from Industry: PIC Math. Council on Undergraduate Research Quarterly 2 (4): 37-42. https://doi.org/10.18833/spur/2/4/2
- Eitzel MV, Cappadonna JL, Santos-Lang C, Duerr RE, Virapongse A, West SE, Kyba CCM, Bowser A, Cooper CB, Sforzi A, Metcalfe AN, Harris ES, Thiel M, Haklay M, Ponciano L, Roche J, Ceccaroni L, Shilling FM, Dörler D, Heigl F, Kiessling T, Davis BY, Jiang Q (2017) Citizen Science Terminology Matters: Exploring Key Terms. Citizen Science: Theory and Practice 2 (1). https://doi.org/10.5334/cstp.96
- Field Museum (2016) *Specimens*. https://www.fieldmuseum.org/discover/on-exhibit/specimens/. Accessed on: 2021-12-28.
- Field Museum (2021) Grainger Science Hub. https://www.fieldmuseum.org/exhibitions/grainger-science-hub. Accessed on: 2021-12-28.
- Frahm J (2008) Bryophyte phytomass in tropical ecosystems. Botanical Journal of the Linnean Society 104: 23-33. https://doi.org/10.1111/j.1095-8339.1990.tb02209.x
- Gerson U (1982) Bryophytes and Invertebrates. Bryophyte Ecology291-332. https://doi.org/10.1007/978-94-009-5891-3_9
- Graham C, Ferrier S, Huettman F, Moritz C, Peterson A (2004) New developments in museum-based informatics and applications in biodiversity analysis. Trends in Ecology & Evolution 19 (9): 497-503. https://doi.org/10.1016/j.tree.2004.07.006
- Gunckel K, Mohan L, Covitt B, Anderson C (2012) Addressing Challenges in Developing Learning Progressions For Environmental Science Literacy. Learning Progressions in Science39-75. https://doi.org/10.1007/978-94-6091-824-7_4
- Heberling JM, Isaac B (2017) Herbarium specimens as exaptations: New uses for old collections. American Journal of Botany 104 (7): 963-965. https://doi.org/10.3732/ajb.1700125
- Hedrick B, Heberling M, Meineke E, Turner K, Grassa C, Park D, Kennedy J, Clarke J, Cook J, Blackburn D, Edwards S, Davis C (2019) Digitization and the future of natural history collections. PeerJ Preprints 7: e27859v1. https://doi.org/10.7287/peerj.preprints.27859v1
- Heigl F, Kieslinger B, Paul K, Uhlik J, Dörler D (2019) Toward an international definition of citizen science. Proceedings of the National Academy of Sciences 116 (17): 8089-8092. https://doi.org/10.1073/pnas.1903393116
- Hentschel J, Von Konrat M, Söderström L, Hagborg A, Larraín J, Sukkharak P, Uribe J, Zhang L (2015) Notes on Early Land Plants Today. 72. Infrageneric classification and new combinations, new names, new synonyms in Frullania (Marchantiophyta). Phytotaxa 220 (2). https://doi.org/10.11646/phytotaxa.220.2.3
- Holmes MW, Hammond TT, Wogan GOU, Walsh RE, LaBarbera K, Wommack EA, Martins FM, Crawford JC, Mack KL, Bloch LM, Nachman MW (2016) Natural history collections as windows on evolutionary processes. Molecular ecology 25 (4): 864-81. https://doi.org/10.1111/mec.13529
- Huttunen K-, Mykrä H, Oksanen J, Astorga A, Paavola R, Muotka T (2017) Habitat connectivity and in-stream vegetation control temporal variability of benthic invertebrate communities. Scientific Reports 7 (1). https://doi.org/10.1038/s41598-017-00550-9
- James S, Soltis P, Belbin L, Chapman A, Nelson G, Paul D, Collins M (2018) Herbarium data: Global biodiversity and societal botanical needs for novel research. Applications in Plant Sciences 6 (2). https://doi.org/10.1002/aps3.1024

- Kolb D, Boyatzis R, Mainemelis C (2014) Experiential Learning Theory: Previous Research and New Directions. Perspectives on Thinking, Learning, and Cognitive Styles227-248. https://doi.org/10.4324/9781410605986-9
- Kolb DA (1984) Experiential Learning: Experience as the Source of Learning and Development. Prentice-Hall, Englewood Cliffs, N.J.
- Kuh GD (2008) High-Impact Educational Practices: What They Are, Who Has Access to Them, and Why They Matter,. Association of American Colleges and Universities.
- Labontu A, et al. (2022) MicroPlant-code v1.0.0Kiosk. Github. https://doi.org/10.5281/zenodo.6324262
- Lang PLM, Willems FM, Scheepens JF, Burbano HA, Bossdorf O (2019) Using herbaria to study global environmental change. New Phytologist 221: 110-122. https://doi.org/10.7287/peerj.preprints.26886v1
- Ligrone R, Duckett J, Renzaglia K (2012) Major transitions in the evolution of early land plants: a bryological perspective. Annals of Botany 109 (5): 851-871. https://doi.org/10.1093/aob/mcs017
- MAA (2021) PIC Math - Preparation for Industrial Careers in Mathematical Sciences. https://www.maa.org/programs-and-communities/professional-development/pic-math. Accessed on: 2021-12-28.
- Mandal NK (2018) Importance of student feedback in improving mechanical engineering courses. International Journal of Mechanical Engineering Education 47 (3): 227-245. https://doi.org/10.1177/0306419018759800
- Morris TH (2019) Experiential learning – a systematic review and revision of Kolb's model. Interactive Learning Environments 28 (8): 1064-1077. https://doi.org/10.1080/10494820.2019.1570279
- National Research Council (2010) Exploring the Intersection of Science Education and 21st Century Skills. The National Academies Press, Washington, DC. [ISBN 978-0-309-15064-4] https://doi.org/10.17226/12771
- Palmer C (2001) Accommodating Interdisciplinary Research. Work at the Boundaries of Science97-121. https://doi.org/10.1007/978-94-015-9843-9_4
- Pandya R (2019) What is Community Science? A Blog and a Quiz. https://thrivingearthexchange.org/what-is-community-science-a-blog-and-a-quiz/. Accessed on: 2022-3-11.
- Pócs T (1980) The epiphytic biomass and its effect on the water balance of two rain forest types in the Uluguru Mountains (Tanzania, East Africa). Acta Botanica Academiae Scientiarum Hungaricae 26: 143-167.
- Roberts J, Banerjee A, Hong A, McGee S, Horn M, Matcuk M (2018) Digital Exhibit Labels in Museums. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems https://doi.org/10.1145/3173574.3174197
- Ruppenthal A (2018) How 11,000 Citizen Scientists Helped Unlock Decades of Biological Data. https://news.wttw.com/2018/03/14/how-11000-citizen-scientists-helped-unlock-decades-biological-data. Accessed on: 2022-1-12.
- Ryser L, Halseth G, Thien D (2008) Strategies and Intervening Factors Influencing Student Social Interaction and Experiential Learning in an Interdisciplinary Research Team. Research in Higher Education 50 (3): 248-267. https://doi.org/10.1007/s11162-008-9118-3

- Soltis P, Nelson G, James S (2018) Green digitization: Online botanical collections data answering real-world questions. Applications in Plant Sciences 6 (2). https://doi.org/10.1002/aps3.1028
- Sweeney P, Starly B, Morris P, Xu Y, Jones A, Radhakrishnan S, Grassa C, Davis C (2018) Large-scale digitization of herbarium specimens: Development and usage of an automated, high-throughput conveyor system. Taxon 67 (1): 165-178. https://doi.org/10.12705/671.9
- von Konrat M (2012) Connecting Biodiversity Research & Collections with Curriculum. https://www.fieldmuseum.org/blog/connecting-biodiversity-research-collections-curriculum. Accessed on: 2021-12-28.
- von Konrat M, Campbell T, Carter B, Greif M, Bryson M, Larraín J, Trouille L, Cohen S, Gaus E, Qazi A, Ribbens E, Livshultz T, Walker TJ, Suwa T, Peterson T, Rodriguez Y, Vaughn C, Yang C, Aburahmeh S, Carstensen B, de Lange P, Delavoi C, Strauss K, Drag J, Aguero B, Snyder C, Martinec J, Smith A (2018) Using citizen science to bridge taxonomic discovery with education and outreach. Applications in plant sciences 6 (2): e1023. https://doi.org/10.1002/aps3.1023
- WeDigBio (2022) WeDigBio. https://wedigbio.org
- Zhang J, Fu X, Li R, Zhao X, Liu Y, Li M, Zwaenepoel A, Ma H, Goffinet B, Guan Y, Xue J, Liao Y, Wang Q, Wang Q, Wang J, Zhang G, Wang Z, Jia Y, Wang M, Dong S, Yang J, Jiao Y, Guo Y, Kong H, Lu A, Yang H, Zhang S, Van de Peer Y, Liu Z, Chen Z (2020) The hornwort genome and early land plant evolution. Nature plants 6 (2): 107-118. https://doi.org/10.1038/s41477-019-0588-4
- Zooniverse (2021a) Unfolding of MicroPlant Mysteries. https://www.zooniverse.org/projects/nvuitton/unfolding-of-microplant-mysteries. Accessed on: 2022-1-18.
- Zooniverse (2021b) MicroPlants. https://www.zooniverse.org/projects/fieldmuseumexhibits/microplants/classify. Accessed on: 2021-12-28.
- Zooniverse (2022) Zooniverse. https://www.zooniverse.org
- Zwillinger D, Kokoska S (2000) *CRC Standard Probability and Statistics Tables and Formulae*. CRC Press

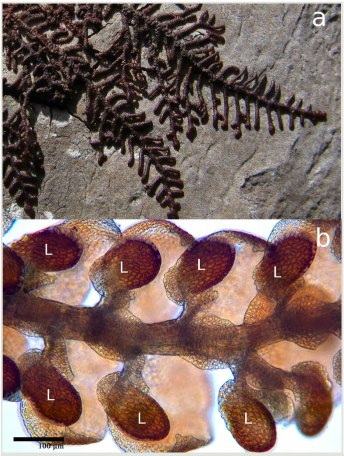

Figure 1.

An example of the liverwort genus *Frullania* a) Growing on bark; b) Ventral view of stem indicating modified leaves or lobules (L) that participants are asked to measure.

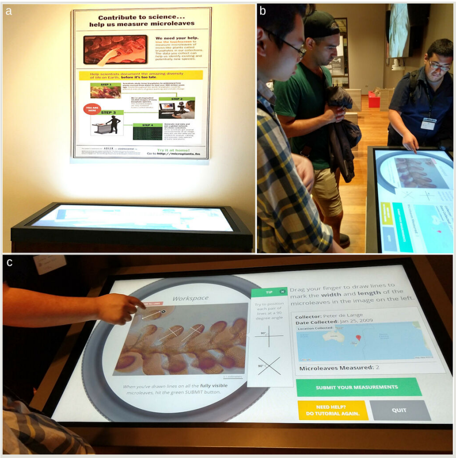

Figure 2.

The online platform, based on Zooniverse, developed into touchscreen technology as part of an interactive kiosk in a high-profile exhibit at Field Museum: a) Instructions were mounted as well as available using the touchscreen; b) Students from Roosevelt University testing the platform; c) Depicting details of the interactive, including the workspace for measuring, map indicating the geographic locality, and number of measurements.

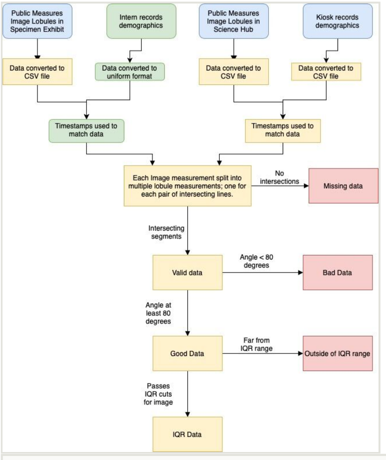

Figure 3.

Data generation and processing. Blue rounded rectangles indicate data from the public. Green rounded rectangles indicate data processed by hand by students. Yellow rectangles indicate automated data processing. Red rectangles indicate data which has been filtered out.

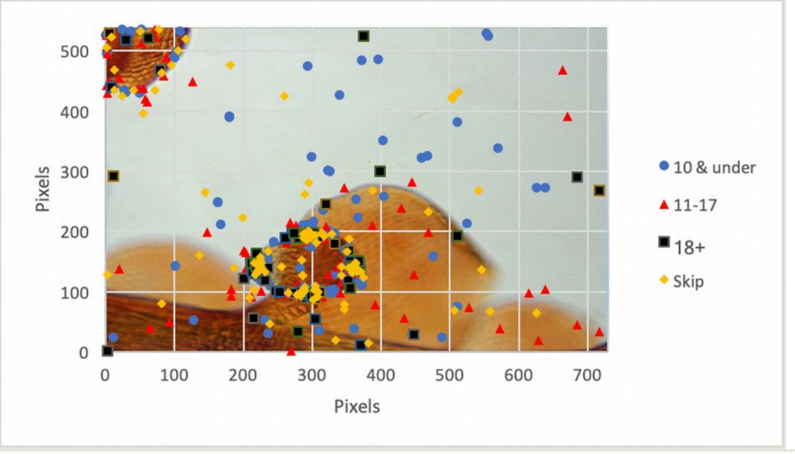

Figure 4.

Full data (without any cuts) for image (ID. No. 8735482). Despite the high contrast between the lobule and background, there are measurements which are far from the actual lobule.

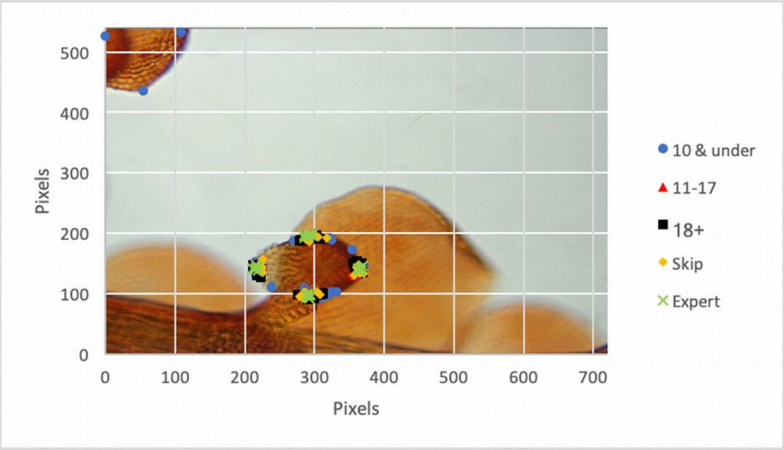

Figure 5.

IQR cuts for image (ID. No. 8735482). The data remaining is on the correct lobule, with the exception of one set on the portion of the lobule on the top left.

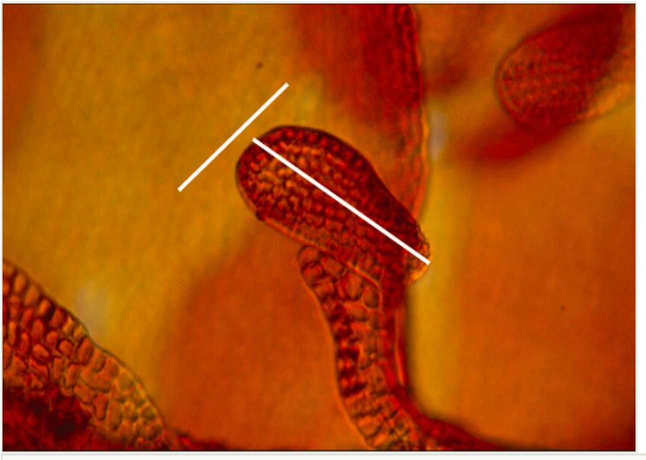

Figure 6.

A lobule with a pair of non-intersecting measurements.

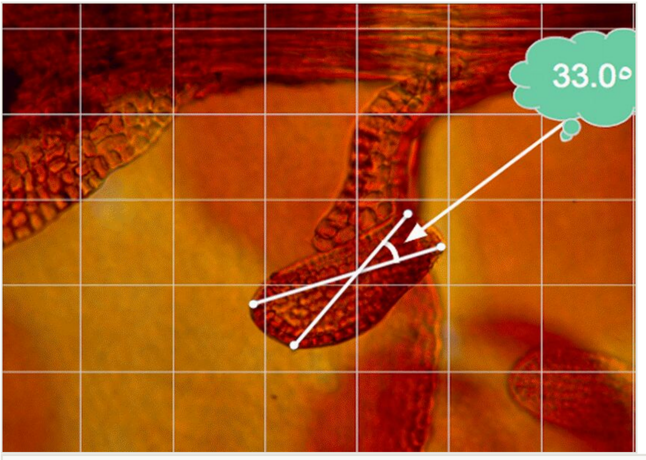

Figure 7.

A lobule with a pair of line segments which intersect, but who do so at a small angle.

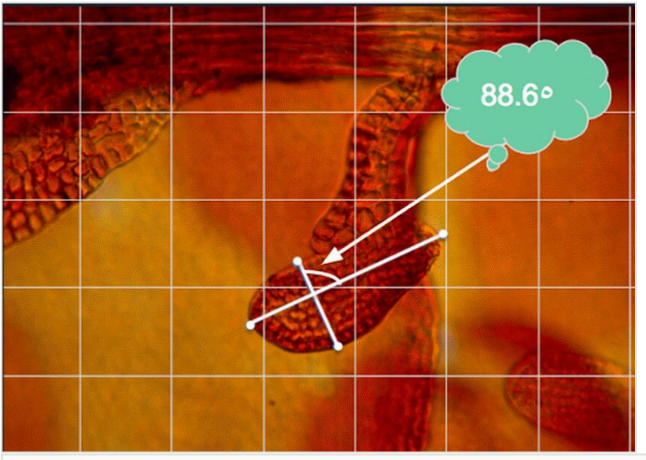

Figure 8.

A lobule with a pair of intersecting line segments whose angle is close to 90 degrees.

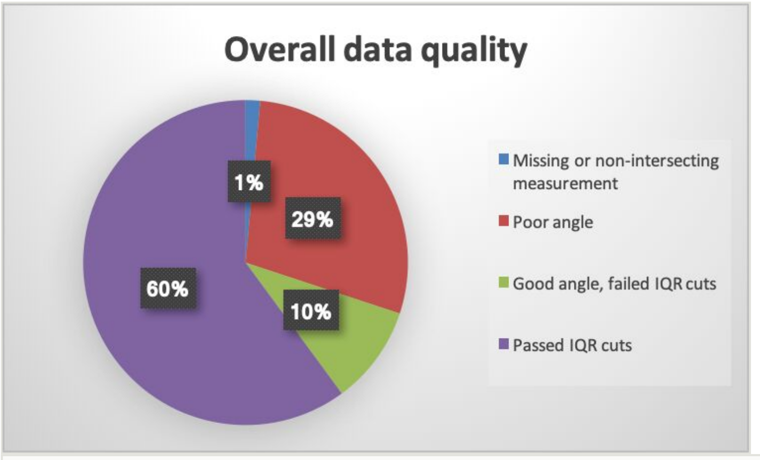

Figure 9.

The majority (60%) of the over 6,000 lobule measurements were of generally high quality, with only a small number of non-intersecting or missing measurements. The majority passed IQR cuts; the most common reason to filter out data was when the angle was under 80 degrees.

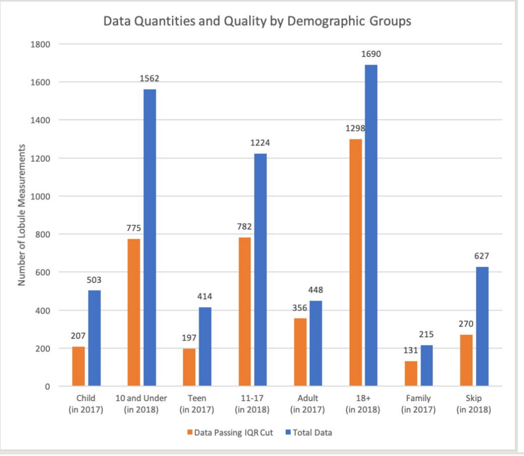

Figure 10.

The total number of lobule measurements and total number that passed IQR cuts broken down by demographic grouping.

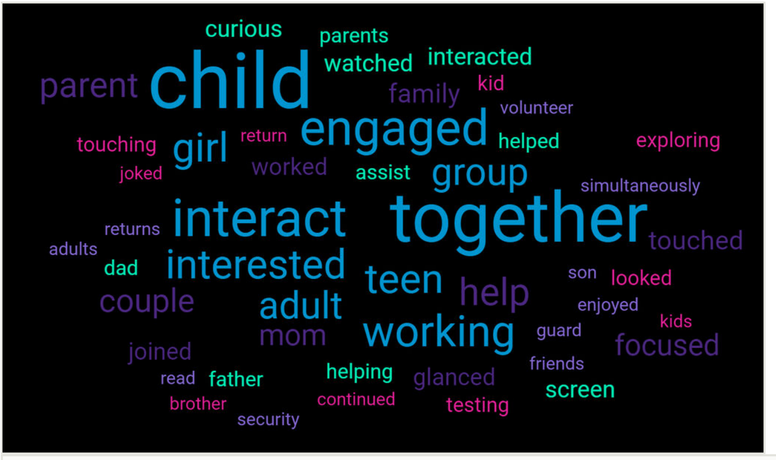

Figure 11.

Word cloud of observer notes of kiosk participants that were recorded from an unobtrusive distance.

Table 1.

Demographics and the number of participants using kiosk in each category in the data set used in this analysis. This does not include all of the people who interacted with the exhibit; rather, it includes the only individuals for whom we have demographic data.

2017 *Specimens* exhibit demographics	No. of participants	**2018 Science Hub demographics**	No. of participants
Child	230	10 and under	319
Teen	107	11 to 17	220
Adult	243	18+	324
Family (group with multiple age groups)	6	Skip (unanswered question)	151

Table 2.

Categories of data used in analysis.

All data	Data collected any time a person pushed the submit button on the kiosk, regardless of quality or even existence of measurements.
Good data	A set of pairs of line segments that intersected for an image and which formed an angle of at least 80 degrees.
IQR cut data	A subset of good data for a particular image where the IQR (interquartile ranges) for both the length and the width are calculated and an image-dependent cut is made based on both of these.

Table 3.

Comparison of measurements done by an expert with those done by the public after cutting based on angles (above 80 degrees) and by IQR.

Comparison of public and expert measurements for image ID. No. 8735482

	Major axis length (pixels)	Stdev	Minor axis length (pixels)	Stdev
Expert	142.65	3.26	93.68	3.00
Public with angle cuts	159.23	84.44	117.22	69.04
Public with IQR cuts	135.89	15.13	96.20	8.56

Table 4.

A comparison of expert measurements and public measurements after and IQR cut for a second MicroPlant image.

Second comparison between public and expert measurements for image 25352420

	Major axis length (pixels)	Stdev	Minor axis length (pixels)	Stdev
Expert	193.79	2.92	96.49	3.99
Public with IQR cuts	187.83	6.17	97.34	8.34

Table 5.

Demographic breakdown of totals and IQR pass work in 2017 and 2018. In this, each number represents the total number of lobules measured, rather than the number of individuals doing the measuring or the number of images used. A kiosk session where no valid measurements were submitted is counted as 1 in the data collected category.

Demographic	Data collected	Number passing IQR	Percent passing IQR
Child (in 2017)	503	207	41%
Teen (in 2017)	414	197	48%
Adult (in 2017)	448	356	79%
Family (in 2017)	215	131	61%
Total 2017 (*Specimens*)	**1,580**	**891**	**56%**
10 and under (in 2018)	1,562	775	50%
11-17 (in 2018)	1,224	782	64%
18+ (in 2018)	1,690	1,298	77%
Skip (in 2018)	627	270	43%
Total 2018 (Science Hub)	**5,103**	**3,125**	**61%**
Overall Total	**6,683**	**4,017**	**60%**

Table 6.

Overall data passing IQR cuts. In this, each number represents the total number of lobules measured, rather than the number of individuals doing the measuring or the number of images used. A kiosk session where no valid measurements were submitted is counted as 1 in the data collected category.

	Data collected	Data which passed combined IQR cuts	Percent which passed combined IQR cuts
2017 *Specimens* exhibit data	1,580	891	56%
2018 Science Hub data	5,103	3,126	61%
Combined data	6,683	4,017	60%

Table 7.

Visitors to kiosk exhibit in Field Museum's *Specimens* exhibit, summer 2017 (June-August).

Total interactive hours observed	44.5
Approximate number of people engaged with exhibit during observation hours	580
Amount of hours people spent engaged with exhibit	12
Approximate percent of exhibit patrons who interacted with the Specimen exhibit kiosk	14-20%