May 2019

Characterizing Novelty as a Motivator in Online Citizen Science

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ABSTRACT

Citizen science projects rely on the voluntary contribution of nonscientists to take part in scientific research projects. Projects taking place exclusively over the Internet face significant challenges, chief among them is the attracting and keeping the critical mass of volunteers needed to conduct the work outlined by the science team. The extent to which platforms can design experiences that positively influence volunteers' motivation can help address the contribution challenges. Consequently, project organizers need to develop strategies to attract new participants and keep existing ones. One strategy to encourage participation is implementing features, which re-enforce motives known to change people's attitudes towards contributing positively. The literature in psychology noted that novelty is an attribute of objects and environments that occasion curiosity in humans leading to exploratory behaviors, e.g., prolonged engagement with the object or environment. This dissertation described the design, implementation, and evaluation of an experiment conducted in three online citizen science projects. Volunteers received novelty cues when they classified data objects that no other volunteer had previously seen. The hypothesis was that exposure to novelty cues while classifying data positively influences motivational attitudes leading to increased engagement in the classification task and increased retention. The experiments resulted in mixed results. In some projects novelty cues were universally salient, and in other projects, novelty cues had no significant impact on volunteers' contribution behaviors. The results, while mixed, are promising since differences in the observed behaviors arise because of individual personality differences and the unique attributes found in each project setting. This research contributes to empirically grounded studies on motivation in citizen science with analyses that produce new insights and questions into the functioning of novelty and its impact on volunteers' behaviors.

Keywords: citizen science, experiment, novelty, motivation

CHARACTERIZING NOVELTY AS A MOTIVATOR IN ONLINE CITIZEN SCIENCE

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Dissertation
Submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in *Information Science & Technology*.

Syracuse University
May 2019

ACKNOWLEDGEMENTS

I am deeply grateful to my advisor, Kevin Crowston, for guiding me through my Ph.D., and for a lifetime worth of constructive, supportive, and honest advice. Kevin taught me how to identify and work on research problems and be an independent researcher. Kevin afforded me incredible opportunities to grow as a researcher and person, and under his tutelage, I became a better researcher and person. I am also grateful to Carsten Østerlund who, in many ways acted as a secondary advisor during my Ph.D. His guidance, advice, and support were profoundly influential in shaping the researcher and person that I am today.

I thank Steve Sawyer, Bryan Seeman, Dan Cosley, and Jeff Saltz, who have served on my committee offering advice and invaluable feedback on this document as well as during my time as a doctoral student at the iSchool. I also owe a thank you all the iSchool/SU staff, special thanks to Jennifer Barclay, Susan Neimer, and Lois Elmore, Bridget M Crary, Maureen O'Connor Kicak, and Jennifer Pulver Jose Tavarez for all their support and logistics throughout my studies.

This thesis focuses on volunteers who contribute to online citizen science projects and would not have been possible without the help of the Zooniverse staff including Stuart Lynn, Laura Trouille, and Sarah Allen who helped implement the experiments. Many thanks are owed to the millions of Zooniverse volunteers who, without their contributions to such a noble cause, this thesis would not have been possible. Specifically, I thank the volunteers who contributed to Higgs Hunters, Asteroid Zoo, and Gravity Spy.

I had the privilege of working alongside members of the SALT lab at the iSchool, notably Yang Wang and Yun Huang. Yang provided me with guidance on several paper submissions where I learned perseverance in the publication process. Yang and Yun welcomed me to their home during many holidays, and for them I am grateful.

During the summer of 2015, I had the great privilege of interning with Laura Anderson and Cheryl Kieliszewski at IBM's Almaden Research Center in Almaden, CA. I thank them for their guidance, support, and advice during my summer at IBM and the years afterward.

I am also grateful for the financial support of Christine Larsen who funded summer research activities during my first three years at the iSchool which afforded me the freedom to explore new ideas and work towards completing Ph.D. milestones.

I have had the privilege of working along many colleagues who I have learned from and who have tremendously influenced my intellectually development and growth including Gabriel Mugar, Katie DeVries Hassman, Matt Willis, Sarika Sharma, Ehsan Sabaghian, Dane Dell, David Pierre, Ariel Ash-Shakoor, Nathan Prestopnik, Delicia Green, David James, Jerry Robinson, and Mahboobeh Harandi, Yaxing Yao, Nata Barbosa, Huichuan Xia. Also, a thank you to the Flannigan Gymnasium noon ball crew who always provided a needed mental break from the stressors of Ph.D. life and the occasional libation.

Completing a Ph.D. is challenging, I am lucky to have been blessed with a fantastic cohort and family in Ehsan Sabaghian and Sarika Sharma.

As an underrepresented student finding community at an academic institution is essential. Gina Lee-Glauser, Patricia Stith, and the Black Graduate Student Association provided spaces for community building for myself and other graduate students at Syracuse University. These events are where I met some of my closest friends during my Ph.D., for this community I am thankful.

In 2017, I relocated to my hometown of Chicago, IL to spend time with family and friends before joining the ranks of academia. While this might have extended my time to completing my Ph.D. and much to the chagrin of my advisor I was happy I made the decision since it allowed me time to reconnect with friends. I cannot imagine what I would have done without the support of friends like Bradley Clarke, Ijeoma Omelogu, Juren Ekwejunor-Etchie, Miguel Sierra, Holly Ekwejunor-Etchie, Chika Umeadi, Caitlin Williams, Jenna Ayares, Christa Harlin, Hatizda Zaganjor and Monica Williams. A special thank you is extended to Audrey Shinn who was a constant support system during the final and most difficult stages of my Ph.D.

I want to thank my family for unwavering support and encouragement including Yvette Griffin, Hector Griffin, Yolanda Foreman, Javin Forman, and Johnny Waggoner, Jahleel Griffin, Jalen Griffin, and Asia Griffin. Lastly, my mother, Marsha Harris Henderson, to whom I dedicate this thesis. It was only through your constant love and support that this kid from the south side of Chicago was able to achieve his goals and for that, I am forever indebted to you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Introduction

1.1 Background and Motivation

The process and methodologies used to conduct large-scale scientific research is changing at a rapid pace. Evidence of this dramatic shift can be observed in stories of scientific discovery described in Hey, Tansley, and Tolle (2009) described how new information and communication technologies in scientific research such as networked devices, high-resolution cameras, and sensors have altered the trajectory of scientific research occasioning an enormous growth in the volume of scientific data generated, the variety of data collected, and the velocity data generation. This shift is further evidenced in Collins (2004) who detailed the construction of new interferometers and utilization of new processes and protocols to aid in the search for gravitational waves by scientists in the Laser Interferometer Gravitational-Wave Observatory (LIGO) consortium (Collins, 2004; 2017). As astrophysicists search for gravitational waves, the production of petabytes of data needing high-performance computing tools for collecting and processing datasets. Advances in the development and accessibility of information and communication technologies have caused the growth of new methods and infrastructure to help alleviate the growing deluge of data. Scalable databases and advanced computer algorithms designed to address niche technical problems have made sharing information, coordinating work, and collaborating over the Internet possible.

More than a decade after Hey et al. (2009) outlined the challenges faced by science teams, the need for innovative methods to collect, process, and analyze scientific research data still exists. While automating data processing and analysis using machine learning and computer vision algorithms seem pliable, for certain types of datasets, computers programs are not yet capable of providing results with high degrees of accuracy and benefit from human judgments.

A novel approach to obtaining human judgments for scientific research datasets is to ask for help from members of the public in an open call over the Internet – or *citizen science*, also called *community science, crowd science, crowd-sourced science, civic science, volunteer monitoring*, or *networked science*. Citizen science enlists people who volunteer their time and efforts to research projects by taking on tasks such as generating research questions and collecting, processing and analyzing data pre-existing datasets (Bonney et al., 2009a). Some projects are in-person where volunteers and professional scientists meet, others are exclusively over the Internet, and some may be a combination of both. *The Galaxy Zoo* project is one an example of a project that happens exclusively over the Internet. *The Sloan Digital Sky Survey* (SDSS), an astronomy collaboration managed by the Astrophysical Research Consortium consists of hundreds of scientists and international institutions working towards creating the most detailed three-dimensional maps of the Universe. Telescopes capture photos of deep outer space generating millions of galaxy images daily. To search for new astronomical phenomenon trained astronomers, many with PhDs in astronomy, examine and categorize astronomical events such as galaxies and black holes that might appear the images. Unfortunately, the process for manually analyzing and applying labels to millions of images is extremely time-consuming. Scientists are unable to analyze each image and machine vision algorithms are not yet capable of the data fast enough to reach useful conclusions. To help process the data, astronomers created Galaxy Zoo, an online citizen science project. Astronomers uploaded 900,000 images from SDSS and within a few days, the volunteers analyze all the images. Given the success of the first Galaxy Zoo, scientists created of updated versions containing new data from SDSS, however, by 2008, 100,000 volunteers made 40 million classifications (Lintott et al., 2008). While datasets produced by citizen scientists require calibration to ensure accuracy and quality, the use of citizen science methods to collect and analyze data has proven to be valuable a number of scientific studies (Lintott et al., 2008).[1] Scientists receive assistance in various phases of the research process, which accelerates the pace and frequency of scientific discovery. *Zooniverse,* an online platform that, throughout its history has hosted more than 100 citizen science projects, has more than 1.6 million registered volunteers and over its history has supported more than 188 projects. Cox et al. (2015) estimated that each Zooniverse project contributed would take a single researcher 34 years to accomplish.

Citizen science has gained popularity across many scientific disciplines including entomology, genomics, botany, ornithology, psychology, neuroscience, and sociolinguistics.[2] Beyond accelerating the pace of scientific research (Cardamone et al., 2009; Lintott et al., 2009), the benefits of citizen science projects have been well documented as both academic scholars and practitioners attest to volunteer and societal benefits. Without formal academic training or extensive research experience, volunteers participate in authentic scientific inquiry, obtaining knowledge about a particular scientific domain and the research process generally (Bela et al., 2016; Bonney et al., 2009b; Jennett et al., 2016; Masters et al., 2016; Price, 2011). Volunteers collaborate with professional scientists learning how to do science and contribute to science. In some instances, citizen science projects find their way into classrooms in primary grades as teachers integrate projects into the science curriculums. In that sense, citizen science is both

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[1] On Zooniverse, an online platform that hosts citizen science projects lists more than 150 publications from studies using data produced by projects hosted on its platform. This is likely a conservative estimate since not all projects report to the platform (see: https://www.zooniverse.org/about/publications)
[2] https://en.wikipedia.org/wiki/List_of_citizen_science_projects

formal and informal learning opportunities for those who take part. Learning is just one benefit for volunteers' others include collaboration with peers and social opportunities. For society, scholars also note the capacity of citizen science to increase public awareness and engagement in science broadly, an important endeavor for most scientific disciplines (Barr, Haas, & Kalderon, 2018a). Projects support innovation, bridge inequalities in educational attainment by engaging traditionally underrepresented groups, and in some cases, shape local policies. In short, citizen projects possess enormous benefits for science, participants, and society as a whole.

There are many types of citizen science projects. The study described and reported on in this dissertation focuses on one form of citizen science called volunteer thinking projects (Haklay, 2013). Volunteer thinking projects engage volunteers exclusively over the Internet. Galaxy Zoo is one example of a volunteer thinking project. In volunteer thinking projects, people visit a website where they train to review and analyze pre-existing datasets. Micro-tasks, defined as small scalable, routine units of work according to protocol outlined by the science team and are executable quickly. While micro-tasks elicit images of assembly line workers clicking buttons to push the process along, scholars have noted the propensity of volunteers to take on more advanced work using existing technical infrastructure on the platforms. Participants often rise to the occasion to assume a host of other responsibilities on the platforms – formally and informally such as platform moderators or responding to the questions of newcomers. In fact, several volunteer led discoveries have been reported in volunteer thinking projects (Cardamone et al., 2009; Keel et al., 2012; Lintott et al., 2009; Straub, 2016). Recently, scientists have asked participants to take on more advanced work such as conducting large-scale data analysis and writing academic articles evoking a different set of cognitive demands and skillsets (Crowston, Mitchell, & Østerlund, 2018).

The continued success of citizen science, and volunteer thinking projects more specifically, depends on the volunteers who contribute time and efforts to ensure the projects are successful. Therefore, the organizations, scientists, project designers, software designers, educators, policymakers, and other stakeholders (henceforth labeled *project organizers*) have a personal stake in supporting people who contribute to citizen science projects. Unfortunately, projects organizers rarely consider how best to support volunteers during the design of projects, which may vary by the type of volunteer thinking project. For instance, the technical infrastructure necessary to support micro-tasks differs from the infrastructure needed to support composing an academic article for publication; needing bespoke project designs emphasizing mechanisms to support collaboration and coordination amongst participants. In short, project organizers need to do more to support the activities of volunteers in online citizen science projects.

Since the success of projects depends on a steady stream of participants who will execute tasks and take on the roles mentioned above, one area project designers might direct their attention during the initial design of citizen science projects is into the factors that facilitate participant motivation. Motivation describes the reasons why organisms (including humans) behave or act in the manner they do with an emphasis on goal attainment. Motivation is a crucial factor in any setting – from the physical world to the virtual world. Motivation describes why people rise in the morning to commute two hours to a job (payment to support a family) or why people donate to a local charity (a desire to do good or altruism). Project organizers need to understand what factors motivate people to join citizen science, precipitate their leaving, enhance their learning, and what specific strategies are necessary to support and encourage existing participants to continue contributing to projects. Knowledge about which factors drive participation and contribution in citizen science projects will allow project organizers to direct experiences to increase motivation which, in turn, could increase the number of people joining projects, decrease the number of people existing projects, and encourage existing participants to do more.

Enhancing the designs of citizen science projects might occur if project organizers considered what role of established frameworks and theories might play supporting motivation. For instance, research originating in academic fields like psychology and organization studies might help project organizers determine, which motives are salient and use these findings to inform the design of future citizen science projects. For example, to improve the design

To that end, this dissertation looks to contribute to a growing body of knowledge about volunteer motivation in citizen science, and specifically online citizen science. Borrowing from the field of psychology, *novelty* might play a role in encouraging existing participants to citizen science to contribute more. Psychologist argue that along with attributes such as surprisingness, change, complexity, and variety, novelty causes a curiosity drive in humans causing exploratory drive behaviors to materialize. Silvia (2006) argued that as individuals engage with interesting environments, they realize rewards (mostly intrinsic) and set up cognitive links between the rewards and engaging with the object.

Given that novelty, is an attribute of a volunteer's experience in citizen science, it *could* be a salient motivator for driving participation in online citizen science projects. The central premise of this study is that the novelty present in citizen science might play a role in inducing curiosity and driving exploratory behaviors. No past research has empirically investigated what role novelty might play in facilitating and sustaining motivation in online citizen science. Contained in this dissertation are three studies that explore the how novelty impacts volunteers' behaviors in online citizen science. An experiment was conducted in three citizen science projects to test the effects of novelty cues (a prompt alerted volunteers when they were the first to classifying data) on volunteer contribution behavior patterns.

The organization of the rest of this chapter is as follows: An overview of existing research on citizen science. Here the emphasis is on unpacking the ecosystem of citizen science projects, tasks, challenges, opportunities, and existing literature on motivation. The next section is a discussion of the literature on motivation in citizen science. Given similar concerns have sprouted up in other fields; projects organizers might also learn from existing studies of motivation on platforms called peer production and crowdsourcing. This discussion follows. Next is a section that provide an overview of the experimental study on which is the basis of this dissertation. Finally, the overarching research questions addressed by this dissertation including sub-questions for each chapter and their abstracts are presented.

1.2 Citizen Science

Citizen Science is the practice of engaging nonscientists in various stages of scientific inquiry including defining research questions, collecting data, analyzing data, and discussing and reporting results (Bonney, Ballard, Jordan, McCallie, Phillips, Shirk, & Wilderman, 2009a; Bonney et al., 2009c; Mason & Garbarino, 2016; Shirk et al., 2012). Public participation in scientific research is not new and some scholars trace the first citizen science projects back to the 1900s. For instance, the National Audubon’s annual Christmas Bird Count created in 1901 by ornithologist Frank M. Chapman who along with other ecological conservationists were growing increasingly alarmed by the declining bird population. Deciding to act, Chapman encouraged people to count birds instead of hunting them on Christmas Day (a popular event during the period). To submit data people simply record the number and species of bird during hiking excursions and submit records to the National Audubon. The first event consisted of Bird Counts throughout North America and yearly events still take place. The results supplied data on winter ranges of birds, which contribute to conversation biology.

During the past decade, the scope, depth, and quantity of citizen science projects have risen substantially. This growth comes in large parts by advances in information and communication technologies (ICTs). While there are no official estimates of the number of citizen science projects, the *SciStarter* website, a platform that helps in recruiting and training citizen scientists list more than 1,100 active and searchable citizen science projects worldwide; a conservative estimate. Increasingly used by scientists and organizations to complete research, citizen science is useful across a diverse set of domains and problems ranging from astronomy to wildlife conservation. Projects can be in-person, exclusively Internet-based, or a combination of both. For instance, the platform *Anecdata* hosts citizen science projects that anyone (even non-scientists) can start where initial interactions are mediated over their website and data repositories are provided, but people also meet in person to conduct projects like tracking and removing plastic and other debris from shorelines e.g., The South Carolina Aquarium.[3] The project asks volunteers to collect trash, record collection, and upload data and photos to the project page.

Scholars have introduced several typologies intended to distinguishing different types of citizen science (Bonney et al., 2009a; Wiggins & Crowston, 2010a; 2012; Yadav & Darlington, 2016). Bonney et al. (2009a) proposes three groupings based on the level of collaboration

[3] https://www.anecdata.org/projects/view/122

between volunteers and scientists - *contributory projects* where volunteers primarily contribute to data collection, *collaborative projects*, where, in addition to data collection, volunteers help analyze data and, in some cases, interpret data or disseminate findings, and *co-created projects*, where scientists and volunteers work together on a variety of tasks defining scientific stages of inquiry. Additionally, Haklay (2013) proposed three types of citizen science: volunteer computing (e.g., Stardust), volunteer thinking (e.g., Foldit), and participatory sensing (e.g., eBird). Wiggins & Crowston (2012) suggests a project's inputs, resources, and outputs might also be useful for distinguishing projects.

This dissertation focuses on *contributory* or *volunteer thinking* projects, more precisely, *online citizen science* projects (henceforth referred to as citizen science). Online citizen science projects take place exclusively over the Internet and employ a range of ICTs to mediate interactions between science teams and volunteers. Since participation is voluntary, most citizen science projects have low barriers to entry, removing registration requirements for participants and lessening the amount of onboarding such as training that needs to occur. These low barriers mean interested participants can begin working on the project at once after visiting the project website.

Most work available to participants in citizen science consists of tasks that decompose from existing scientific workflows and consists of small scalable units of work (called micro-tasks). The specific information entered as people execute tasks are pre-defined by the science team and volunteers have little autonomy to deviate from this data template. Tasks differ depending on the data collected by the scientists and include analysis of diverse types of data objects including audio recordings and scans. For instance, participants might listen to audio recordings of bats and categorizing their calls (e.g., Bat Detective) or review and transcribe digitized logs collected from ships (e.g., OldWeather). Image labeling, however, appears to be the dominant task for citizen science. The work in Galaxy Zoo gives a prototypical example of the image labeling task. Astronomers need to identify various types of galaxies, their morphological properties, and evolutionary characteristics, in order to characterize the development of galaxies. To that end, participants in Galaxy Zoo label pre-existing images of galaxies produced by telescopes (See Figure 1. Screenshot of Galaxy Zoo classification interface.). The task requires participants to answer questions pre-defined by the science team including selecting the transient properties of the galaxies e.g., the direction of arm rotation. Multiple volunteer label the images and retire a classification threshold reached and a consensus label applied. The data then shared with the Galaxy Zoo science team. In some form, this process characterizes many citizen science projects. The tight controls placed on tasks in citizen science projects means the work is often repetitive and can be quite monotonous for volunteers.

While the primary function of citizen science projects is to achieve the data collection and analysis outlined by the science team, work that is highly singular, socializing with other participants is supported in most projects. Participants use discussion forums to post and answer questions to the community, share information, report findings, discuss their views and opinions, etc. While not initially considered valuable, discussion forums have proven a crucial tool for supporting collaboration and coordination in projects; evidenced by reports of volunteer-led discoveries e.g., facilitation of Hanny's Voorep there (Keel et al., 2012).

Figure 1. Screenshot of Galaxy Zoo classification interface. Volunteers examine the image and indicate whether galaxies are present. Volunteers are also asked sub-questions from the pre-listed options on the right based on their responses.

1.2.1 Participation in Citizen Science

Most people who contribute to citizen science are non-scientists with no formal education or training in the project's science. Despite the lack of qualifications, people volunteer their time and efforts to help a project achieve its scientific goals. There are only a handful of surveys reporting the demographic information on volunteers. However, we do know projects volunteers tend to be primarily male, white, middle-aged and educated (Cox et al., 2016; Raddick et al., 2013). In a survey of Galaxy Zoo volunteers, Raddick et al. (2013) found 80% of volunteers were male, the average age was 43, and 52% possessing a bachelor's degree or higher. These statistics are consistent with astronomy projects and the field of astronomy (Price, 2011; Price & Paxson, 2012). A reasonable assumption is these demographics categorizes most projects.

Turning to participation dynamics on the site, projects characterized by a core-periphery structure. That is, the majority of participation exists on the periphery where many volunteers contribute very little work and tend to drop-out after one work session; a phenomenon labeled "dabbling" by Eveleigh et al. (2014). In a study of contribution in Galaxy Zoo and Milky Way, the percentage of volunteers dropping out after one session was 67% in and 73% respectively (Ponciano, Brasileiro, Simpson, & Smith, 2014). Suggesting projects have only a small window to make an impression on volunteers. The core, on the other hand, consists of a small cadre of dedicated volunteers who contribute most of the work and tend to contribute across multiple sessions. These volunteers also take on important social and organizational roles, which may exist formally as a moderator or informally as answering questions or curating information on the discussion boards. Despite the challenges associated with achieving more diverse participation and sustained contribution, volunteers have made scientific discoveries (Cardamone et al., 2009; Keel et al., 2012; Lintott et al., 2009; Straub, 2016). A new class of galaxies labeled *Green Peas*, was discovered by volunteers in Galaxy Zoo (Cardamone et al., 2009; Straub, 2016). A volunteer named Hanny van Arkel, discovered a rare quasar ionization echo called *Hanny's Voorep* (Dutch for Hanny's object) and in Stardust@Home, when a volunteer discovers a dust grain, they receive a listing as a co-author on the article announcing the discovery.

1.2.2 Challenges and opportunities for citizen science

The collaboration of large numbers of contributors distributed geographically and temporally has produced challenges, which project organizers should address. Challenges exist across the citizen science landscape including technical issues in building the projects, addressing usability concerns (Crowston et al., 2018; Skarlatidou, Hamilton, Vitos, & Haklay, 2019), ensuring broad participation by expanding the cultural, social, and geographic diversity (Masters et al., 2016; Pandya, 2012), ensuring the data quality (Kosmala, Wiggins, Swanson, &

Simmons, 2016), and reducing skepticism about the ability of nonscientists to contribute to science (Cohn, 2008; Golumbic, Orr, Baram-Tsabari, & Fishbain, 2017).

1.2.3 Motivation in online citizen science

Encouraging people to contribute is one critical design challenge for digital platforms (Kraut et al., 2011). A person's willingness to stick around and contribute is directly related to feelings of motivation which may or may not be attended to by a project. The success of projects depends on keeping a critical mass of volunteers to classify data and volunteers' involvement in projects dictated by the benefits and enjoyment realized from taking part. Thus, project organizers need to do more to understand the motivations driving participation and attend to these factors in the design of citizen science projects.

The literature on motivation in citizen science has grown in recent years (Alender, 2016; Cox et al., 2016; 2018; Curtis, 2015; Iacovides, Jennett, Cornish-Trestrail, & Cox, 2013; Jackson, Østerlund, Mugar, Hassman, & Crowston, 2014; Jennett et al., 2016; Jennett & Cox, 2017; Lee, Crowston, Harandi, Østerlund, & Miller, 2018; Nov, Arazy, & Anderson, 2011a 2011b; Price & Paxson, 2012; Raddick et al., 2013; 2010; Reed, Raddick, Lardner, & Carney, 2012; Rotman et al., 2014; 2012; Wald, Longo, & Dobell, 2016) and findings indicate that motivation is a complex and dynamic phenomenon and a mixture of motives driving participation in citizen science.

Motivation is an important topic for citizen science because when motivations are satisfied it facilitates the maintenance of interest. For instance, Pearce (1993) in describing the behaviors of organizational volunteers point to a host of factors that dictate people's commitment to the organizations in which they volunteer. For example, when organizations and volunteers' values overlap people will contribute to participate. Nencini, Romaioli, and Meneghini (2015) found a complex relationship between the volunteer work and interpersonal relationships among long-term member's satisfaction and commitment to the work as sustained by the presence of positive interpersonal relationships with other volunteers. When motives are satisfying positive internal and external rewards, people strive to continue to pursue the experiences, which prompted rewards.

Motivation has been divided into two categories: intrinsic and extrinsic sources. Intrinsic refers to sources of motivation where the activities itself is enough for satisfaction and the rewards internalize in the individual e.g., altruism. Extrinsic refers to externally generated sources of motivation e.g., peer recognition. Most studies investigating motivation in citizen science finds intrinsic sources tend to drive contribution. Raddick et al. (2010) surveyed 11,000 Galaxy Zoo volunteers and found twelve categories of motivation: learning, desire to discover, social interaction, use of the project as a resource for teaching, the beauty of the images, fun, amazement by vast scale of the universe, desire to help, interest in the project, interest in astronomy, and interest in science in general. Results from a survey of 199 volunteers on the Zooniverse platform revealed three factors explaining why volunteers contribute: social engagement with other volunteers, interaction with the site, and volunteering (Reed et al., 2012). Volunteers in the Foldit project have a similar set of motives including contribution to science, background interest in science, intellectual challenge, curiosity, liking puzzles, liking computer games, to learn something new, friendly competition, visual appeal/aesthetics and relaxing (Curtis, 2015). Cox et al. (2016), applying the Volunteer Functions Inventory (Clary, Snyder, & Stukas, 1996), which measures motivation in six areas protective, enhancement, social, values, understanding, and career found that understanding and values were most salient, while career and social were lesser sources of motivation.

Other scholars have highlighted the importance of collective motives e.g., identification with the group and its norms as important for some volunteers (Nov, Arazy, & Anderson, 2011a). Sociodemographic and organizational factors also moderate motivation. In a study of Galaxy Zoo volunteers, Raddick et al. (2013) found motivation related to learning science and astronomy rated significantly higher by men than women. Other factors like the design of task and workflows also influence motivation (Hutt, Everson, Grant, Love, & Littlejohn, 2015; Millette & Gagné, 2008; Sprinks, Wardlaw, Houghton, Bamford, & Morley, 2017). Sprinks et al. (2017) discovered that volunteers preferred task interfaces with greater autonomy and variety.

Several scholars also note that motivation is dynamic and changes over time (Crowston & Fagnot, 2008; Rotman et al., 2012). In one study of citizen science volunteers, Rotman et al. (2012) found feelings of egoism, e.g., curiosity about the subject matter or prior engagement in science projects tended to dominate motives during early stages, but were not a significant factor affecting long term contribution. Crowston & Fagnot, (2018) distinguishes three stages of motivation – initial, sustained, and meta in user-generated content projects like Wikipedia, arguing that the primary motives driving participation each phase of a contributor's tenue is different. An empirical test of the model noted motives such as curiosity and learning are primary drivers of early contribution while motives such as feedback and seeking to gain reputation drive participation in sustained and meta stages.

Identifying and designing motivational probes and integrating experiences that will positively affect volunteers' attitudes towards the project is one strategy to encourage contribution. A handful of experimental studies have sought to determine how and whether certain designs will influence a volunteer's contribution levels (Jackson, Crowston, Mugar, and Østerlund, 2016b; Millette & Gagné, 2008; Prestopnik and Tang, 2015). Jackson et al., (2016b) drew on theories of goal-setting, anchoring, and social bonding to design work tracking dashboards. Prior to starting a work session, volunteers responded to set classification of goals in prompts having varied elements of anchoring and social bonding (social anchoring prompts) e.g., "*Citizen scientists like you have contributed 50 classifications in a session*". The findings revealed that goal-setting increase contribution, and mediated by receiving prompts referencing the contribution of peers, as opposed to self. In another study, Lee et al. (2018) designed recruitment e-mails to determine what motives would garner the most responses from potential members. The most salient messages were those that emphasized the project's science and learning.

Millette and Gagné (2008) showed task enhancements i.e., increased autonomy positively influenced motivation and resulted in higher satisfaction and better performance while Prestopnik and Tang (2015) compared two gamification approaches and showed story-based gamification was more motivational than points-based gamification.

1.3 Motivation in crowdsourcing and peer production platforms

Citizen science has been grouped along with other modes of production on the Internet where individuals volunteer in open calls, specifically *crowdsourcing* and *peer production*. Project organizers stand to benefit from relying on existing knowledge of salient motivators and strategies to enhance participation, however, to date the literature on motivation in citizens science has been largely a theoretical and exploratory. Studies focused on motivation in crowdsourcing and peer production platforms tend to emphasize several motivational frameworks and findings, which explain individuals' desire to contribute. Building up a library of design claims from other domains and projects might better support design choices in citizen science.

In the sections below, a brief introduction to crowdsourcing and peer production with a description of the processes in prototypical examples. While both modes of production are like citizen science, there are differences, which means some findings directed towards influencing certain aspects of motivation might not be useful for citizen science. For instance, the task structures found in many peer production projects have little resemblance to the micro-task structures that define the citizen science projects researched here. The overview is not intended to be exhaustive, but instead, show commonalities, which may help articulate the designs and features not applicable to citizen science.

1.3.1 Crowdsourcing

Crowdsourcing, a portmanteau of crowd and outsourcing and defines a new mode of production in which organizations rely on crowds of undefined people to complete work in an open call (Howe, 2008). Crowdsourcing relies on the *wisdom of crowds* where the collective opinions and efforts of the crowd consistently outperform those of experts in areas of problem-solving, decision making, and prediction (Surowiecki, 2005). While ill-defined, crowdsourcing described practices including designing and voting on t-shirts designs to collaboratively writing research proposals to tackle climate change.

Combining more than thirty definitions of crowdsourcing in the academic literature, Estelles-Arolas & Gonzalez-Ladron-de-Guevara (2012) defines crowdsourcing as:

> A type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task. (p. 197)

There exists a diversity of crowdsourcing practices. Yuen, King, and Leung (2011) grouped crowd platforms by their application – voting systems (e.g., Amazon's Mechanical Turk also called *MTurk*), information sharing (e.g., Wikipedia), gaming (e.g., Google Image Labeler), and creative systems (e.g., I*nnoCentive*). Geiger, Rosemann, and Fielt (2011) grouped systems into four categories (crowd rating, crowd processing, crowd solving, and crowd creation) based on the type of contributions and the organizing structure for members. Citizen science most closely resembles the crowd voting systems described by Yuen et al. (2011).

A typical process for crowdsourcing voting involves an organization, which shows a task that needs completion and posts the task in an open call on the Internet. Several platforms such as like Amazon's Mechanical Turk or MTurk (Figure 2), Crowd4U (Figure 3) and InnoCentive are general-purpose marketplaces where individuals and organizations post tasks and advertise to members of the crowd. On MTurk individuals and organizations (called requestors) identify and design tasks (called human intelligence tasks of HITs), develop recruiting messages, set criteria for worker performance and demographics, stipulate compensation, and publish the task in an open call to the pool of workers on the site. Microwork, that is small independent and modularized units of work that can be completed quickly requiring little cognitive effort define most task structures in crowdsourcing. For instance, to aid in the search for Jim Gray (a well-known database researcher who disappeared at sea), a HIT requiring workers to examine and label satellite images posted to the platform (Doan, Ramakrishnan, & Halevy, 2011). From a participant perspective, workers (called Turkers) review the list of available HITs and determine which HITs feel qualified to complete. If they accept the HIT, they complete the tasks and send it to the requestor. Upon completion, the HIT goes back to the requestor, reviewed for quality, and compensation awarded for satisfactory completion of the task. While typical, the process described above does not cover all forms of crowdwork. For instance, more sophisticated task structures define some crowdsourcing systems. Tasks posted on InnoCentive are more complex problem-solving challenges often requiring workers with experience in the subject matter. For these types of crowd work workers receive substantial compensation for their work.

Figure 2. Screen shot of Amazon's MTurk landing page for workers. Here, the can view open tasks, the time allotted to complete the task, the compensation amount.

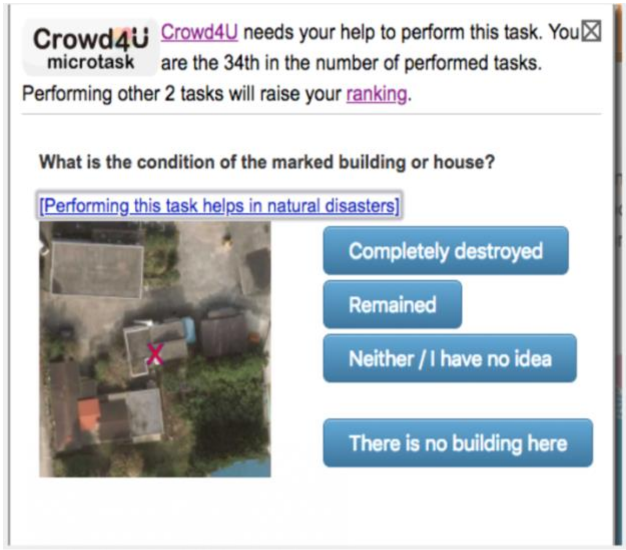


Figure 3. Screen shoot of Crowd4U platform. Volunteers review satellite images and supply labels to indicate damage from a natural disaster

The ability of crowdsourcing applications to harness voluntary contributions is one of the most discriminate characteristics of crowdsourcing. The ESP game is one popular example of volunteer-based crowdsourcing work. The goal of ESP is to create metadata for images on the web by having humans apply labels. The labels improve the accuracy of search algorithms on the web and enhance accessibility of information on the web for people who are visually impaired since labels can now have verbalized descriptions (Von Ahn, 2005). Another example include the practice of individuals and organizations who contribute to disaster response efforts. Starbird and Palen (2011) describe how volunteers engage in *crisis tweeting* efforts of people who, during natural disasters offer a helping hand by translated tweets, directing people to resources, and challenged misinformation. These efforts have no centralized platform and instead rely on exiting social networking sites like Twitter. There are, however, more formalized efforts to contribute to disaster relief in projects like Humanitarian OpenStreetMap (HOT), Ushahidi, Zooniverse Planetary Response Network, which asks volunteers to help supply spatial information about infrastructure damage following earthquakes.

The meteoric rise of crowdsourcing occurred because of the added information and communication technologies (ICTs) that help greater collaboration on the Internet. The success of crowdsourcing systems and applications depends on mass participation making motivation a concern for crowdsourcing systems and applications. Several parallels from the crowdsourcing mentioned above are similar to those found in citizen science, particularly in the areas of task and governance structures found in paid crowdwork and social and participatory structures of volunteer-based crowdsourcing. Citizen science as a mode of production is crowdsourcing. Professional scientists develop and define tasks and crowds execute the work. Similar tasks structures and approaches to governance tend to link paid crowdsourcing and citizen science. Both tasks and governance structures are hierarchical (top-down) where experts define tasks, manage, and distribute resources, and assign tasks to workers. Workers have little autonomy in the conduct of their work. Managers of paid crowdsourcing tasks tend to exert tight control over the means of production. For instance, managers compose training materials and the output supplied by workers is primarily under the ownership of the individual or organization who initiated the task. To that end, citizen science could benefit from drawing on research on worker motivation in paid crowdsourcing systems and applications that focus on the motivational aspects of task design and governance.

Theories like the *Job Characteristics Model* (Hackman & Oldham, 1976), *job enrichment* (Herzberg, 1968), *job crafting* (Wrzesniewski & Dutton, 2001), *work adjustment* (Dawis, Lofquist, & Weiss, 1968), and *the demand-control-support model* (Karasek, 1979) may be useful for project organizers in designing motivational citizen science tasks. Hackman & Oldham (1976) presented five characteristics that influence the motivational attitudes of employees in organizational settings including arguing that skill variety, task identity, task significance, autonomy, and job-based feedback play a significant role influencing personal and work-related behavioral outcomes e.g., work with high autonomy increases retention and decreases turnover. Karasek (1979) showed added motivational attributes such as responsibility, achievement, competence specialization, feedback, problem solving, job complexity that might play a role in employees' motivational attitudes.

1.3.2 Peer Production

Peer production describes a mode of production in which the contributors own the product and the means of production. Peer production is characterized by: (a) decentralized approaches to setting and executing problems and solutions; (b) a diverse set of motives driving contributors (with little reliance on monetary incentives); and (c) non-traditional governance and management structures e.g., participatory, meritocratic and charismatic factors governing social capital (Benkler, Shaw, & Hill, 2015). The online encyclopedia Wikipedia is the most dramatic examples of peer production on the Internet. Participation on Wikipedia is open to any person with an Internet connection and people contribute voluntary. Wikipedians not only write and edit articles, but they also play a key role in setting the tone and direction of the community. In that sense, Wikipedia is self-organizing. Some Wikipedians participant in project governance by developing and voting on policies that dictate user conduct on the platform and procedures for enforcing rules and guidelines outlining best practices such as article naming, stylistic standards, and behaviors. For example, the neutral point of view (NPOV), dictated by volunteers, explained that written articles should be non-judgmental in tone (Kriplean, Beschastnikh, McDonald, & Golder, 2007). Wikipedians also assume functional and social roles in the community such as technical administrator, quality assurance, privacy commissioner, social networkers, and substantive experts (Arazy, Ortega, Nov, Yeo, & Balila, 2015; Welser et al., 2011) all of which help sustain the project. Similar arrangements are in other peer production platforms including Linux and open source software (OSS) projects.

The most obvious parallels between peer production and citizen science is in the contribution patterns of members, social interactions, and the motives that drive participation. The same core-periphery structure described in the next section in peer production as contribution on several platforms report distributions approaching *Pareto and Zipf's law*. For instance, in one study of an OSS project, Lakhani & Wolf (2007) found that 4% of members gave 50% of responses to peer-to-peer questions. In Wikipedia, 2.5% of members contribute 80% of the project's content (Rafaeli & Ariel, 2009). Indeed, these few dedicated members handle much of the success experienced by these projects. Additionally, the low barriers to entry and exit mean peer production projects face an important challenge in supplying positive experiences for its members from day one to lessen negative experiences and decrease the number of dropouts.

Studies on motivation across a variety of communities find a similar cocktail of motives driving participation. In Wikipedia, motives include altruism, fun, ideology, enhancement, understanding, career, values, protective, accomplishment, collectivism, and benevolence (Ghosh, 2005; Hippel & Krogh, 2003; Kuznetsov, 2006; Nov, 2007; Oreg & Nov, 2008; Yang & Lai, 2010) and in OSS projects one finds learning, creativity, intellectual stimulation, and improving programming skills driving participation (Hars & Ou, 2002).

Several experimental studies in peer production have sought to implement motivational probes known to positively influence contributors' motivational attitudes (Ciampaglia & Taraborelli, 2015; Farzan, Dabbish, Kraut, & Postmes, 2011; Halfaker, Keyes, & Taraborelli, 2013; Lakhani & Wolf, 2007; Ling et al., 2006; Narayan, Orlowitz, Mawr, Morgan, & Hill, 2017; Narayan, Orlowitz, Morgan, & Shaw, 2015; Tausczik, Dabbish, & Kraut, 2014; Zhu, Zhang, He, Kraut, & Kittur, 2013). For instance, noting declining engagement in Wikipedia and the number of lurkers (people reading, but not contributing), Halfaker et al. (2013) designed a tool called Article Feedback Tool, to elicit contributions. Using bond-based attachment, Ling et al. (2006) was able to increase the number of contributions to *MovieLens* by telling one group of movie raters they were members in a pretended group; members made 65% more ratings than those not assigned to a group. Other experiments have shown that designing for factors such as feedback (Zhu et al., 2013) and community identification (Lakhani & Wolf, 2007) can positively impact individual motivation.

The extent to which existing research on motivation in peer production can supply empirical support for designing motivational probes that emphasize these perspectives might also be useful for citizen science projects.

1.4 Encouraging contributions through designing for novelty

Research in psychology, sociology, management, and marketing provide insights into human motivation in the physical world and borrowing from existing theories and frameworks in these fields could prove valuable for enhancing motivation online (Kraut, Resnick, & Kiesler, 2011). The literature in psychology posits that novelty is an attribute of objects and environments that give rise to curiosity in humans (Berlyne, 1950). The literature on novelty and curiosity link argued that when satisfying human curiosity drives, there are positive rewards. Novelty is in many digital platforms, however, the relationship between novelty with motivation and human behaviors needs increased research. In this dissertation, the hypothesis is that positive rewards arise in individuals when they encounter new data causing heightened individual curiosity, exploratory drives, and responses. These responses include more attention towards the classification task. The description of the origin and functioning of novelty is detailed in Chapter 2. The experiments occurred in three projects hosted on the Zooniverse citizen science platform – Higgs Hunters, Asteroid Zoo, and Gravity Spy.

1.5 Research Questions

With the aim of articulating the basis and function of novelty as a motivator in online citizen science, the researcher designed and with the assistance of project organizers at Zooniverse, executed several online field experiments to determine if and how novelty influences contribution behaviors in citizen science. The following three research questions guide this study:

RQ1: How does novelty impact volunteer engagement in online citizen science projects?

RQ2: What factors mediate novelty's impact across online citizen science projects?

RQ3: How do novelty cues lead to sustained engagement in over time?

1.6 Chapter Summaries

1.6.1 Guess What? You're the First to See this Event (Chapter 3)

Originally published in the ACM International Conference on Supporting Group Work - Jackson et al. (2016a)

In **Error! Reference source not found.**, I describe the design, implementation, and results of an online field experiment design to test several hypotheses about the effects of novelty cues on volunteer behavior in citizen science projects. This chapter addresses the research question: *How does novelty impact volunteer engagement in online citizen science projects?* The experiment was conducted in the Higgs Hunters project; a citizen science project hosted on the Zooniverse platform. In the experiment, volunteers were showed a message indicating when they were the first person to see a data object (the novelty cue). The goal of showing messages was to induce curiosity and thus what the psychology literature described as exploratory drive behaviours (or motivation).

This research makes two important contributions. First, I describe the implementation of an analytical method for experiment research called intention-to-treat (ITT). The ITT approach is used to examine experimental studies in medical clinical trials when subjects who were assigned to the treatment group fail to receive the treatment (either because of protocol violations, loss to follow-up, withdrawal from the study, and noncompliance), a characteristic of some subjects in this experiment. Second, when administering novelty cues during work sessions volunteers' motivation increases significantly. On average, volunteers in the treatment group executed 34.4 (an 88% increase) more classifications during their sessions. Greater effects were observed when analyzing a subset of the population, newcomers (first time contributors). Newcomers who saw novelty cues contributed 30 (+137%) more classifications than volunteers who were not treated. The results of this study reveal that novelty cues do facilitate motivation and are salient for encouraging volunteers to contribute to citizen science.

1.6.2 Moderating Influences for a Novelty Motivator (Chapter 4)

Error! Reference source not found. is an extension of the experimental study described in **Error! Reference source not found.**. However, these experiments were launched during different time periods and were not included in the results published in **Error! Reference source not found.**. To determine generalizability of the results reported in **Error! Reference source not found.**, experiments were conducted in two additional citizen science projects – Asteroid Zoo and Gravity Spy. Both projects are hosted on the same platform as Higgs Hunters. The assumption guiding this research is that similar effects should emerge when projects having a set of seemingly homogenous features i.e., citizen science projects hosted on the same platform, are compared. The research question answer here is: *What factors mediate novelty's impact across online citizen science projects?* While the intervention was the same across projects, the results from my analysis of the experiments revealed mixed results. The analysis revealed that showing novelty cues to volunteers in Asteroid Zoo and Higgs Hunters significantly increased the number of classifications (88% and 37% respectively). Novelty cues also significantly reduced the number of drop-outs in the projects. In Gravity Spy, however, the results showed novelty cues failed to elicit more contributions, as volunteers executed 7 fewer classifications (- 9%,), but not significant and the dropout rate remained the same. To explain these mixed results, I argued that project organizers need to consider the various social, technical, and organizational arrangements in projects as these factors are likely to be implicated in the extent to which novelty cues, and other motivational re-enforcers might influence volunteer behaviors.

1.6.3 How Long Do Treatment Effects Last? (Chapter 5)

In articulating novelty's psychological functions, scholars argue that eventually the drive produced as a result of interacting with stimuli becomes satiated. That is, over long periods the effects observed during initial exposure to novel stimuli tend to be decremented. The research addresses the question: *Does novelty lead to sustained engagement in over time?* The analyses presented in **Error! Reference source not found.** determines novelty's habituation effects on volunteers' positive exploratory behaviors. Habituation, a process that results in decreased responsiveness of individuals attention after frequent exposure to a stimulus, is used as a theoretical framing to guide the analysis. This chapter determines the optimal period at which volunteer's responsiveness habituates to novelty cues. The results in **Error! Reference source not found.** show that habituation times vary by project with volunteers in Higgs Hunters habituating after administering the 7^{th} novelty cue and volunteers in Asteroid Zoo habituating after the 9^{th}. The data used to analyze habituation in Gravity Spy however, was inconclusive.

Chapter 2 Literature Review: Novelty

2.1 Introduction

The success of digital platforms depends on the voluntary contribution of people who, in Wikipedia write and edit articles, in free/libre open source software (FLOSS) projects compile software code and documentation, and in citizen science projects help scientists analyze scientific datasets. Digital peer production and crowdsourcing platforms have a persistent problem around encouraging people to join and once they join encouraging them to remain active contributors to the platform. People leave digital platforms for a variety of reasons including limited social support, usability, lack of positive experiences, boredom, dissatisfaction with moderators, harassment and time constraints (Brandtzæg & Heim, 2008). In a study of Wikipedia editors, Halfaker et al. (2011) found newcomers received discouragement from contributing because of the hostile nature of reverts (edits to their articles) by experienced Wikipedia editors.

Other research studies have shown people's attitudes about their participation can be manipulated by re-enforcing motivational attributes of interactions. Efforts to increase the contributions from members of crowdsourcing and peer production regularly materialize through the design, testing, and implementation of social experience and technical features intended to positively influence individuals' motivational states. Experiments have shown that by integration known motivators such as feedback (Zhu et al., 2013) and community identification mechanisms (Lakhani & Wolf, 2007) projects can positively influence people's attitudes in digital platforms resulting in increased satisfaction and more contributions.

For research in the fields of computer supported cooperative work (CSCW) and human-computer interaction (HCI), efforts to manipulate individual motivation states receives support, in part, by a push towards theory-based design (Kraut et al., 2011), drawing on established theories, conceptual frameworks, and methods originating in academic fields including psychology, feminist studies, cognitive science and organizational studies. The literature on motivation in CSCW and HCI yields empirical research grounded in theories and conceptual frameworks (e.g., social recognition, feedback, goal-setting) that introduce both intrinsic and extrinsic rewards as motivators to entice people to persist as contributors. In practice theory-based design has elicited positive benefits for both the system and the individual contributor. For example, the Job Characteristics Model (JCM) dimensions proposed by Hackman and Oldham (1976), which postulates outcomes such as internal motivation, satisfaction, decrease absenteeism and work effectiveness happen when jobs possess skill variety, autonomy, task identity, task significance, and feedback. JCM is the foundation of many studies. While the JCM was originally proposed in the 1960s, it is still useful and evaluated in in peer production and crowdsourcing with attempts to design more motivational tasks (Anya, 2015; Houghton, Sprinks, Wardlaw, Bamford, & Marsh, 2019; Kaufmann, Schulze, & Veit, 2011; Kittur et al., 2013; Kobayashi, Arita, Itoko, Saito, & Takagi, 2015; Patterson, Gellatly, Arazy, & Jang, 2007; Sprinks et al., 2017; Zuchowski, Schlagwein, & Fischbach, 2016).

The linkages between systems and experiences that positively affect individual motivation are well known. Therefore, citizen science projects managers will receive help from research directed towards determining which motives are salient and how these can incorporate into the design of citizen science projects to positively influences people’s motivational states, leading to increased contribution.

Novelty is a characteristic of objects and environments often associated with increased human attention. Novelty as a psychological phenomenon, suggests that novel characteristics of an object or environment, do not fit individuals' expectations existing or categorization schema. A short description of novelty states that as humans engage with new stimuli and receive rewards, it establishes cognitive links between these rewards and engaging with the object causing individuals to continue to seek out rewards (Silvia, 2006). The interaction between stimuli and rewards perpetuates a positive feedback loop giving rise to exploratory behaviors such as increased fixation on the object (Berlyne, 1966).

Novelty is of interest to digital platforms for several reasons. First, as people spend time exploring information and interacting with others on the Internet and they receive constant exposure to novel objects and environment. Determining people's reaction to newness online can help digital platforms know when and how to present information to people. For instance, Hirsch and Silverstone (1992) suggested that individual difference in consuming information online can come from the possession of a novelty trait, which causes some people to place a high value on stimulus provided through the unfamiliar and perceive the known as boring.

Second, as digital platforms battle for the time and attention of online users, making explicit the novelty of experiences is crucial. For instance, online social networking sites (SNS) such as Facebook and content sharing platforms like YouTube place a premium on the creation and consumption of new content. Content creators are encouraged to develop new content for the platforms, which plays a crucial role in driving traffic to the site. Visitors to SNS are made aware of the new content through feeds serving up content using computer algorithms prioritizing frequent connections and popular distributors. Crowdsourcing and peer production platforms like citizen science might adopt similar approaches for serving up articles requiring editing in Wikipedia, code that needs debugging in open source projects, or data objects needing a final review by citizen scientists. The main idea here is that exposure to novel objects and environments in digital platforms may compel people to continue contributing.

In this chapter, an overview of the literature on novelty, unpacking its theoretical basis, neurological processes, physiological responses, and empirical research exploring its effects on human behaviors.

2.2 Novelty and its origins

In the sections below, an overview of novelty and its historical origins is presented.

2.2.1 Novelty and human curiosity

Across several manuscripts published in experimental and exploratory psychology journals, scholars have argued that in addition to environmental attributes such as surprisingness, change, complexity, and variety, novelty produces certain emotions, chief among them is curiosity(Berlyne,1950; Berlyne, 1954; Berlyne,1957; Berlyne,1960; Berlyne, 1966; Glanzer, 1958; Smock & Holt, 1962). Scholars have argued curiosity plays an important function in human activities such as learning (Oudeyer, 2018), problem solving (Hardy, Ness, & Mecca, 2017), creativity (Hagtvedt, Dossinger, Harrison, & Huang, 2019), and general human development (Jirout & Klahr, 2012). Curiosity is what drives humans to explore and is a foundational part of human behavioral responses to novelty making it worth looking at in more depth in this chapter.

Behavioral psychologists looked at early accounts of curiosity where curiosity was a basic drive having no direct cause for its occurrence. However, as behaviorism declined, psychologists began to consider more broadly the underpinnings of curiosity in both animals and specifically the human animal. Berlyne's (1950, 1954, 1957, 1960, 1966) work influenced the articulation of curiosity's development and influences on human behavior (Glanzer, 1958; Smock & Holt, 1962). Berlyne (1966) defined curiosity as "the condition of discomfort, due to the inadequacy of information, that motivates specific exploration" (p. 2). He authored several volumes detailing how curiosity operated in humans. The most useful writings came when Berlyne (1954) made the distinction of curiosity among humans and non-humans. Here Berlyne found *perceptual* and *epistemic* curiosity. Perceptual curiosity is a basic form of curiosity with driving forces seeking out novel stimuli associated with non-humans lacking goal orientation. Conversely, epistemic curiosity, causes humans to seek out and get information bearing stimulation for the purposes of bridging knowledge conflicts. A goal not seen in non-humans. Berlyne (1954) argued that conflict arises when inadequate information arises, creating tension in one's knowledge base creating a drive to reconcile the tension. An example of this form of conflict is in the type of curiosity induced because of the introduction of new concepts to students in a classroom. As students see new concepts which they cannot place squarely in existing knowledge structures, curiosity drive arises with the goal of directing efforts to reconcile the conflict between the new information and existing knowledge structures. As individuals learn they reduce conflicts and curiosity abates.

Berlyne also pointed out additional dimensions called *specific* and *diversive* curiosity where specific curiosity is directed toward resolving precise bits of information usually without any extrinsic incentives while diversive curiosity has a tie to the desire for perceptual or cognitive stimulation (Kidd & Hayden, 2015). However, these two forms are present in humans and non-humans. While limited in number, contemporary studies of curiosity seem to coalesce on its alignment with information-seeking behaviors and suggests that is predominately, although not exclusively, internally motivated (Oudeyer, 2007).

Berlyne (1954) disentangled curiosity and its underpinnings in humans covering forms of curiosity (i.e., epistemic and perceptual), the role of conflict in reconciliation of curiosity, and the magnitude of curiosity's arousal. His writings articulated several important points in evaluating human responses to curiosity. First, curiosity responses are not homogenous and depend on the factors of individual's preferences for curiosity and the environment in which curiosity arise. Simply some animals are more curious than others, leading to different responses to stimuli. The second, is that governing responses are factors such as familiarity with the object and/or environment. Berlyne (1954) argued that the most curiosity arousing objects are those at which there is an intermediate level of familiarity. Objects for which we are completely unfamiliar with arouses too few response tendencies (an important operator for inducing curiosity) and objects for which we are completely familiar with are not interesting enough to induce curiosity. Third, recurrent exposure to stimulus evoking curiosity will have diminishing effects on behavioral responses overtime arguing these will decrease or disappear.

2.2.2 Curiosity, novelty, and the human brain.

Why does novelty and curiosity work? To explain why novelty affects human behaviors, one must look towards how the human brain processes emotion. Only recently, with the advent of technology like functional magnetic resonance imaging (fMRI) could neurobiologists empirically see linkages between human brain functions and novelty. Most notably, Bunzeck and Düzel (2006) attempted to identify the relationship between novelty and brain function. Using an fMRI imaging, the authors looked to determine how people reacted to novel images. In their experiment, Bunzeck and Düzel (2006) showed people a series of images, some of which were novel. The results of their study revealed novelty traits activated the region of human brains labeled the substantia nigra/ventral segmental area (SN/VTA). In the same experiment, Bunzeck and Düzel (2006) showed that when displaying novel images, subjects' SN/VTA regions showed an increased brain activation. Additionally, the researchers looked to determine whether the fMRI could capture the magnitude of the novelty. Bunzeck and Düzel (2006) showed subjects images with varying degrees of novelty and recorded SN/VTA activations. The responses to varying novelty scaled according to the size of novelty.

While there are only a few studies employing fMRI imaging to evaluate human responses to novelty, existing ones implicate the hippocampus, the amygdala, and dopamine as the primary neural mechanisms dictating human response to novelty (Bunzeck & Düzel, 2006; Knight, 1996; Murty, Ballard, Macduffie, Krebs, & Adcock, 2013; Ranganath & Rainer, 2003; Wittmann, Bunzeck, Dolan, & Düzel, 2007). The hippocampus plays a role in memory and learning, and implicated in curiosity as curiosity invoking experiences. The more curious the more motivated one is to learn an engage. The amygdala may play a role in regulating emotions and hypothesized to play a role in avoidance behaviors with respect to curiosity for those not displaying a novelty seeking trait. The most relevant neural mechanism for explaining curiosity, novelty and brain function is dopamine. Dopamine is a neurotransmitter that regulates a variety of brain functions including movement, learning, and emotional responses to the environment and mediates the brains reward system. The main correlate between dopamine and curiosity is that dopamine is the chief proponent allowing humans to realize cognitive rewards. Interacting with and anticipation of novelty releases dopamine in the brain supplying the sensation of reward igniting a desire to continually seek out experiences leading to hormone releases.

Much like physiological responses governing emotions such as curiosity, anger, and happiness guiding later action, curiosity too has responses. Studies point to several standard behavioral response to curiosity and novelty including behaviors such as amplified eye movements (Baranes, Oudeyer, & Gottlieb, 2015; Berlyne, 1966), increased fixation on objects (Smock & Holt, 1962), and prolonged engagement (Koster, Seow, Dolan, & Düzel, 2016; To, Ali, Kaufman, & Hammer, 2016).

2.2.3 Novelty cues to drive curiosity

Berlyne (1950) outlined two postulates governing the function of curiosity, and re-stated in (Glanzer, 1958) which are applicable here: "when a novel stimulus affects an organism's receptors there will occur a drive stimulus-producing response called curiosity"
And "as a curiosity-arousing stimulus continues to affect an organism's receptors, curiosity will diminish" (p. 303).

Empirical work on novelty has appeared across a diverse set of contexts from consumer behavior (Hirschman, 1980), information search and retrieval (Zhang, Yuan, Lian, & Xie, 2014), game design (Gallagher, 2011; To et al., 2016), and many several others (Baranes et al., 2015; Jeno, Vandvik, Eliassen, & Grytnes, 2019; Koster et al., 2016). When exposed to novelty, a surge of dopamine stimulates excitatory processes in the brain e.g., curiosity and resulting physiological responses as increased fixation with objects for instance. Silvia (2006) argued that as individuals engage with interesting environments they gain rewards (mostly intrinsic) and establishing cognitive links between these rewards and engaging with the object. Objects and environments which have novel attributes do not fit expectations or existing categorizations and gives rise to certain physiological responses in humans such as increased interestingness eye movements or prolonged interaction with the object.

The excitement derived from interacting with novel objects is dependent on a host of personality, cultural, psychophysiological, and environmental states. Like curiosity, the degree to which novelty affects a person's behaviors is dependent on an individual's baseline preferences for novelty of whether they have a novelty trait. Observed effects on human behaviors is not unitary as some individuals have more impact by novelty. Those having no novelty trait are unlikely to realize the cognitive rewards associated with exposure to novelty. Earlier studies have pointed to low percentages of the population who have the trait and expected to have a behavioral influence by novelty. Some individuals have an urge to escape monotony and boredom and can increase the quantity and magnitude of interaction by those interacting with objects. Gallagher (2011) argued neophiliacs, a term used to describe the population of people excited by novelty, represent approximately 15% of the U.S. population.

Adding to the complexity of measuring novelty behavioral responses at the individual level, environmental factors also shape human response to novelty. Oudeyer and Kaplan (2007) pointed out that "the most rewarding situations were those with an intermediate level of novelty, between already familiar and completely new situations" (p. 2). In a study in which participants saw visual patterns of varying complexity more eye movements occurred when images were new to the participant, but not entirely novel (Berlyne, 1966).

Finally, the effect of novelty on human motivation are not permanent. Research studies showing links between novelty and curiosity drive suggested that while human responses to novelty may fluctuate, there is a strong tendency for a reduction of curiosity drive or habituation. This reduction would in turn lead to decreases in positive cognitive and physiological responses overtime (Berlyne, 1950; Silvia, 2006). For example, Murty et al. (2013) observed decrementing responses times as participants were exposed to novel, but unfamiliar stimuli. Koster et al. (2016) attest to these findings.

In another experiment on novelty's influence on impulsivity choice behaviors, Koster et al. (2016) monitored subjects' motor responses to novel and familiar images to determine the linkages between impulsivity choice and novelty. The authors asked participants to omit or perform actions by pressing a button based on the cues presented. Koster et al. (2016) found that motor actions were faster when cued by novel images showing more excitement towards novelty.

Based on prior studies, novelty associated with objects and environments help curiosity drives, which lead to increased interaction with objects and environments. However, as the studies reported above has shown, researchers should be aware of complexities that may dictate responses to novelty including individual personality differences, the magnitude of novelty people are exposed to, and periodicity of novelty exposure.

2.3 Inducing curiosity with a novelty experiment

Exposure to novelty is an intrinsic motivator giving rise to exploratory drive namely curiosity. When satisfied curiosity offers realization of positive rewards e.g., dopamine which cause people to continue to seek out positive rewards. The process implicates humans in a feedback loop where novelty is looked for to receive positive rewards. No other study has tried to test the veracity of novelty in helping motivation of people in digital platforms. To bridge this gap, the researcher conducted a series of field experiments to test the effects of novelty on volunteer' behaviors. The experiments used three citizen science projects hosted on the Zooniverse platform: Higgs Hunters, Asteroid Zoo, and Gravity Spy. Each project centered around an enormous collection of data objects i.e., images uploaded to the project site by project organizers. The site requested volunteers help scientists by making judgements (or classifying) each data object answering a set of pre-defined questions posed by the scientists. For instance, in Gravity Spy, volunteers help scientists model the noise profiles appearing in images (called glitches) produced by instrumentation used to detect gravitational waves. Volunteers reviewed each data object and selected whether the glitch's morphological characteristics resemble those from a set of known glitch morphologies. Figure 4 (left) shows the classification interface. Each data object received multiple independent judgements and the results aggregated and a consensus glitch label applied to each image. The results supplied to the scientists who use the volunteer classified data to train machine learning algorithms to automatically detect glitches in the data stream. As continuous runs of observation instruments generate new data objects, scientists funnel new data to the project to receive volunteer classification. This means during some periods, there are new data objects that volunteers have not previously seen. This process is prototypical across most projects on the Zooniverse platform.

Currently, the projects do not reveal which data objects are new or whether a data object has already received a classification from a volunteer, making this an opportunity to experiment with novelty and determine its effects on volunteers' contribution behaviors. To empirically test the effects on novelty, the researcher designed a novelty cue presented to volunteers during the process of their classification. The message reads *"You're the first to see this subject!"*. Figure 4 is an example of the cue. The messages appeared only for images that volunteers had not previously seen or classified by other volunteers on the platform.

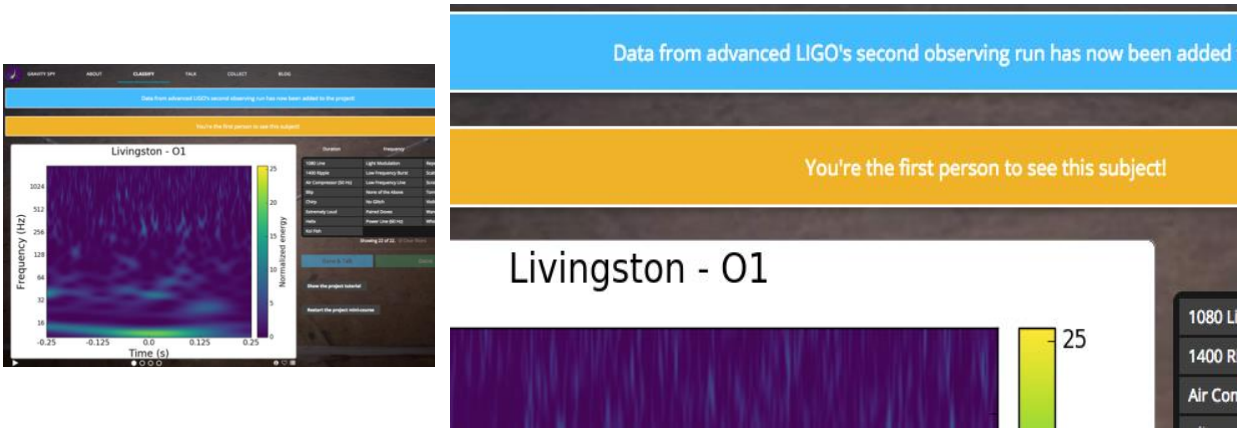


Figure 4. Classification interface on Gravity Spy. An example of the classification interface of Gravity Spy (left) and pop-up message shown to volunteers as they executed classification of a data object that was novel (right).

Most citizen science projects on Zooniverse use a single template meaning process and features dictating how people see data are the identical across projects. Data routed to volunteers use a queueing algorithm, which randomly selects data objects from a database on the backend. Volunteers then cycle through images in their queue. For images that are new, the novelty cue displayed while the volunteer classified.

One difference across the experiments did appear as implementation occurred over a three-year period. During the first Higgs Hunters and Asteroid Zoo experiments, the Zooniverse platform did not support random assignment of volunteers into a treatment or control group so the intervention included, all volunteers who had new data objects in their cue. This made these two experiments quasi-experiments. By the time the experiment in Gravity Spy launched, Zooniverse had implemented an experiment protocol that allowed random assignment to the treatment and control.

During each experiment, the system recorded all the classifications submitted by volunteers and other relevant metadata including the user name of the person who classified the data object, whether they saw the novelty cue on a specific classification, and a timestamp indicating the exact date and time the classification posted to the system.

The expectation was novelty cues will drive curiosity leading to sustained motivation. The central hypothesis for testing is that that as volunteers classify data objects, being alerted about the novel attributes of the data object will lead to positive attitudes establishing a positive feedback loop and encouraging the volunteer to classify more data.

Chapter 3 "Guess What! You're the First Person to See this Event"

3.1 Introduction

The linkages between novelty, curiosity, and motivation described in Chapter 2 suggest novel cues in an individual's environment produce curiosity, which results in sustained interactions towards the object. Novelty has been overlooked in the literature except for a few scattered studies explaining the behaviors of crowd workers (Law, Yin, Goh, Terry, & Gajos, 2016), computer hackers (Raymond, 1996), cell phone users (Leung, 2008), wiki contributors (Wohn, Velasquez, Bjornrud, & Lampe, 2012), movie recommenders, (Zhang et al., 2014), and online shopping (Zhang et al., 2014). Research by Wohn et al. (2012) found members of *Everything2*, a wiki-style community where users conduct *write-ups* of a variety of topics, engaged in reading write-ups primarily because of the presentation of novelty information. On *Mechanical Turk*, Law et al. (2016) used image presentation upon completion of a task to determine if the showing a novelty image would increase the likelihood of retention. The authors showed the intervention improved worker retention, presumably because they were curious to see the image. In his book on open-source communities and hacker culture, Raymond (1996) noted neophilia is a trait of hackers. They get excited and pleased by novelty. For instance, Leung (2008) surveyed mobile phone users and found volunteers who scored high on sensation seeking, used the phone to make calls more often and tended to use more phone features. These motives have support in research that shows the reasons for action such as novelty seeking (neophilia), sensation seeking, and curiosity. A handful of other studies have explicitly interactions to highlight an objects novelty, maximizing individuals' knowledge of their chances of gaining new experiences (Clarke et al., 2008; Kapoor, Kumar, Terveen, Konstan, & Schrater, 2015; Zhang et al., 2014).

The studies above suggest exposure to novelty to be a motivating factor for contribution. Citizen science projects are well suited for exploring novelty as a motivator. Empirical and anecdotal evidence suggested motivation for contributors to citizen science projects occurred by a project's task characteristics such as the likelihood of seeing novel data which could lead to serendipitous discovery. In fact, many projects advertise the possibility of scientific discovery in recruiting materials. For instance, in Asteroid Zoo tutorial, a passage reads, "Your goal is to find the moving dots in the images. These could be asteroids no one has ever seen before".

It is hypothesized that mentioning that a data object has not been viewed by other citizen scientists would appeal to a volunteer's desire for discovery, to be first, or to experience novel occurrences. By reinforcing novelty by providing cues when new data are shown might be a salient motivator, extending session times and improving retention. The first hypothesis:

> ***H1***: Notifying volunteers about the novelty data objects positively impacts their behavioral responses.

The context for this study is citizen science, Section 1.2 describes the contribution patterns of volunteers to citizens science. In this section, I noted that most volunteers contribute once and sessions are relatively short. This suggests strategies are needed to increase motivation of first-time contributors (newcomers) either through extending the current session or encouraging newcomers to return for another session. Wohn et al. (2012), for example, found that the presence of novelty (or information seeking) positively predicted whether a user would return to

Everything2, a peer production community. Thus, the second hypothesis is focused on the subset of newcomers:

H2: Newcomers contribute more in their first session when shown novelty messaging than newcomers contributing in their first session not shown a novelty message.

3.2 Research Setting

3.2.1 Higgs Hunters

Astrophysicists at CERN are engaged in several scientific research projects with the goal of discovering the Higgs boson particle. The CERN ATLAS project uses the Large Hadron Collider (LHC) to detect new particles. The LHC detector produces images containing off-center vertices, or tracks extending away from a central collision point (Barr, Haas, & Kalderon, 2017). The detector images show results of two beams of particles colliding, which produce a shower of new particles, possibly including previously unknown particles, such as the Higgs. Charged particles leave traces in the image; classification of these events helps to show the presence of a new particle; a discovery that be extremely significant to the scientific community.

To handle the large amount of data produced by the research project, the ATLAS physicists, in partnership with developers from Zooniverse, launched Higgs Hunters in 2014 (Barr et al., 2017; Barr, Haas, & Kalderon, 2018b; Karren & Barringer, 2002). At the time of writing, more than 20,000 volunteers from 179 countries have contributed to the Higgs Hunters project. The Higgs Hunters project shows volunteers collisions recorded by the ATLAS experiment and asks volunteers to help uncover the properties and origins of various particle's by classifying detector images. More explicitly, scientists are interested in uncovering the new particles called *baby bosons*. The task for the volunteers is to classify the detector images for decay anomalies or appearances of off-center vertexes, which are indications of the creation of a new uncharged particle that decayed into other charged particles. Not all images have off-center vertexes from particles, so seeing a new particle is akin to finding a needle in a haystack. While not detecting baby bosons, Andy Barr, a physicist working on the ATLAS project suggests the results of volunteer classification will be useful to train machine learning algorithms to automatically detect particles[4].

Figure 5 depicts the classification interface. To record a find, volunteers click on “Off-center vertex” on the right-hand side of the window, then mark the location of the vertex and how many tracks appeared. Volunteers do not receive any feedback about whether their classifications are correct or if the image is useful for science, because at the time of classification, they are unknown. Classifications are independent for the purpose of preventing one volunteer's decisions about an image to influence the classifications done by others.

[4] https://atlas.cern/updates/atlas-news/become-higgs-hunter

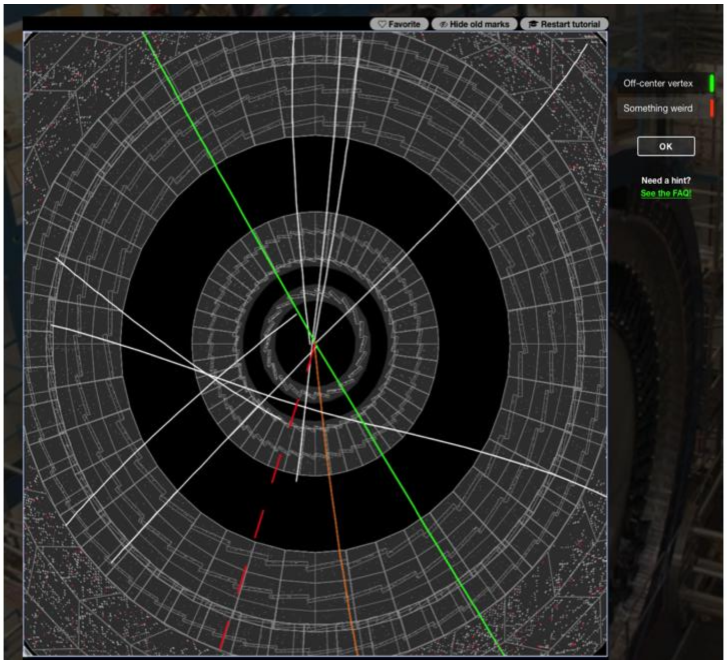


Figure 5. Classification interface for Higgs Hunters project. Volunteers review the image and mark the number of off-center vertexes.

3.3 Experiment Design

A field experiment conducted by the researcher to assess how novelty cues influence volunteers' contribution behaviors in Higgs Hunters. Zooniverse, the domain supporting the project's infrastructure has a standardized model for projects scientists to manage create, read, update and destroy actions on the platform (Simpson, Page, & De Roure, 2014). As the LHC detector produces images the data goes into a local datastore. Periodically, scientists upload new detector images to Higgs Hunters project.

At the time of the launch of the experiment, Zooniverse did not support customization of user control variables such as assigning novel images to a proportion of volunteers, thus randomization of volunteers into treatment and control periods was not achievable. Since detector images periodically upload to the system, there are periods when novel images are present in the system. This was an opportunity to show volunteers the novelty cues. These periods were treatment and control groups making this a quasi-experiment. The novelty cues presented to volunteers were as banners reading “Guess What? You're the First to See this Event”. The data collected during these timeframes are useful to make statistical comparisons and evaluate the significance of the differences.

3.4 Data collection

The collection of experiment data came from log files on Zooniverse servers in October 2015. The dataset contained all the classifications done by volunteers up to that time, including a timestamp for each classification and whether the volunteer saw the novelty banner (i.e., if they were the first person to see that image).

The dataset includes 683,970 classifications contributed by 6,354 volunteers. Analysis was at the session level with grouping of classification events by volunteer and then into sessions. Classifications included in the same session if the gap between the current classification and the earlier classification was less than 30 minutes. The intuition is that a volunteer does a number of classifications in a single sitting (with a short break between classifications) and then takes a longer break, e.g., until the next day. A session was the unit of analysis to test the hypothesis that a message might increase interest and lead to the volunteer's extending the time and activity on the system, resulting in a longer session. There were 17,353 sessions, ranging in length from 1 to 1,504 classifications, with an average of 39 and median of 16 classifications.

For each session, a recording of how many pop-up messages came up. A recording of a total display of 28,577 messages in 3,096 sessions to 1,867 volunteers (i.e., about 18% of sessions had a message and about 29% of volunteers saw a message). Below, Figure 6 shows the number of sessions done per day over time; sessions with at least one message are in blue and sessions with no messages in yellow. From the blue areas in the figure it is easy to show the dates which included the addition of new images to the system. Immediately after the addition of new images, a volunteer may see many new objects in a single session. At other times though, all images will have had at least one classification, and a session will have no messages. Note, the very large spike in work done in the first few weeks of the project and the decline in activity over time.

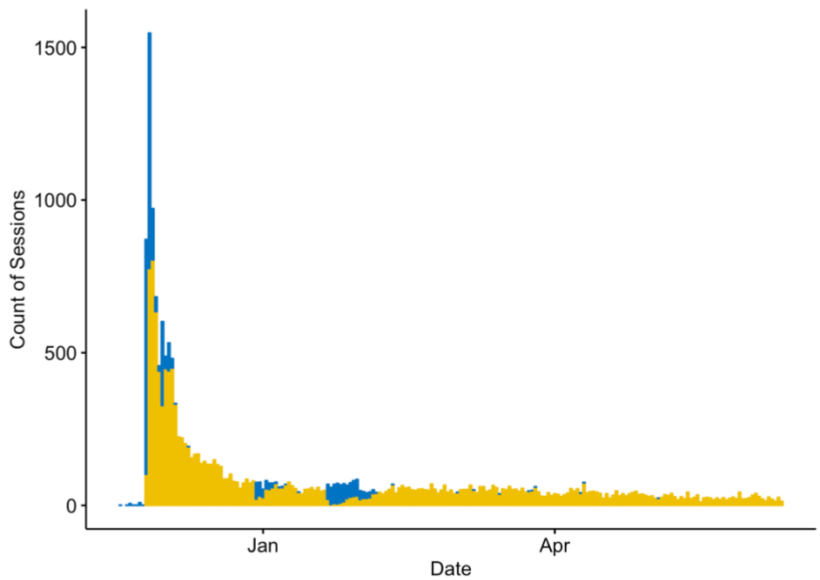


Figure 6. Number of sessions per day over time. The graph shows the number of sessions per day over time. Sessions with at least one pop-up message are in blue; those without, in orange. The inset shows the periods selected as the treatment period (blue bar) and the two periods selected for the control periods (two purple bars).

3.5 Data Analysis

This section includes a discussion of the two types of data analyses. Data analyses included a within-subjects and between-subjects approach.

3.5.1 Within Subjects

The first analysis was within-subjects, comparing for the same volunteer, the length of sessions that had or did not have a pop-up message. A simple *t*-test for the difference in session length would be confounded by the large differences in contributions from different volunteers. It might be the case that volunteers who contribute more, e.g., because of higher interest, also see messages more often. Therefore, it was necessary to control for the individual volunteer by carrying out a repeated measures analysis. Comparing sessions within a subject helped control for the very high variability of contribution to the project, but only partly.

The decision to analyze the data using mixed models was necessary since they are more sensitive to within-subject variance (Field, Miles, & Field, 2012), which is a characteristic of the data. Analysis of the data using the *R* Statistical package nlme (Pinheiro, Bates, DebRoy, & Sarkar, 2011). Since obtaining *p*-values for mixed models isn't straightforward, the approach relied on comparison of the mixed models using likelihood ratio test, which is the probability of seeing the data collected given a model (Winter, 2013). A comparison of a null model (i.e., a model disregarding the fixed effect of treatment) and a *full model* with treatment as a fixed effect occurred. The comparison of the models used an ANOVA, which yielded a chi-squared value, degrees of freedom, and the *p*-value. With this, the conclusion can be that the fixed effect of treatment is significant if the difference between the likelihood of these two models is also significant. The advantage of the within-subject design is that it uses more of the data. A possible confound to this design is that at certain points in the project, seeing a pop-up message becomes a matter of chance, as a part but not all the images are new. Because, during those periods, rather than messages causing sessions to be longer (the primary hypothesis), a longer session increases the chance of seeing novelty messages.

3.5.2 Between Subjects

To avoid the confound noted above, a between-subjects analysis on a subset of the data occurred using a quasi-experimental design. To form the treatment group (sessions with at least one novelty cue), the study took place during a two-week period where new images were available. A later period was chosen when the number of sessions done per day was beginning to plateau, meaning that the sample is not from early joiners whose behavior may differ from other volunteers, and the plateau could not be attributable to non-project events such as holidays. To get rid of outside influences from prior experiences on the system, we only used sessions from volunteers who had their first session during the period, meaning the restriction of this analysis was to the impact on newcomers. For this analysis, inclusion of all sessions done by those volunteers in the two weeks after their first session (i.e., the group includes some sessions beyond the treatment period for volunteers who joined late in the period). Note though that not all sessions during this period had a pop-up message (as shown in Figure 7), an issue we discuss below.

The formation of the control group (sessions with no novelty cues) was in a similar fashion. However, because the number of sessions per day was steadily declining over the life of the project, a control for maturation was necessary by selecting one week just before and one week just after the treatment period. Because the study used volunteers for two weeks after their first session, there was a week's gap between the first control period and the treatment period. Even so, we had to drop two sessions from the control group that edged into the treatment period and included a pop-up message. Both control and treatment periods were multiples of 7 days to include all days of the week equally.

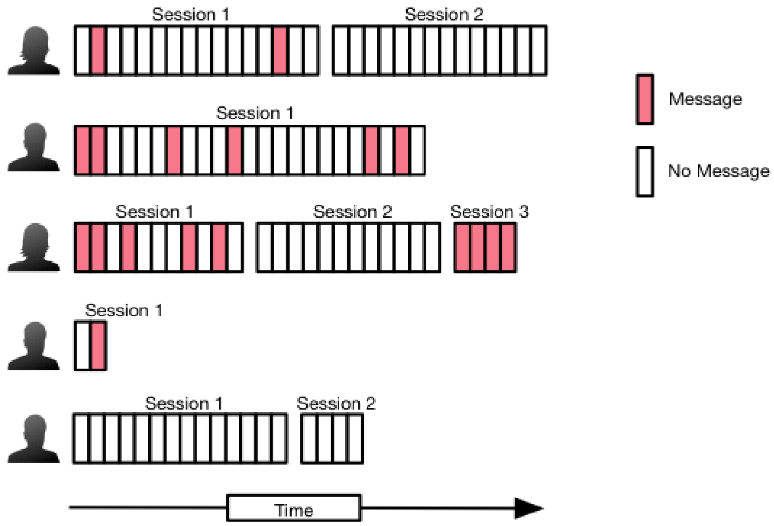


Figure 7. Sample of volunteer sessions.   Each shadow outline represented a unique volunteer. The series of rectangular boxes represented a classification. The boxes shaded in red are those in which a volunteer saw the novelty message. New data are shown at irregular intervals and in some cases, volunteers might never experience the reinforcer even when assigned to the treatment.

3.6 Results

The contributions of volunteers in online citizen science projects typically follow a long-tail distribution: many volunteers contribute little content, e.g., only a single session, while a dedicated handful of volunteers contribute most of the content. Higgs Hunters volunteers are no different: most volunteers (71%) contribute in only one session. A handful of dedicated volunteers (eight) contributed more than 11,000 classifications each---a stark contrast in behavior. The average number of sessions by volunteers is 2.73. A 1% trimmed mean to illustrate how little work most volunteers contribute. In the trimmed distribution, the average number of sessions dropped to 1.32 (σ = 11.52) and the average number of classifications dropped from 107.65 to 30.47 (σ = 699.36). Again, pointing to the extremes in volunteers' contribution patterns.

3.6.1 Encouraging Contributions to via Novelty Cues (Within-subjects)

An analysis of the effects of a message on the number of classifications submitted during sessions. Since the within-subjects comparison relies on a minimum of two observations, the creation of a subset of cases was necessary where a volunteer had at least one session where they saw a message and one session where they did not receive a novelty message. This resulted in 365 unique volunteers and 6,973 volunteer sessions. Novelty messages popped up during 1,355 (19%) sessions. The results revealed that in sessions where messages showed, volunteers contributed more classifications (See Figure 8). The sessions in which messages popped up had an average of 77.5 (σ = 107.6) classifications and a 5% trimmed mean of 55.4 classifications while sessions with no messages shown included on average 41.6 classifications (σ = 77.8) and had a 5% trimmed mean of 25.5 – a mean increase of 35.9 classifications during treatment sessions.

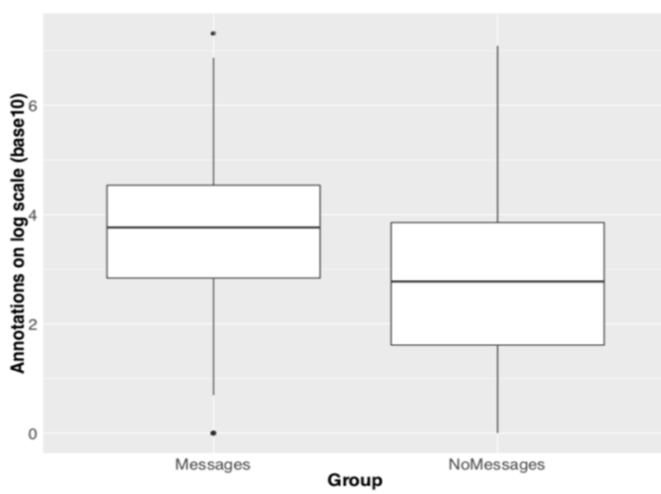


Figure 8. Group differences. This figure depicts the group differences in the number of classifications in sessions where participants received the treatment and the control.

To address the skew in the distribution of session lengths, we log transformed the dependent variable - classifications. Since the data is a repeated measure, the use a linear mixed effects model compared the number of classifications submitted during sessions of individuals in which they receive a novelty message to those when they failed to receive a message.

To test the significance of this difference, a comparison of two models occurred: a full model (with the fixed effect treatment) against a reduced model without the fixed effect. As mentioned in the methods chapter, an evaluation of these models using the likelihood ratio test through a chi-squared comparison determined whether the fixed effect had an impact on the independent variable (i.e., classifications). The results of the comparison revealed that the treatment fixed effect was significant (x^2 = 171.9, $p < 0.0001$).

3.6.2 Encouraging Contributions to via Novelty Cues (Between-subjects)

In the between-subject analysis, a comparison of the length of sessions done by those who joined during the treatment period with many pop-up messages to those who joined during a control period without such messages. During the treatment period, 217 new volunteers joined and contributed across 356 sessions (TG). During the first control period, 107 new volunteers joined the project and contributed classifications in 144 sessions, and in the second period, 76 new volunteers joined and contributed in 141 sessions, for a combined total of 183 new volunteers contributing in 285 sessions during the pooled control periods (PCG). The average number of classifications done in those sessions is in the final column of Table 1. A *t*-test showed that the difference between the average session's length in the TG (46.4) and PCG (27.3) is statistically significant at $t(639)=3.83$, $p < .001$, suggesting that the pop-up messages do increase the length of a session.

Experiment Group	Observation Period (days)	Volunteers	Sessions	μ Class. (σ)
Control Prior (CPrG)	Jan. 8 – Jan. 14 2015 (7)	107	144	18.1 (26.1)
Control Post (CPG)	Feb. 5 – Feb. 11 2015 (7)	76	141	36.8 (53.6)
Pooled Control (PCG)	14	183	285	27.3 (43)
Treatment (TG)	Jan. 21 – Feb. 3 2015 (7)	217	356	46.4 (74.7)

Table 1. Descriptive statistics of treatment and control groups.

The estimate above is conservative, since as noted above, not all sessions in the treatment group experienced the treatment. Specifically, of the 356 sessions in TG, only 223 had a pop-up message (62.6%); the remaining 133 (37.4%) did not. As a result, our estimate of the impact of the treatment diluted by the sessions in which there was no treatment. The 223 sessions in the subset of treated sessions (TT) had 64.7 (σ = 84.6) classifications on average, while volunteers' sessions in the treatment but not treated (T-NT) subset contributed only an average of 15.7 (σ = 37.94) classifications.

To obtain a better estimate of the impact of a pop-up message, the researcher applied an intention to treat analysis. Figure 9 shows the division of the subjects into the analysis control and treatment groups, and how there is further division of the treatment group into treated and untreated groups. We can see the average length of a treated session (T-T, 64.7 classifications), so the problem is to find a suitable comparison group of untreated sessions. It is impossible to compare T-T to T-NT or the entire control group (PCG) because of the confound noted above: at sometimes seeing a pop-up message is a matter of chance, so a longer session (i.e., from a more interested volunteer) is more likely to have a pop-up. Resulting in volunteer assignment of the T-T group is not random, but is related to the outcome variable, meaning the difference between T-T and the other groups could be due to selection rather than the treatment (as shown in Figure 9).

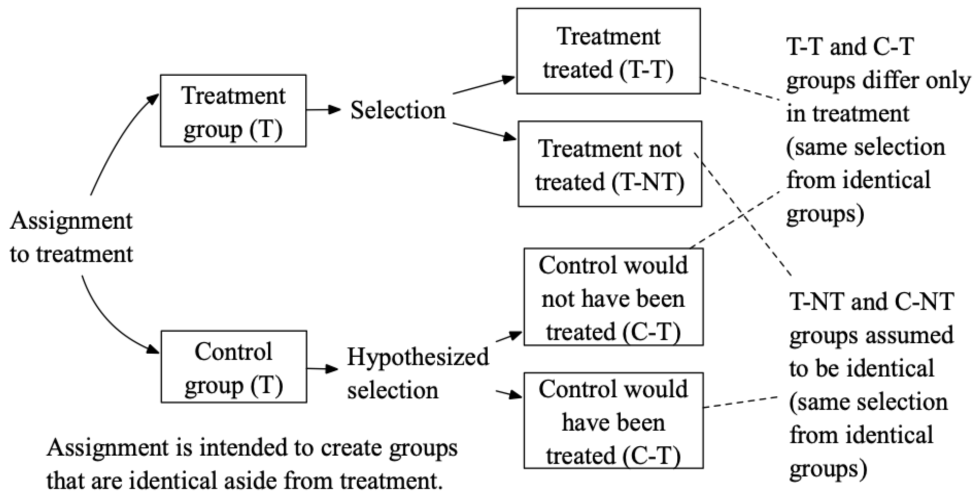


Figure 9. The logic of intention to treat analysis. Regular font indicates observed groups; italics indicate hypothesized groups.

To create a comparison group for T-T, it was necessary to select a comparable subset of the control group. Fortunately, it is not necessary to literally carry out the selection; instead, we can do it hypothetically and compute the results. An assumption that the control and treatment groups are identical aside from the treatment. Such comparability is the goal of experimental design and is an assumption of a quasi-experimental design. Therefore, had the control group been treated, it would have split in the same proportion as T into a subset that would have received the treatment (C-T, e.g., sessions from more interested control group volunteers) and a subset that would not have received the treatment (C-NT, e.g., sessions from less interested volunteers). The selection of volunteers of the C-T subgroup are in the same way as the T-T subgroup, they should be comparable to the T-T-subgroup, aside from the treatment; and similarly, for the C-NT and T-NT subgroups.

The researchers can compute the properties of the C-T subgroup indirectly. Since they are identically selected subsets of assumed-to-be identical groups, T-NT and C-NT the assumption made is to have identical properties: the same mean number of classifications (15.7) and same standard deviation (37.9). Given the observed properties of C as a whole and the assumed properties of the C-NT subset (the same as T-NT), one can compute the properties of the C-T subgroup to compare to T-T. The results are in Table 2. A *t*-test comparing the mean number of classifications in T-T (μ = 64.7, σ = 84.7) to the hypothesized number in C-T (μ = 34.3, σ = 44.4) shows a statistically significant difference, $t(400) = 4.35$, $p < .001$. As expected, this difference is larger than the difference between the means for the entire control and treatment groups.

	Experiment Group	Session	μ Class. (σ)
Treatment (T)	Treated (TT)	223 (62.6%)	64.7 (84.6) $^{+}$
	No Treated (T-NT)	133 (37.4%)	15.7 (37.9) $^{+}$
Pooled Control (PC)	Hypothetically treated (C-T)	106 (62.6% of 285)	34.4 (44.4) $^{++}$
	Hypothetically Not treated (C-NT)	106 (37.4% of 285)	15.7 (37.9) $^{+++}$

Table 2. Descriptive statistics for treatment and hypothetically derived control groups. In the table + indicates observed values from population, ++ indicates computed values based on observed PC and assumed PC-NT, and +++ assumed to be same as T-NT.

Note that these two analyses answer slightly different research questions. The comparison of the whole treatment and control groups showed the impact of implementing the intervention on the expected average length of a session, diluted because not all sessions received treatment. The second shows the expected impact of the treatment on a treated session.

3.6.3 Getting newcomers to do a little more (Between-subjects)

The researchers carried out the same intention to treat analysis examining just the volunteers' first sessions. Doing this allowed for an examination of whether the experimental manipulation had an impact on a population (who was unlikely to contribute in future sessions). Such a comparison is interesting because as noted earlier, many volunteers contribute to only one session, so increasing the length of this session may have a significant impact on the project. This comparison included 135 sessions in the treatment treated subset (TTN-Newcomer), 82 in the treatment not-treated (T-NT-Newcomer), 114 in the hypothesized pooled control who would have been treated (HPC-T-Newcomer), and 69 in the hypothesized pooled control which would not have been treated (HPC-NT-Newcomer). The descriptive statistics for the population of first sessions are in Table 3. Treated newcomers (TTN-Newcomers) contributed 51.9 classifications (σ = 69.3) while those in the hypothesized control (those who would have been treated, HPC-T-Newcomer) contributed only 24.9 (σ = 34.4) classifications, a statistically significant difference of 27 classifications, $t(247) = 3.8$, $p < .001$.

	Experiment Group	**Session**	**μ Class. (σ)**
Treatment Newcomer (TN)	Treated (TNN-Newcomer)	135	52.9 (69.3)
	Not treated (T-NT-Newcomer)	85	7.1 (10.9)
Pooled Control (PC-Newcomer)	Hypothesized – Treated (HCP-T-Newcomer)	114	24.9 (34.4)
	Hypothesized – Not treated (HCP-NT-Newcomer)	69	7.1 (10.9)

Table 3. Newcomer experiment groups with outcome variable classifications. In the table * indicates observed values from population, ** indicates computed values based on hypothesized control group, and *** assumed to be same as T-NT.

3.7 Chapter Conclusions

Taking stock of the factors that facilitate positive attitudes in citizen science tasks (and projects) essential for encouraging volunteers to contribute. In this chapter, I demonstrated that designing motivational re-enforcers into existing task structures can increase volunteer motivation and lead to positive outcomes for citizen science projects. I proposed a novelty cue to alert volunteers when they were exposed to new data objects as they classified and tested the cues in an online field experiment on the Higgs Hunters citizen science project. Empirically, I confirmed two hypotheses relating exposure to novelty cues to volunteers’ contribution behaviors. First, *H1* was confirmed as during treated sessions in which volunteers were exposed to novelty cues, the number of classifications executed almost from 34.4 to 64.7. To provide additional support, I also tested this effect using a within-subjects analysis. Again, *H1* was supported as volunteers contributed significantly more classifications (77.5 vs. 41.6) in sessions where they were exposed to a novelty cue. Second, *H2* was supported as novelty cues were also a salient motivator for newcomers increasing the number of classifications executed in sessions from 24.9 to 51.9.

3.8 Limitations

There are four limitations for this study. First, is the experimental design itself: a quasi-experiment. Given the wholesale introduction of the treatment to the population, this design was the only workable way to analyze the data from the system. A true randomized controlled experiment would have been the preferred, but the Zooniverse system was not able to support randomized assignment. However, the researcher mitigated the problem by using the intention-to-treat approach and the within subjects' analyses.

Second, there is the possibility that the effects of the treatment last longer than the single session we analyzed. For example, the effects of a novelty cue seen during a volunteer's first session might inspire them to return for a second session or have continuing impacts in that session.

Third, no examination as to whether seeing multiple messages in a session increased the impact of the treatment or if they instead become habituated to the treatment. This issue will be addressed in Chapter 5. A discussion will include the temporal dimensions of the effect.

Finally, while an experiment gives compelling evidence for a causal relationship between a treatment and an outcome, there is a trade-off for the richness of data. For example, our analysis does not include differences in volunteers not captured by the system (e.g., demographics, education, personality). Nor does it give the rich data needed to illuminate the mechanism of the effect, which is, why volunteers found novelty motivating. Prior research found that volunteers report being so motivated but understanding in more detail exactly why is a question for further in-depth investigations employing more qualitative data on interviews.

Chapter 4 Moderating Influences for a Novelty Motivator

4.1 Introduction

The results in described in Chapter 4 showed alerting people to the novel attributes of stimulus drives curiosity resulting in response behaviors, particularly increased attention. As eluded to in Chapter 2, however, both novelty and curiosity are complex and dynamic emotions and a multitude of factors may govern individual response behaviors to novelty cues; among the factors potentially influencing how people experience novelty is the setting in which novelty is presented. Research would benefit from a thoughtful articulation of novelty's influence as a driver of motivation in different projects. The chapter seeks to do so by addressing the following questions: (1) *What factors mediate novelty's impact across online citizen science projects?* This research addresses this question by exploring results from two additional field experiment assessing the impact of novelty cues on volunteers' contribution behaviors.

4.2 Research Setting(s)

This analysis uses classification data collected from the submission of citizen scientists in three projects on the Zooniverse platform. The projects were chosen for convenience. Having collaborated with software developers and managers of the Zooniverse platform for several years they graciously implemented the experiment in two additional projects - Asteroid Zoo and Gravity Spy. Each project is described below.

4.2.1 Higgs Hunters

A description Higgs Hunters is presented in the previous chapter.

4.2.2 Asteroid Zoo

Asteroid Zoo supports the National Aeronautic Space Administration's (NASA) Near-Earth Object Observation Program (NEOO). The goal of NEOO is to discover and catalogue near Earth objects (NEOs). The Catalina Sky Survey (CSS) is a program using powerful telescopes to produce mappings of the sky and produces millions of images per year. The NEOO is mandated to catalogue 90 percent of the population of NEOs larger than 140 meters some of which are hazardous and pose a threat to Earth. In 2018, approximately 1,058 NEOs were detected. The deluge of data produced by the CSS remains a significant challenge for scientists.

The Asteroid Zoo project was launched to help scientists filter NEOs. Volunteers are asked to help scientists search for NEOs by reviewing some of the images. Listed on the site are several scientific goals guiding the efforts of the scientists – identify near-earth asteroids, catalog objects for asteroid mining, study the solar system, and collect training images for future machine classification. The classification task (shown in Figure 10) requires volunteers examine a temporally linked set of images from the sky survey to identify moving objects which could be indicative of NEOs such as asteroids or potentially hazard space artifacts. The classification interface is in volunteers inspect the data object including: inverting the image, changing the resolution for viewing and cycling through several data objects in the series.

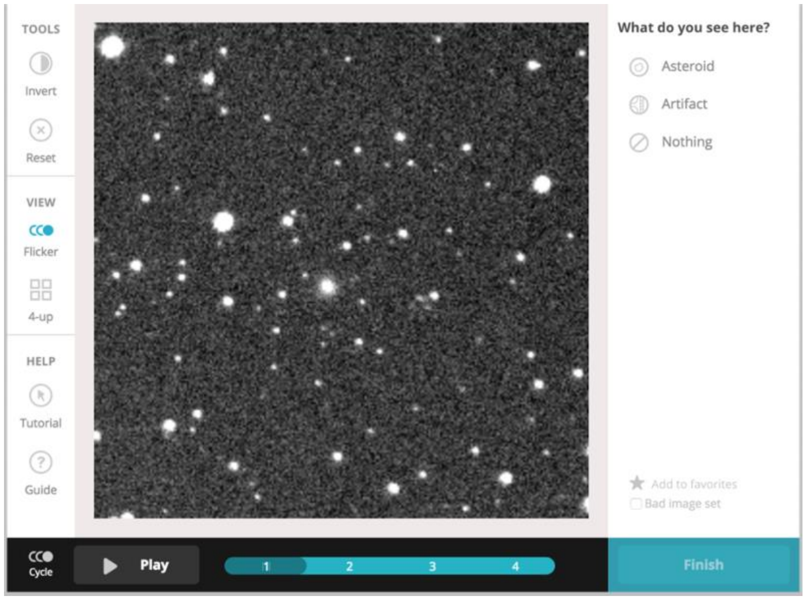


Figure 10. The Asteroid Zoo classification interface. Volunteers examine the image to determine whether asteroids or other extraterrestrial artifacts are present.

4.2.3 Gravity Spy

Launched in October 2016, the Gravity Spy project asks for the help of volunteers in categorizing datasets generated from the Laser Interferometer Gravitational-Wave Observatory (LIGO) collaboration. To detect gravitational waves, LIGO uses interferometers, which detect interference in light patterns. The machines are extremely sensitive to noise (or glitches) surrounding the instrumentation. The instrument to record gravitational waves produces a spectrogram. Occasionally, events such as birds chirping can be recorded by the interferometers and represented in the spectrogram images. To detect gravitational waves, scientists need to identity and remove the noise from datasets. In the Gravity Spy project, volunteers determine whether the glitches represented in the spectrogram share a similar morphological structure to a set of pre-defined categories. An example of a glitch and the classification interface is shown in Figure 11. Scientists then use the labeled dataset to isolate noise in potential gravitational wave signals.

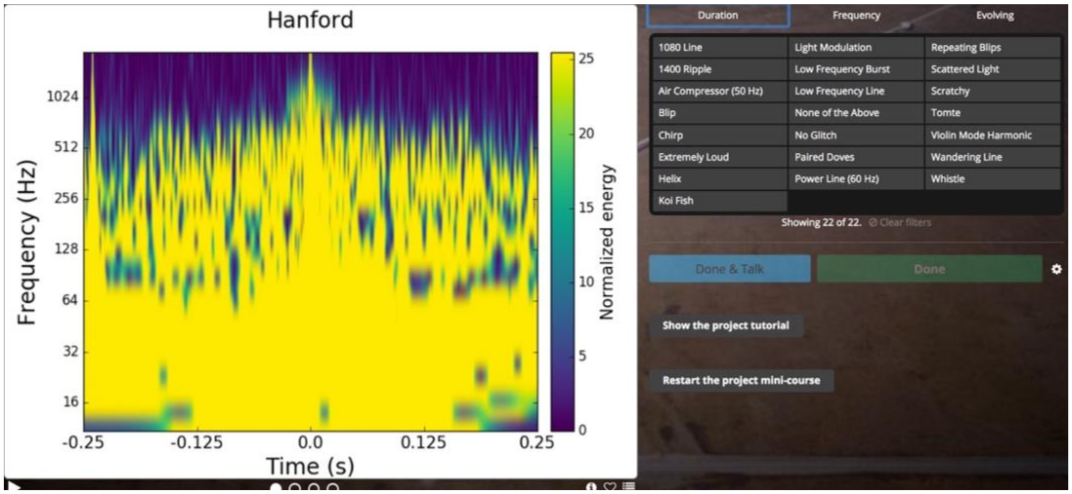


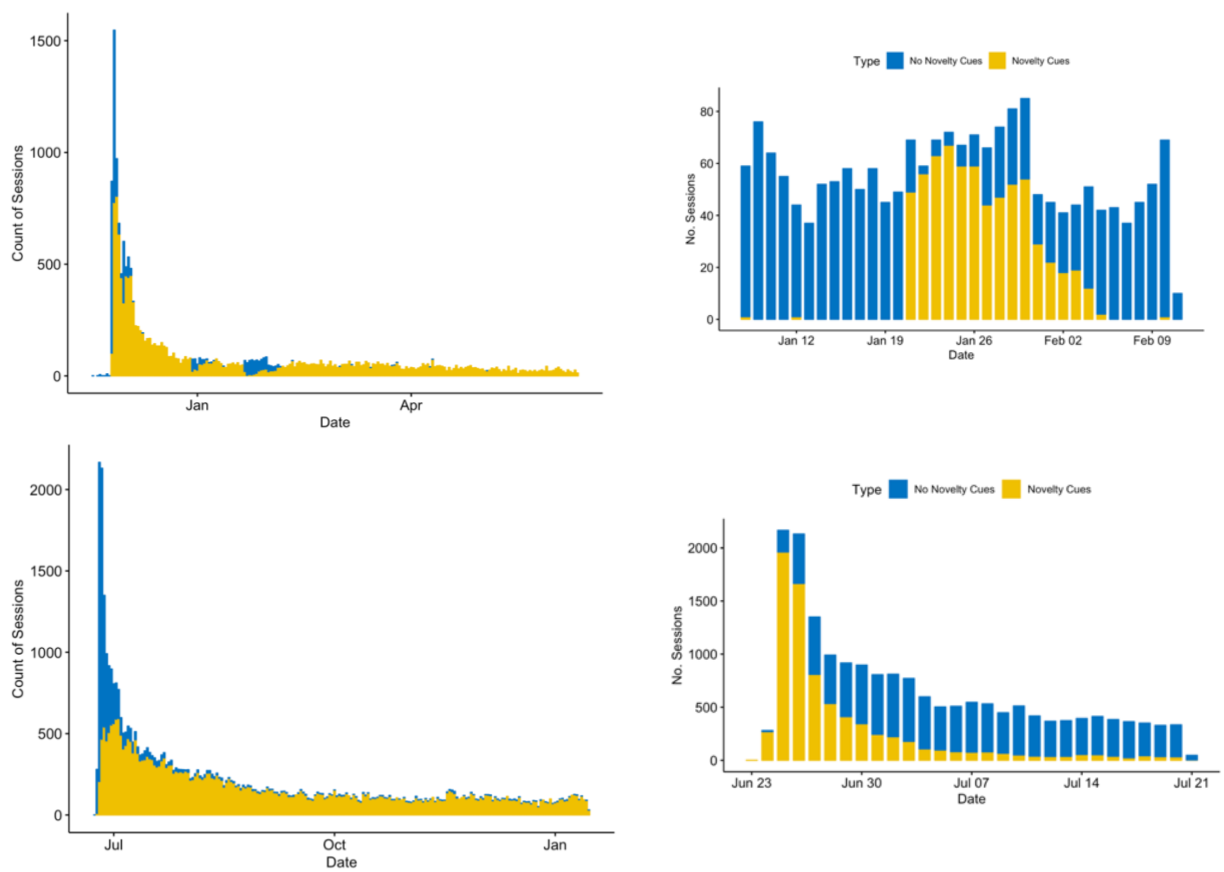
Figure 11. The Gravity Spy classification interface. Volunteers examine the glitch image on the left and make a judgment about the similarity of the glitches morphological shape to a list of known glitches in the list on the right.

4.3 Data and Methods

4.3.1 Overview of experiment design

The experiment setup used in Asteroid Zoo that of Higgs Hunters. Again, random assignment was not possible, and all the volunteers received the treatment during a single period and selection of a comparable control made Asteroid Zoo a quasi-experiment. Since assignment of the volunteers to either a treatment or control group was not random, data analysis compared treatment and control periods. Selection of the control periods for Higgs Hunters were temporally adjacent to the treatment periods for the purpose of preserving ecological validity of the experiment. The researcher chose two control periods for Higgs Hunters – one spanning a week prior the experiment period and another after the treatment period (See Figure 12, top). Asteroid Zoo had only one control period, adjacent to the experiment period (See Figure 12, middle). Finally, in Gravity Spy since the design was as a true experiment with A/B splits where volunteers received random assignment to either a treatment condition or the control the periods for each are the same (See Figure 12, bottom).

Still, we were unable to alter the queuing of data objects to volunteers meaning the irregular spacing in the Higgs Hunters was an attribute of the Asteroid Zoo and Higgs Hunters. Again, since volunteers may have dropped out prior to seeing novelty messages in their data queue, the treatment could correlate (contributing longer has a higher likelihood of seeing new data) to the outcome variable of interest. A discussion includes how we mitigated this limitation.



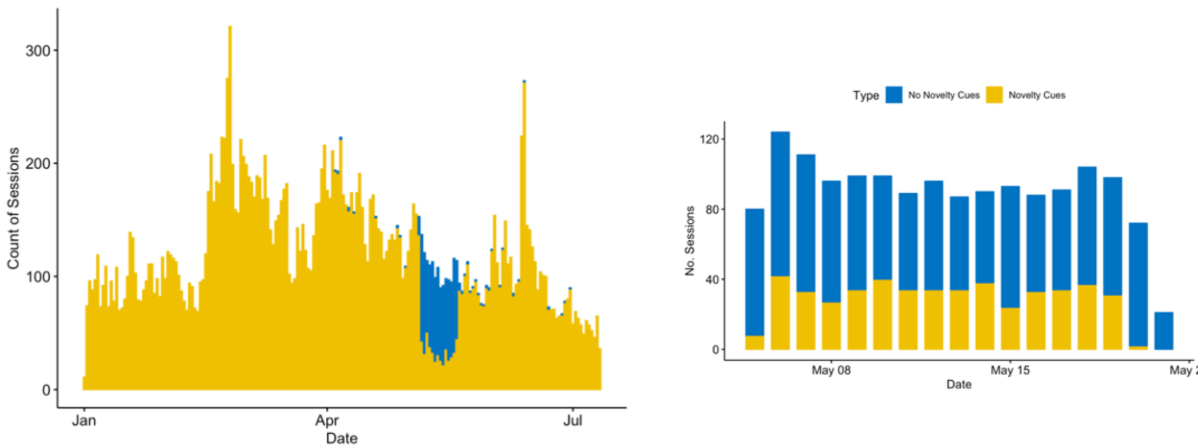


Figure 12. The control and treatment sessions were drawn from in each project.

4.3.2 The Data and Analysis

The experiment datasets for Asteroid Zoo and Gravity Spy were acquired and analyzed in a similar fashion to the dataset in Higgs Hunters. To determine whether the results from the data analysis would yield the same results, data analysis of the results of the experiment looked to determine if group and individual differences emerged resulting from exposure to the novelty cues. Again, applying the intention to treat (ITT) approach to analyze the results of the experiment for (a) the total population and (b) a subset of population in which it was a volunteer's first session.

To address the research questions, several complimentary analyses occurred and the results reported in chapter 4. Addressing the question posed in this chapter means a comparative analysis of the same experimental study described in chapter 4 evaluating the same hypothesis on the impact of novelty on the total population volunteers (*H1*) and newcomers (*H2*).

4.4 Results

Table 4 presents the descriptive statistics for each project during the observation periods. These statistics include data that were not selected for the treatment and control periods. These data are helpful to understand the activity in the project during the time of the launch of the experiments in each project. There are noticeable differences in some of the statistics reported (See Table 4). First, while having approximately congruent observation periods there were fewer volunteers and sessions represented in Higgs Hunters (volunteers = 1,867, sessions = 3,096) when compared to Asteroid Zoo (volunteers = 3,741, sessions = 8,496). The number of volunteers in Gravity Spy (volunteers = 319, sessions = 1,097) is even smaller if controlling for the number of days in the observation period. This discrepancy likely comes from the time frame in which the experiments launched. The observation period in Higgs Hunters began on January 1st 2015 and lasted until February 11th 2015 (44 days after the project officially launched). The observation period for Asteroid Zoo began June 23rd 2014 and ended July 21st 2014 (beginning the day the project officially launched) and May 5th to May 21st 2017 in Gravity Spy (5 months after the project's testing launch and x days after the live version of the project was made open to the public).

Project	Observation Period (Days)	No. Volunteers	No. Sessions	No. Class.	No. Messages
Higgs Hunters+	Jan. 1- Feb. 11 2015 (41)	1,867	3,096	195,970	28,577
Asteroid Zoo+	Jun 23 -July 21 2014 (38)	3,741	8,496	392,750	45,195
Gravity Spy++	May 05- May 21 2017 (16)	319	1,097	82,895	4,622

Table 4. Descriptive statistics for each project. + indicates a quasi-experiment with non-randomized assignment to a treatment/control. ++ indicates randomized assignment to treatment/control.

Selection of the treatment and control periods were for investigation are shown in Table 5. The selection of the treatment and control periods were so that they are temporally adjacent and had a similar number of volunteers contributing. The data reveal that during treatment periods in Higgs Hunters and Asteroid Zoo, volunteers executed more classifications than those in the control; 19.2 more in Higgs Hunters and 5.3 more in Asteroid Zoo. However, in the treated Gravity Spy sessions resulted in 4.2 fewer classifications executed.

Since the system could not change to ensure every session during the treatment actually saw new data. During some sessions in the treatment period no messages displayed to volunteers (treatment – not treated). A possible confound, however, is that seeing a novelty message becomes a matter of chance since some and not all data are new. This means that for treatment periods, rather than the messages causing sessions to be longer, a longer session could increase the changes of seeing a novelty message.

<table>
<tr><th>Project</th><th>Type</th><th>Date (days)</th><th>Volunteers</th><th>Sessions</th><th>μ Class. (σ)</th></tr>
<tr><td rowspan="4">Higgs Hunters</td><td>CP-1</td><td>Jan. 8 – Jan. 14 2015 (7)</td><td>107</td><td>144</td><td>18.1 (26.1)</td></tr>
<tr><td>CP-2</td><td>Feb. 5 – Feb. 11 2015 (7)</td><td>76</td><td>141</td><td>36.8 (53.6)</td></tr>
<tr><td>PC</td><td rowspan="2">(14)</td><td>183</td><td>285</td><td>27.3 (43)</td></tr>
<tr><td>T</td><td>217</td><td>356</td><td>46.4 (74.7)</td></tr>
<tr><td rowspan="2">Asteroid Zoo</td><td>PC</td><td>Jul. 08-Jul. 21 (14)</td><td>1,367</td><td>6,136</td><td>23.20 (33.64)</td></tr>
<tr><td>T</td><td>Jun. 23-Jul. 07 (14)</td><td>3,905</td><td>13,279</td><td>28.60 (51.13)</td></tr>
<tr><td rowspan="2">Gravity Spy</td><td>C</td><td rowspan="2">May 05-21 (14)</td><td>229</td><td>909</td><td>55.29(95.42)</td></tr>
<tr><td>T</td><td>193</td><td>824</td><td>51.04 (77.51)</td></tr>
</table>

Table 5 Descriptive statistics for the three projects during the selected experiment periods. Higgs Hunters and Asteroid Zoo were designed and analyzed as quasi-experiments where control groups were derived from periods when no novelty messages were shown. The second column Type indicates whether the observation was a Control Period (CP), Pooled Control (PC), Control (C), or Treatment (T) period.

4.4.1 Increasing Motivation by Reinforcing Novelty

To mitigate the confound described in the previous section the same intention to treat analysis conducted on this dataset. The ITT analysis used the population statistics from the treatment group to infer statistics i.e., mean and standard deviation for a hypothetically treated control group (PC-T). A comparison of the hypothetically treated control group against the session in the treatment that were actually treated (T-T) occurred.

Table 6 are the results of the intention to treat analysis. When teased out from the entire experiment period, the T-T group had noticeable increases in the mean number of classifications executed during a session. It is worth noting that in applying intention to treat, the hypothesized control mean values are higher than those observed by simply taking the mean of the control period; evidence that the analysis doesn't simply attempt to suppress values in control period. The differences seen by comparing the treatment treated (T-T) and the hypothetically treated (PC-T) groups were only statistically significant in Higgs Hunters and Asteroid Zoo. Volunteers executed 34.4 (σ = 44.4) more tasks in Higgs Hunters at $t(400) = 4.35$, $p < .001$ and 10.24 (σ = 44.4) more in Asteroid Zoo at $t(10232) = 8.25$, $p < .001$. However, volunteers in T-T group in Gravity Spy contributed 7.22 fewer classifications when exposed to the novelty treatment. However, the difference was seemed to be non-significant at $t(1018) = -1.21$, $p = 0.19$.

	Higgs Hunters		Asteroid Zoo		Gravity Spy	
	Sessions	**μ Class. (σ)**	**Sessions**	**μ Class. (σ)**	**Sessions**	**μ Class. (σ)**
Treatment (T)						
Treated (T-T)	223	64.7 (84.6)	7,000	41.28 (65.1)	484	70.52 (84.87)
Not treated (T-NT)	133	15.7 (37.9)	6,279	14.46 (20.64)	308	23.17 (54.71)
Control (PC)						
Hypothetical treated (PC-T)	179	34.4 (44.4)	3,235	30.04 (40.44)	537	77.51 (144.6)
Hypothetical Not treated (PC-NT)	106	15.7 (37.9)	2,901	14.46 (20.64)	434	23.17 (54.71)

Table 6 Descriptive statistics for treatment and hypothetically derived control groups. The statistics comparison is made vertically for each project on the mean number of classifications, that is the T-T and PC -T dimensions. ** indicated statistics significance for the comparison.

4.4.2 Novelty and First Session Behaviors

For many newcomers to online citizen science projects their first and last session occur in the same sitting. Thus, strategies to encourage contributions during this period are valuable. To determine whether reinforcing novelty cues could apply equally to newcomers, an analysis of classifications executed by this subset of volunteer contribution histories occurred. Again, since not all volunteers who contributed during the treatment period received the intention to treat analysis application.

The results of the analysis are in Table 7 and show newcomers executed significantly fewer classifications in the PC-T in Higgs Hunters and Asteroid Zoo than in the T-T group. The average number of tasks executed in T-T for Higgs Hunters was 51.9 (σ = 69.3) compared to 24.9 (σ = 34.4) in the PC-T. The difference of 27 classifications significant at $t(247) = 3.8$, $p < .001$. In Asteroid Zoo, newcomers in the PC-T executed, on average, 27.67 (σ = 36.75) classifications while newcomers in the T-T executed only 3.75 (σ = 9.7) more at 30.23 (σ = 55.1). The difference observed between newcomers in the PC-T and T-T was non-significant $t(3{,}331) = 0.82$, $p = 0.28$ indicating the novelty messages were ineffective in encouraging newcomers to execute more classifications. The results for newcomers in Gravity Spy, revealed similar outcomes, that novelty messages have no effect on the number of tasks volunteers executed. In the T-T group volunteers executed fewer classifications (μ = 108.42, σ = 118.56) compared to the PC-T group (μ = 114.62, σ = 103.44) the 6.21 difference was not significant at $t(124) = -0.23$, $p = 0.39$.

	Higgs Hunters	**Asteroid Zoo**	**Gravity Spy**
	μ Class. (σ)		
Treatment (T)			
Treated (T-T)	51.9 (84.6)	30.23 (55.1)	108.42 (118.56)
Not treated (T-NT)	7.1 (37.9)	7.73 (15.3)	13.97 (21.38)
Pooled Control (PC)			
Hypothetical treated (PC-T)	24.9 (44.4)	27.67 (36.75)	114.62 (103.44)
Hypothetical not treated (PC-NT)	7.1 (37.9)	7.73 (15.3)	13.97 (21.38)

Table 7. Newcomer classifications using the intention to treat analysis.

4.4.3 Preventing Dropouts

The literature on participation patterns reveal that most volunteers in citizen science dabble and contribute in a single session (Eveleigh et al., 2014). One potential benefit of exposing volunteers to novelty cues is that they will be excited about the possibility of seeing more novel data in the future and will be motivated to return to the project to continue classifying. One way to measure excitement to return to the project is to determine whether novelty cues decrease the dropout rate for volunteers exposed to the novelty cues. However, since novelty cues do appear to encourage newcomers to contribute more under some conditions, novelty cues might also play a role in decreasing the number of volunteers drop-outs.

This section focuses on volunteer behaviors after a volunteer's first sessions (S) in which they were treated (T) or non-treated (N-T). The proportions of volunteers who were treated in their first session S-T and not treated S-NT in Table 8.

	S-T	**S-NT**	**x^2 (p-val.)**
	Higgs Hunters (N= 463)		
Drop-out	96 (71%)	266 (81%)	5.9 **
Sustained	40 (29%)	61 (19%)	
	Asteroid Zoo (N=4,369)		
Drop-out	1,390 (45%)	752 (57%)	50.6 ***
Sustained	1,666 (55%)	561 (43%)	
	Gravity Spy (N=147)		
Drop-out	42 (66%)	60 (73%)	0.47
Sustained	22 (34%)	23 (27%)	

Table 8. A contingency table showing the proportions of volunteers who are treated and return after their first session (S) being treated (T) or not treated (N-T). A chi-squared test of proportions was conducted to determine equality of proportions. Significance levels *** p < 0.001, ** p< 0.01, * p > 0.05.

For each project, the percentage of volunteers returning for an additional session increased when seeing a novelty cue during their first session increased compared to the population of volunteers not receiving a novelty cue during the first session. In all projects, the proportion of returning volunteers was greater than in the S-T than the proportion in S-NT. To determine whether the proportions were equal in both groups, a chi-squared test of proportions occurred. In Higgs Hunters, the results of the tests revealed significant differences x^2(1, N = 463) = 5.9, p < 0.01 as did the test for Asteroid Zoo; x^2(1, N = 4369) = 50.6, p < 0.001. Thus, one can conclude for Higgs Hunters and Asteroid Zoo the proportion of volunteers returning in the S-T was significantly different from those in the S-NT. In Gravity Spy, although in sessions where volunteers were exposed novelty cues performed slightly better than volunteers not receiving the novelty cues, the difference was not significant, x^2(1, N = 147) = 0. 47, p = 0.49.

4.4.4 Returning Sooner with Novelty

If volunteers' motivational requirements are satisfied, they may also be more excited return to the project sooner than other volunteers. To determine whether exposure to novelty during the first session precipitated faster return to the project for those volunteers who did eventually return for a second session. Calculating the time to return was simply by subtracting the time after a volunteer's first session concluded and the start of their second session. The results are in Table 9 and show the time (in days) between a volunteer's first and second session. In all projects, volunteers who received treatment during their first session (S-T) took less days to return than those who did not receive treatment during their first sessions (S-NT). The results of an independent samples *t*-test revealed significant difference in the days to return for S-T (μ = 4.11 σ =15.38) and S-NT (μ = 5.5, σ = 19.6) in Higgs Hunters $t(269.15) = 1.98$, $p < 0.05$; and Asteroid Zoo (S-T μ = 5.53, σ = 19.38) (S-NT μ = 9.7, σ = 29) at $t(863.77) = 3.4$, $p < 0.001$. However, the return time in Gravity Spy was not significant $t(155.35) = -0.22$, p = 0. 82.

		Higgs Hunters	**Asteroid Zoo**	**Gravity Spy**
Time (in days) between the first and second sessions	S-T	7.1 (17.4)	5.5 (19.6)	6.8 (10.8)
	S-NT	12.1 (25)	9.7 (29)	6.5(15.1)
Independent samples t-test		4.56*	3.4***	-0.22

Table 9. The mean time (in days) to beginning the second session for volunteers who were treated T or not treated (N-T) during their first session (S). Significance levels *** p < 0.001, ** p< 0.01, * p > 0.05.

4.5 Chapter Conclusions

Motivation is an important area of research for citizen science, and online communities more generally, understanding the human motivational process and the appropriate context surrounding the introduction and use to motivational reinforcers can help improve user experience and increase performance associated with tasks such as those found in online citizen science. However, when testing motivational reinforcers experimentally, this research showed that different conclusions are possible. This chapter showed how designing a motivational reinforcer affects volunteer performance in three citizen science.

Two additional experiments occurred in citizen science projects where volunteers saw the same novelty cues when they were the first person to see new data objects when they classified on the system. The results above show promising, but in some cases mixed results suggesting further investigation is necessary. The next chapter will include a discussion as to why in two of the three projects studied exposing volunteers to novelty cues during sessions resulted in significantly more classifications that in sessions where no novelty cues seen by volunteers.

Volunteers in Higgs Hunters executed 34.4 more classifications while volunteers in Asteroid Zoo executed 10.24 more classifications. The results from the analysis of Gravity Spy, while disappointing, might have occurred because of the fact that the experiment launched more than five months after the project launched and many volunteers assigned to control were experienced contributors. Only a small percentage of volunteers in the experiment implements on Gravity Spy appeared to be new while many more volunteers had been contributors to the project in the period prior to the experiment launch. This difference in population could explain some of the non-significant results. Perhaps old-timers are not influenced by novelty. These volunteers are likely to have the motives satisfied by other features of the project making it less likely novelty would cause a change in their contribution behaviors. Exposure to novelty cues did reduce the dropout rate in all projects, however, the test of proportions revealed this to be true only for Higgs Hunters and Asteroid Zoo.

The differences observed in the experiments reported here do call into question whether studies like these are generalizability to other seemingly homogenous settings and lead one to question what role temporality, task design, and other organizational and social features might play as confounding factors in explaining the results. Some of these topics are addressed in the conclusion of the next chapter.

Chapter 5 How Long do Treatment Effects Last?

5.1 Introduction

Everyday people serendipitously or contentiously meet novelty stimuli. Exposure to new experiences may arise when we explore new environments visiting new neighborhoods, trying new foods, etc. On digital platforms, people may become exposed to novel stimuli when they search for information recourses and open SNS websites and mobile applications like Facebook or Instagram. The previous chapters in this dissertation provide *some* empirical support for the proposition that novelty tends to result in sustained interaction in the environment in which one has been alerted to novelty, however, unknown is when novelty ceases to motivate volunteers' attention towards specific objects in the environment.

While increases in motivation can ascribe to novel stimuli, the mechanisms associated with repeated exposure to a stimulus is unknown. The literature review suggested that behavioral outcomes observed during initial exposure to novelty decreases over time. Additionally, this decrement may depend on a host of individual dispositions to novelty and the setting in which an individual becomes exposed to novelty. A reasonable conclusion is that stimuli will attract attention only for a limited period before one becomes *habituated*.

Habituation describes the process by which responsiveness to stimuli decreases (Blumstein, 2016; Rankin et al., 2009; Thompson & Spencer, 1966). Scholars have put forth several rules suggesting how habituation might materialize. In a review of literature on habituation, Thompson & Spencer (1966) outlined characteristics of habituation such as its tendency to recover after some period and the transfer potential of one stimuli response to other stimuli. A clear understanding of the mechanism of habituation is the aim of this chapter as habituation can describe human responsiveness to not only motivational prompts, but many stimuli in the real-world and online. Questions about the process of habituation, factors that could lead to habituation and optimizing habituation could benefit the research on using novelty cues to motivate volunteers in citizen science.

In this chapter, the examination includes habituation to novelty cues at the classification level. The goal here is to determine the characteristics of habituation and determine the optimal point during which project organizers might cease administering novelty cues to volunteers since they are no longer influences by them. The analysis conducted and reported on in this chapter use data from the three experiments reported in previous chapters. To my knowledge, no research has been undertaken to understand the habitational effects of experimental treatments in citizen science. The question posed in this chapter is: *What are the habitual characteristics of novelty cues on volunteers' contribution behaviors over time?*

5.2 The Rules of Habituation

The description of habituation is as a process that results in decreased responsiveness of individuals attention after frequent exposure to a stimulus. Thompson & Spencer (1966) reviewed existent literature on behavioral habituation and developed nine "rules" of habituation. Revisions and expansions to Thompson and Spencer's nine rules are outlined in Rankin et al. (2009) and Blumstein (2016) who argue more than forty years of new research on habituation necessitates modifications. The parameters of habituation are described below. I also describe how these rules may interact with novelty in the context of the novelty cues administered to volunteers in the citizen science projects researched in this dissertation.

Rule 1. Applications of a stimuli should result in a decline in the magnitude of some response parameter to an asymptotic level. The original rule in Thompson & Spencer (1966) suggests that the decrease is expected to be a negative exponential function of the number of stimuli presented however revisions in Rankin et al. (2009) suggest other relationships are possible e.g., linear. This rule is the basic foundation of habituation that stimuli lose their effectiveness over time. In evaluating the novelty stimuli responsiveness can be measured as the time after administration until a volunteer stops contributing in a session and the amount of time until a volunteer stops contributing in a session.

Rule 2. Recovery of response parameters (to pre-stimuli levels) ensues as the result of withholding stimuli. This phenomenon labeled response recovery and describes a constant procedure of stimuli exposure and withholding for extended periods to measure response parameter. Lengthy periods in stimuli withholding eventually adjusts response parameters to the same values revealed prior to the reveal of the stimuli. As the presentation of novelty stimuli repeat to volunteers and response parameters such as time spent classifying a data object measured, if the novelty stimulus is withheld for a period, similar behaviors that were observed prior to administration of the novelty stimuli are expected.

Rule 3. After successive administration of a stimulus and spontaneous recovery, habituation becomes more rapid (this phenomeno**n** called potentiation of habituation**)**. With a sustained processes of stimulus exposure and recovery, habituation time **should** decrease. For novelty stimuli, repetitions cycling through exposure to data objects with novelty stimuli and non-novelty data objects, the time to habituation decreases

Rule 4. The more frequent stimulation occurs the more rapid/pronounced habituation. Stated simply the more regularly the experience of a stimulus is occurring within the course of the training, the quicker habituation happens. During high stimulation frequencies of the stimulus, it the expectation is that volunteers reach habituation faster than those exposed to the stimuli at lower frequencies in the session.

Rule 5. At the asymptote of the response parameter, continuous exposure to stimuli may delay spontaneous recovery. When a stimulus administered repeatedly, it is possible for response to stay at levels observed with administration of the stimulus. For novelty, successive administration of messages will plateau the response parameter.

Rule 6. The intensity of a stimulus impacts the speed of habituation. The rule here is that less intense stimuli increase the rate of habituation while intense stimuli results in slower or no habituation. Without proper intensity comparisons, it is challenging to measure and evaluate the rate of habituation with stimuli with varying levels of intensity

Rule 7. Elongated response recovery to pre-stimuli levels or dishabituation is possible. After some period of non-exposure an individual's response time will return to levels seen prior to the administered stimuli. Novelty should work in the same fashion. After seeing the response associated with a stimulus, an individual's response time will revert to levels seen prior to the first administration of the novelty message.

Rule 8. While dishabituation is possible for a stimulus, another series of repeated exposure to may lead to habituation. After dishabituation occurs, it is possible to restart the habituation process. After a period of dishabituation, administration of novelty messages will revive the habituation process.

Rule 9. Habituation can transfer from one stimulus to another. If two stimuli are sufficiently related the habituation process does not restart, but transfers between the stimuli. Rankin et al. (2009) introduces a tenth rule of habituation:

Rule 10. Some stimulus repetition protocols may result in properties of the response decrement (e.g. more rapid re-habituation than baseline, smaller initial responses than baseline, smaller mean responses than baseline, less frequent responses than the baseline) that last hours, days or weeks. Simply put the timeline for habituation properties may vary**.**

5.3 Methods

The next sections will describe how to operationalize habituation, the dataset used to analyze habituation, and the analysis approach.

5.3.1 Measuring habituation with novelty stimuli

The goal of this section is to determine when volunteers become habituated to novelty cues (Rule 1). Habituation is a mental state, making it difficult to see, however most studies tend to consider response times to stimuli as an approach to measure habituation. Consistent with theory and other experimental studies, the researcher considered habituation by measuring volunteers' *response times* during classifications. As exposure of volunteers to novelty cues, measurement of habituation can be as the amount of attention in time spent analyzing an image. As volunteers become habituated to novelty cues, one expects their response times during later administrations of a novelty cue or classification to decrease.

5.3.2 The dataset and analysis.

Collection of data from all volunteers during the experiment periods. A sample of the dataset is in Table 10. Each record represents a single classification executed by a volunteer and contains metadata about the classification such as the unique identifier of the volunteer who executed the classification, the session in which the classification was made, the sequence of the classification in a session, and whether the novelty cue was displayed. Response time was manually calculated by subtracting the time difference between the current and next classification record for the same volunteer in the same session. Since no information about when the last activity before leaving, computation of the response time for the final classification was not possible.

ID	Session	Order	Date	Subject ID	Novelty cue seen	Response time (secs.)
3234	1	1	2015-01-30 21:54:20	202	Yes	6
3234	1	2	2015-01-30 21:59:14	234	No	38
3234	1	3	2015-01-30 22:00:53	158	Yes	32
3234	1	4	2015-01-30 22:01:00	094	No	-
0943	1	1	2015-01-30 21:54:20	1224	No	68
0943	1	2	2015-01-30 21:55:28	5893	Yes	-

Table 10. A Sample of the Dataset used to Analyze Habituation

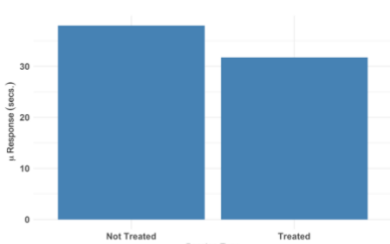
To analyze the data, the researcher performed several statistical comparisons in which mean response time was the outcome variable of interest and examined only the data from a volunteer's first session. Selection of first sessions were to reduce the amount of data needed to be modeled, but also since most volunteers contribute in only one session, project organizers might focus on encouraging *dabblers* to contribute a little more during their first session.

5.4 Responses to novelty cues.

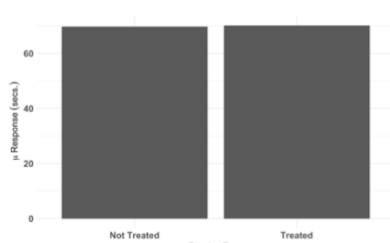
In this section, the focus is on an exploration of volunteers' behavioral responses to classifications and novelty cues. The behavioral responses here help to set a baseline for behavioral comparisons made later. The baseline helps set an expected level of contribution at the session level so comparisons during treatment periods can occur. The data used here contains only those activities for volunteers. For Gravity Spy since the population of volunteers was much smaller, we did not limit classifications to first sessions.

5.4.1 Comparing response times for treated and not-treated sessions.

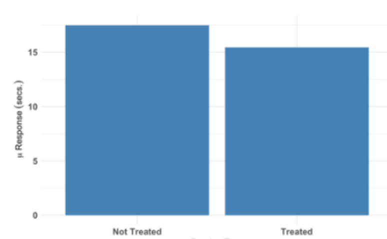
Figure 13 shows the mean response times during the first sessions. Across all projects, volunteers treated tended to have a lower mean response rate when compared to not-treated sessions. In Higgs Hunters, the median response time in treated sessions was 15 (μ = 31.7, σ = 80.4) and not-treated sessions the response time was 18 (μ = 38, σ = 88.3), a median difference of 3 seconds. In Asteroid Zoo, the median response in treated sessions was 39 (μ = 70, σ = 121) seconds compared to 38 (μ = 69.7, σ = 119.3) during sessions in which volunteers were not-treated and in Gravity Spy, a median difference of 1 second when comparing the treated sessions (median = 7, μ = 15.4, σ = 59.6) and not-treated sessions (median = 8, μ = 17.4, σ = 56).



(a) Higgs Hunters



(b) Asteroid Zoo



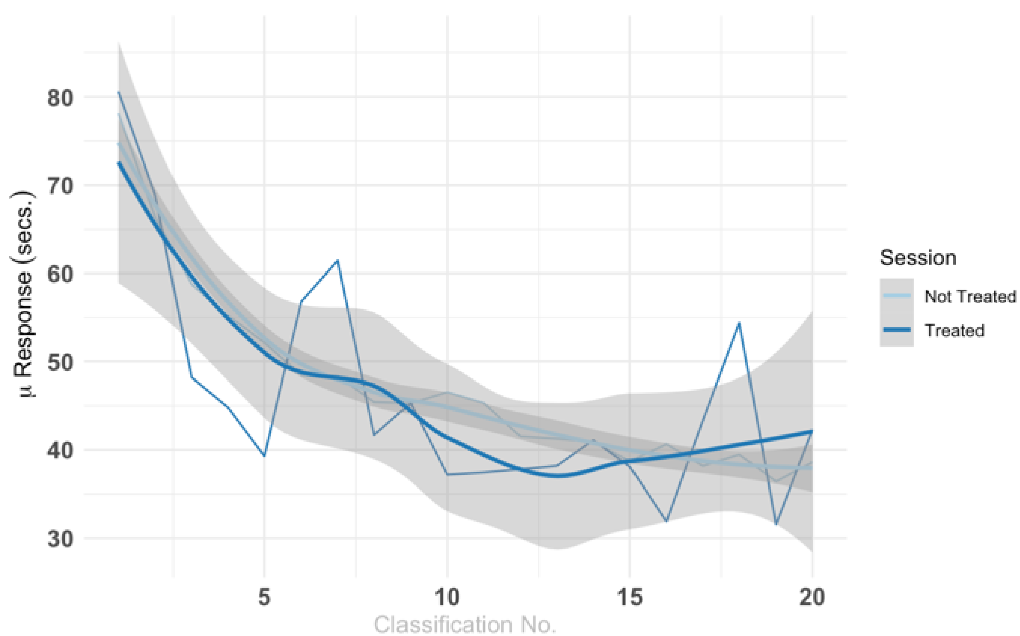
(c) Gravity Spy

Figure 13. Bar plots showing the mean response time during sessions that were treated and not-treated.

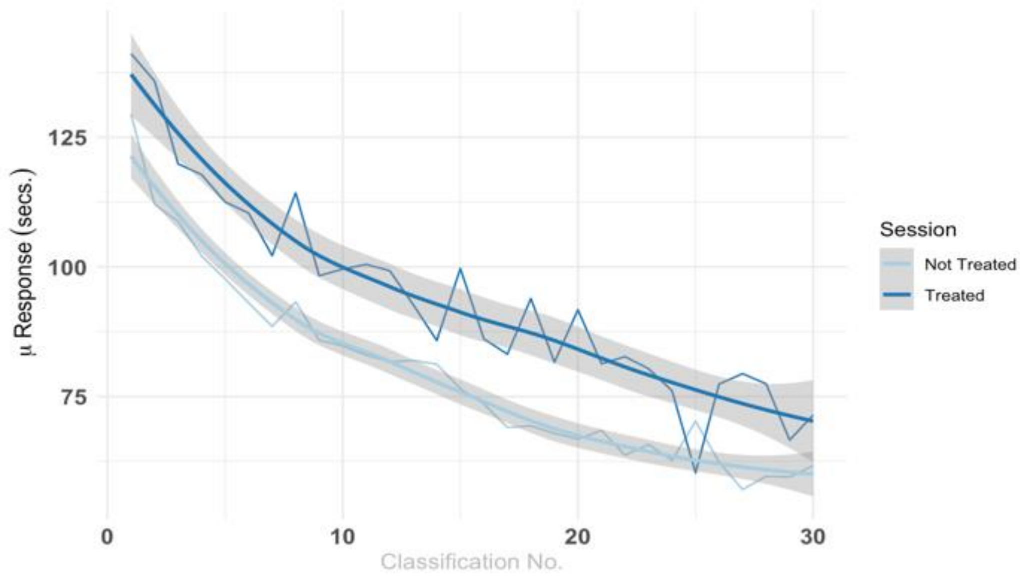
To determine whether the differences in response times between treated and not-treated sessions was significant, the researcher used a Wilcoxon rank sum test (See Table 11). The results of the test showed mean response time was significantly lower for Higgs Hunters Z = 4734100000, p < 0.001. Significant differences were observed in Asteroid (Z = 2944800000, p < 0.001) and in Gravity Spy (Z = 1.261e+09, p < 0.001).

		Higgs Hunters	**Asteroid Zoo**	**Gravity Spy**
Response time (secs.)	Treated	31.7 (80.4)	113.63 (108.1)	15.4 (59.6)
	Not-Treated	38 (88.3)	138.8 (167.6)	17.4 (56)
	Wilcoxon rank sum test	4734100000***	2944800000***	1.261e+09 ***

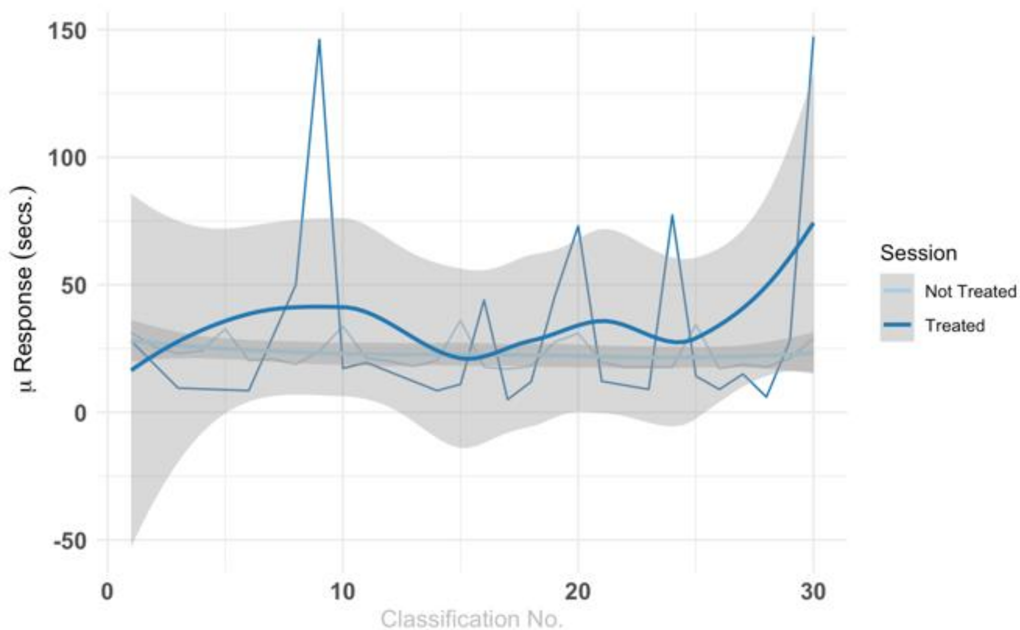
Table 11. Mean response time for images in treated and non-treated session during session one. (sig. levels *** p < 0.001, ** p< 0.01, *p > 0.05).



(a) Higgs Hunters



(b) Asteroid Zoo



(c) Gravity Spy

Figure 14. The response parameters for the first 30 classifications during session one.

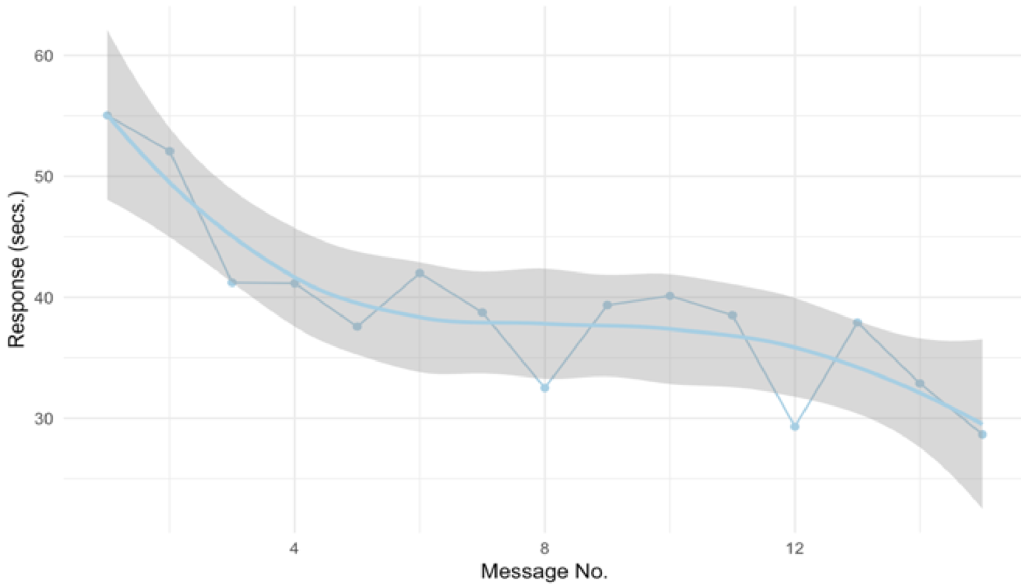
5.4.2 Response decrement during treated sessions

Next, a determination of exactly how the response size decrements occur as volunteers execute more classifications. The literature on habituation suggests that a decline in the magnitude of a response parameter is to seen over time, however, one might expect the response decrement to occur differently in treated and not-treated sessions.

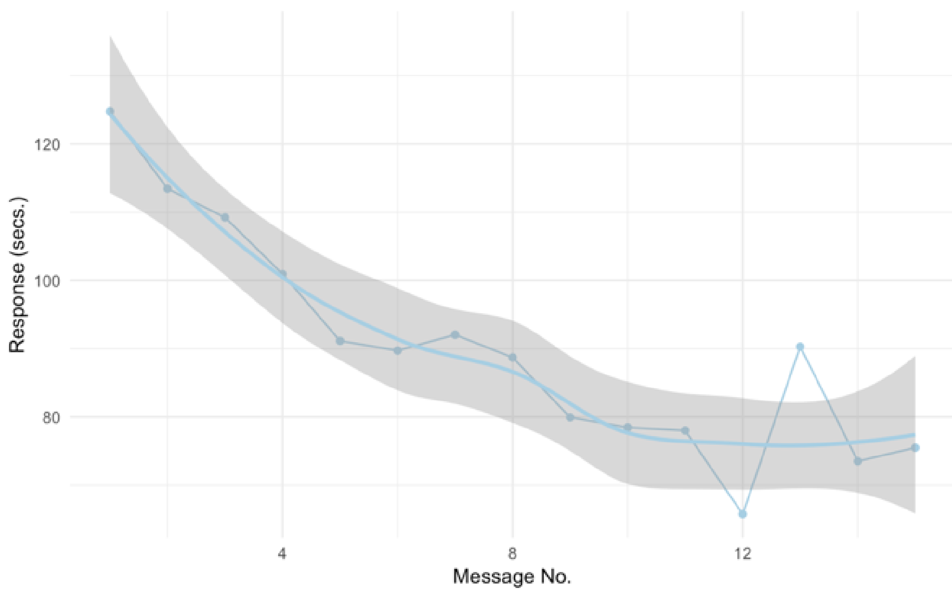
5.4.2.1 Habituation to Novelty Cues.

The line graphs in Figure 15 show the mean response times for messages the first 15 messages administered during treated sessions. The figures show two lines, the mean response at each message interval and a smoothed line to aid in detecting overall patterns. The mean response times tend to fluctuate over the observation period, however, fitting a smoothed trend line reveals a steady decreasing response parameter in a curvilinear fashion as the exposure to the number of messages a volunteer receives to (x-axis) increases. The pattern suggests a complex non-linear relationship at various levels of the variables.

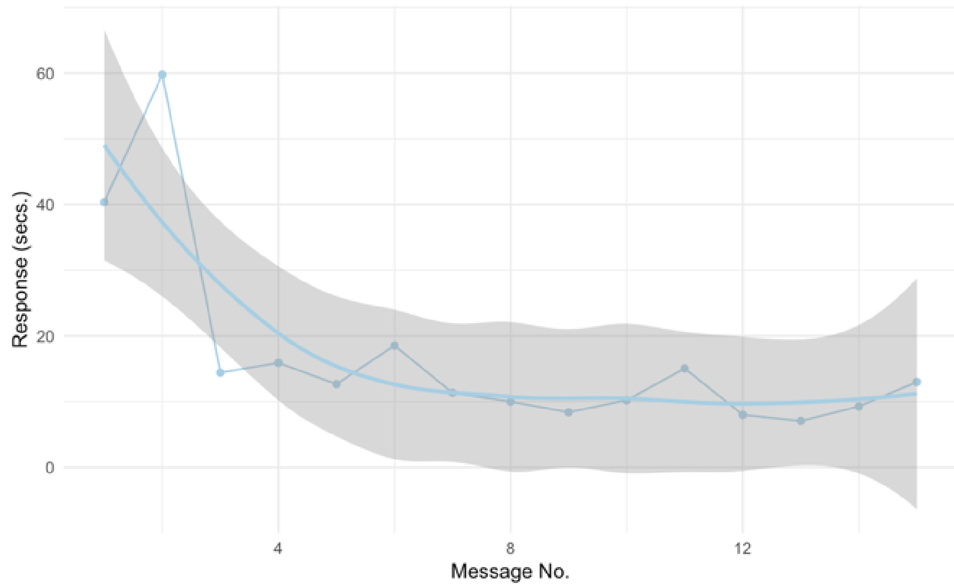
As noted above, the baselines response times tend to differ by project and volunteer. Even when evaluating volunteers at a common start point, the trend lines evolve differently at the project level. The gradient of the curvature for the lines in Asteroid Zoo do appear to decrease more rapidly than those in Higgs Hunters and Gravity Spy. Both smoothed response times for Asteroid Zoo and Gravity Spy do appear to plateau towards at the 10^{th} and 8^{th} administration of the novelty cues while Higgs Hunters appears to first plateau around message 6 then then dip again after message 15.



(a) Higgs Hunters



(b) Asteroid Zoo



(c) Gravity Spy

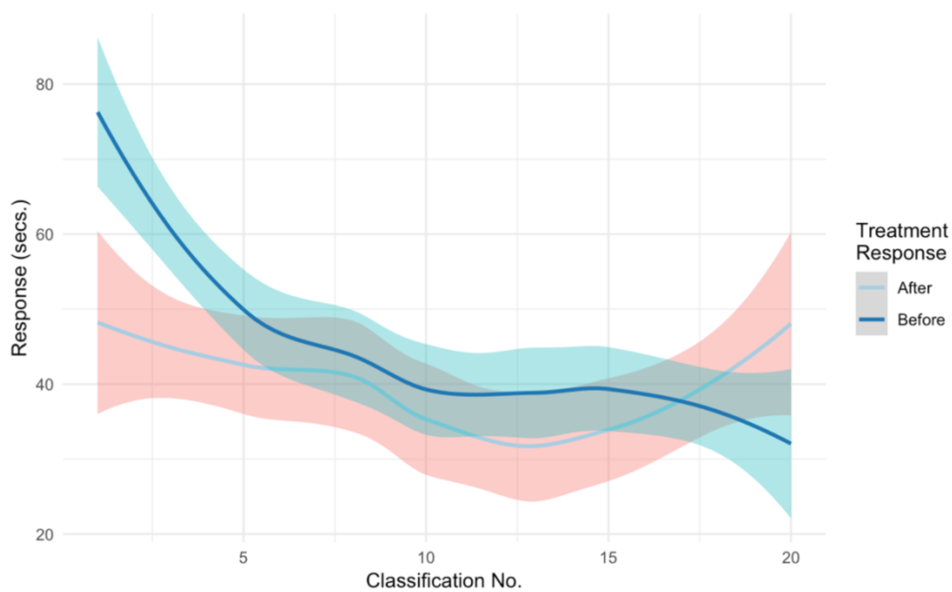
Figure 15. Average time classifying non-treated classifications for the first 15 classifications. Figures a and b represented a subset of first sessions. Since there wasn’t enough data to represent only first session in Gravity Spy (c), the data show all sessions.

5.4.3 Habituation to a single novelty cue.

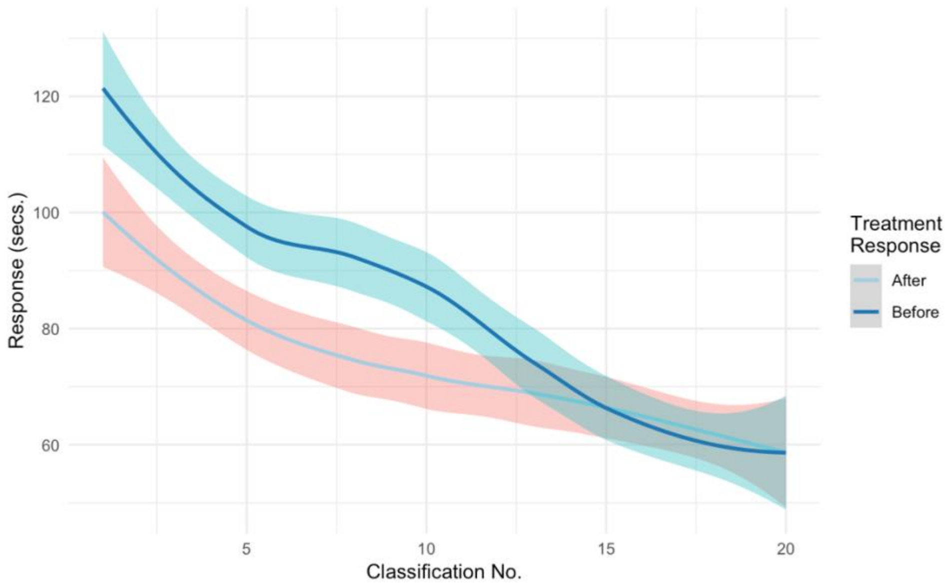
Measurement of habituation could occur if all volunteers in the treatment received a single novelty cue at a regular interval. One could, then, record the response parameter of later classifications. Since no administration of novelty cues were at regular intervals, this could not be done in this study. However, we could set a hypothesized treatment of the same sort by selecting volunteer’s exposure to one message during their sessions and measuring their response decrements. This might help project organizers determine at which point to administer another novelty cue.

To determine when volunteers become habituated in this scenario, the researcher selected volunteers exposed to exactly one novelty cue during their first sessions and had performed classifications before and after the administration of novelty cues. Separating these series of classifications into a treated and not-treated periods, we can then plot the mean response times allowing for inferences about Habituation by comparing the mean response times for the population at each classification interval to determine the point at which volunteers' response times recover to their pre-treatment value.

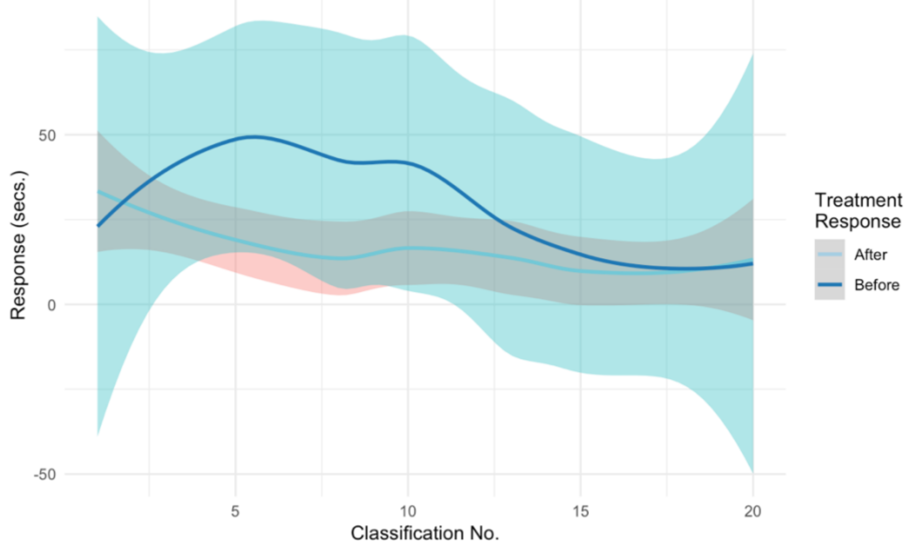
The graphs presented in Figure 16 show the response decrements for the selected treated population for each project. The dark blue line shows the mean response decrement for volunteers prior to begin exposed to the treatment, while the light blue line shows the mean response decrement after administration of a novelty cue. Visual inspection of the three charts in in Figure 16 showing response times in Higgs Hunters and Asteroid Zoo appear to show habituation between the 7th and 10th message the 12th and 15th respectively. Measuring habituation using the approach outlined above appears to be indeterminant for the curves in Gravity Spy however as there appears to be no period when the curves completely separated. It is interesting however, to see the error for classifications after a volunteer was exposed to the treatment behaving in a more predictable manner than before the treatment was administered.



(a) Higgs Hunters



(b) Asteroid Zoo



(c) Gravity Spy

Figure 16. A within-subjects comparison of the response times to across classifications that were treated and not treated.

Table 12 quantifies the data represented in in Figure 16. The mean response times for the potential habituation periods mentioned in the earlier section are at beginning at the first classification for Higgs Hunters and Gravity Spy, and the fourth classification after the treatment for Asteroid Zoo. For this study, the researcher defined habituation as the classification before which three or more successive comparisons of the response parameter were not-significant. A Mann–Whitney U test determined when the threshold was met comparing all classifications at each interval to determine whether the habituation threshold described above was met. Based on threshold, habituation in Higgs Hunters occurred after the 7th classification and after the 9th classification in Asteroid Zoo. Note there was also testing of the mean responses for classifications 1-3 in Asteroid Zoo. The results were inconclusive in Gravity Spy as there were no periods in which mean response times were significantly different as a starting point.

Higgs Hunters				**Asteroid Zoo**				**Gravity Spy**			
Trial	*Response Prior*	*Response After*		*Trial*	*Response Prior*	*Response After*		*Trial*	*Response Prior*	*Response After*	
1	83.2 (150.2)	57.5 (155.9)	***	**4**	102.2 (161.3)	82 (126)	***	**1**	16.8 (9.6)	12.7 (13.6)	-
2	66.9 (141.4)	39.7 (81.1)	***	**5**	89.1 (49.4)	112.1 (137.7)	*	**2**	17.2 (9.8)	57.8 (145.6)	-
3	53.12 (90.1)	36.8 (60.5)	***	**6**	**88.6 (47.8)**	115.3 (131)	*	**3**	15.1 (10.6)	22.2 (48.3)	-
4	48.5 (75.1)	44.7 (128.0)	***	**7**	95.8 (139.8)	77.3 (125.3)	*	**4**	153.7 (457.3)	26.6 (44.5)	-
5	46.4 (88.5)	39 (123.3)	***	**8**	97.5 (152.3)	75.8 (129.7)	**	**5**	41.1 (56.6)	20.4 (21.7)	-
6	49.4 (82.1)	45.9 (137)	*	**9**	92.1 (146.1)	59.2 (61)	*	**6**	11.2 (8.3)	7 (2)	-
7	**50.5 (99.7)**	**35.9 (67.1)**	*	**10**	84.3 (133.9)	77.3 (150.6)	-	**7**	12.7 (10.8)	7 (1.9)	-
8	39.0 (75.0)	45.2 (138.2)	-	**11**	87.7 (136.3)	75.4 (135.8)	-	**8**	14.1 (12.6)	9 (2)	-
9	39.6 (79.7)	47.7 (102.4)	-	**12**	72 (100.2)	73.9 (126.0)	-	**9**	99 (201.3)	19.5 (29.9)	-
10	47.0 (114.9)	28.2 (36.0)	-	**13**	70.4 (78.1)	67.8 (113.1)	*	**10**	79.7 (142.8)	31.7 (34.1)	-

Table 12. Mean Response Time for Treatment of a Single Novelty Cue. The mean response (in seconds) at trial (classifications) x for volunteers who were treated in a session where only one novelty cue was shown. Differences between responses times before and after a novelty cue was administered to determine habituation. The classification highlighted in blue is where habituation

is assumed to occur based on comparisons using the Mann–Whitney U test. (sig. values *** $p < 0.001$, ** $p< 0.01$, * $p > 0.05$, - not significant).

5.5 Chapter Conclusions

Knowing the degree and magnitude of habituation to features and experiences implemented with the goal of re-enforcing motivation is important for project organizers. Understanding habituation means for some platforms they might be able to regulate administration. Most volunteers contribute once/infrequently so strategies to encourage contributions should focus exclusively on obtaining contributions from first time volunteers. If novelty cues are a limited resource, then understanding habituation might help project organizers better direct these to volunteers who they know will be most impacted by receiving them.

The results in this section focused primarily on unpacking habituations mechanisms and the findings are consistent with several rules on habituation in that response decrement was observed (Rule 1). The main benefit of this research is in determining when volunteers recover to match their earlier response times. The analysis revealed that after receiving just one novelty cue, Higgs Hunters volunteers' response recovery occurred at the 7th classification while response recovery occurred at the 9th classification in Asteroid Zoo.

More analysis is necessary to determine how habituation occurs across sessions and if understanding personality traits can come from examining volunteer traces data. For instance, we might be able to statistically measure the slope of the response parameters and do so by volunteer to set their baseline susceptibility to novelty cues. Additionally, we might also explore how the magnitude of the treatment's administration affects habituation (Rule 4). Other moderating variables like such as a volunteer's tenure in the project or whether the data object is sufficiently interesting to call for added attention might also play a role in habituation.

Chapter 6 Conclusions

The literature on motivation on digital platforms point to a variety of strategies to motivate people to contribute to projects. Few studies have deeply explored the motivational properties of novelty but have simply considered how new objects influence individual motivation and behavioral outcomes. In short, there is a link between novelty and dopamine, a neurotransmitter associated with processing rewards motivating volunteers to continue to seek out rewards executing classifications. The results described in this dissertation are promising, however mixed. In this section, the researcher attended to teasing apart the results and offering some theoretical and methodological insights along the way.

6.1 Characterizing novelty as a motivator in citizen science

The results reported in chapters 3 and 4 are in Table 13 and show mixed results. In some circumstance novelty cues increased contributions and in other projects novelty cues appeared to have no significant impact on volunteers' contribution behaviors. Significant positive effects seen for the sessions in which volunteers saw novelty cues in Higgs Hunters and Asteroid Zoo. In these projects' volunteers executed 34.4 (+88%) and 10.24 (+37%) more classifications than sessions included in the control groups. Further supporting these results were the within-subjects analysis comparing earlier not treated sessions of volunteers who had treated sessions at some point and showed that administering novelty cues leads to more contributions, 77.5 classifications in treated sessions vs. 41.6 in not-treated sessions. Earlier studies support these findings conducted in laboratory settings, which showed that when exposed to novel stimuli people tend to explore more than people exposed to non-novel stimuli (Smock & Holt, 1962).

The results in Gravity Spy, however, showed that for the total population, sessions with the administration of a novelty cue resulted in a decrease (-7.22) in classifications executed. The difference, however, was not significant.

For newcomers, the observation of significant differences in contribution were in Higgs Hunters only where during treated sessions newcomers classified 27 more data objects when exposed to novelty cues. Observation of non-significant differences were in both Asteroid Zoo and Gravity Spy.

	H1 (population)	**H2 (newcomers)**
Higgs Hunters	***Supported***, volunteers made 34.4 more classifications during treated sessions	***Supported***, volunteers made 27 more classifications during treated sessions
Asteroid Zoo	***Supported***, volunteers made 10.2 more classifications during treated sessions	***Not supported***, non-significant difference in contribution
Gravity Spy	***Not supported***, non-significant difference in contribution	***Not supported***, non-significant difference in contribution

Table 13. A summary of the experiment results.

Second, the relationship between habituation and novelty allows us to answer several questions around the features long-term impact on volunteer behaviors in the projects with the implementation of the novelty cues. The section on habituation measured in response time to a stimuli conflicts with initial propositions about initial responses to novelty. Berlyne (1954) argued that novel stimuli induce longer visual exploration of the stimuli since individuals are curious about the new stimuli, however, this habituation analyses in chapter 4 conflicted with this finding as volunteers who experienced novelty cues tended to have significantly shorter response times than volunteers not exposed to novelty cues. The analysis also showed the varying magnitudes of habituation which was different in every project. Measuring responses times in treated classifications and those not treated in the same position showed that for volunteers in Higgs Hunters habituation to novelty occurred at the 7th classification and at the 9th classification in Asteroid Zoo. The results for Gravity Spy were inconclusive.

6.2 Theoretical Insights

The results reported in this dissertation show that under some circumstances novelty is a salient motivator for encouraging people to contribute to digital projects. Like all theories, however, novelty in the context of citizen science, and online platforms more generally is subject to some revision. To that end, the findings above raise several questions about novelty's effects and in particular how contextual determinants, that is, the social, organizational, and technical features of a project that might influence our ability to fully illuminate for novelty's impact on volunteer behaviors. In this section, the discussion centers on the characteristics that might explain the results described above.

6.2.1 The Role of Contextual Determinants

In addition to personality differences, people's response to novelty may depend on other factors such as the organizational and environmental constraints, what argue represent *contextual determinants.* Contextual determinants may dictate people interactions system more generally. These factors could potentially influence curiosity drive and contribution behaviors. Existing studies note how the varied social, organizational, and technical assemblages might also play factor into how volunteers experience a project and are motivated (Prestopnik & Crowston, 2012; Rosser & Wiggins, 2018; 2019; Wiggins & Crowston, 2010b). Other contextual variables such as time constraints and other motivational drivers appearing in the environment. For instance, the level of gamification may moderate people's responses to novelty cues.

6.2.2 Teasing out the contextual differences in novelty

Personality differences driving behavioral response are well known and not difficulty to assess. However, contextual differences in environments dictate how an individual's curiosity drive manifests. There are four that are especially relevant to novelty in the context of citizen science and digital platforms more generally: degree of novelty, discovery, task and workflow design, and time and stage influences.

Degree of novelty. Citizen science projects are novel to the population of newcomers. Therefore, initial interest is driven by a desire to explore the totality of newness associated with the environment opposed to just new data objects. The discussion boards where volunteers post comments are a unique environment, the guide where volunteers can read explanations of the classification categories are new.

Several experimental studies found that the magnitude of a stimulus' novelty also influenced behavioral responses. Bunzeck & Düzel (2006) showed some regions linked to novelty responses in the brain were only activated for images with absolute novelty i.e., images that were not seen previously by the research participant as opposed to images with relatively novelty i.e., images possessing some degree of familiarity to the research participant.

The projects researched here show volunteer data that can be at times familiar to volunteers. For instance, Figure 17 shows four different glitches from the Gravity Spy task that a volunteer may be asked to classify. The two images on top are *blip* and while having slightly similar morphological shapes they are familiar if a volunteer had exposure to blips. However, the two images below are completely new and might cause volunteers to linger a bit longer to take account of its nuances. In Gravity Spy, volunteers do come across completely new morphologies that could be another glitch they had not had previous exposure to, which is also likely to cause volunteers to examine the data more closely perhaps decreasing habituation.

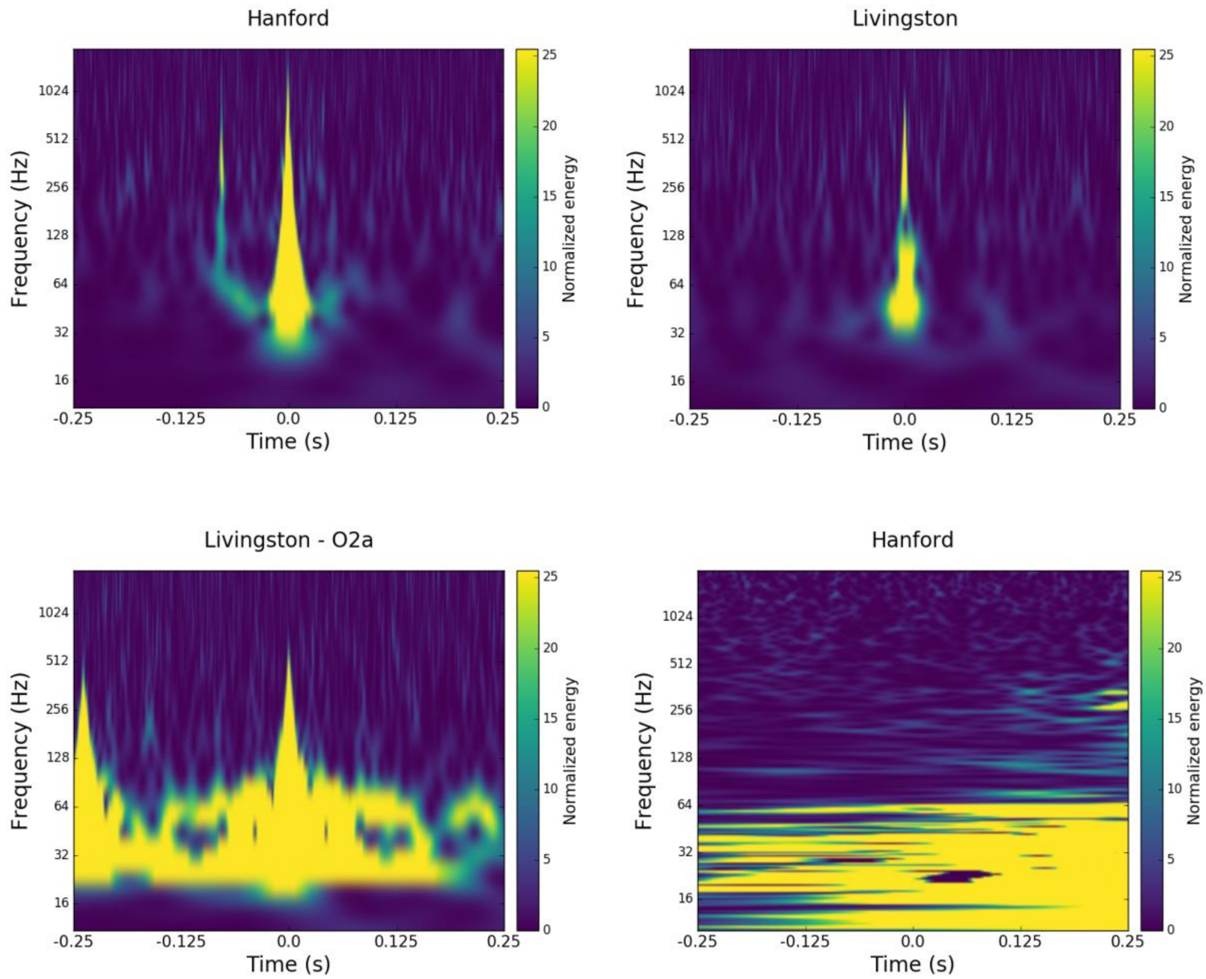


Figure 17. Several examples of a glitch having the same base morphological characteristics. However, each data object is not completely novel if the volunteer was exposed previously.

Making Discovery. While not a feature of every project, the chance to make a scientific discovery could drive volunteers' exploratory behaviors. Some volunteers are attracted to citizen science projects because of the potential to make scientific discoveries. Among motives such as interest in astronomy, contribution to science, the beauty of galaxy images, and learning about galaxies, Raddick et al. (2010) found volunteers were motivated by discovery (specifically, "I can look at galaxies that few people have seen before”). Jackson et al. (2014) found that some volunteers reported being motivated by the possibility to find anomalies that others had not previously identified.

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Citizen science literature has documented several cases of serendipitously volunteer-led discoveries including one of the most well-known cases, the discovery in Galaxy Zoo of a novel astrophysical object by a Dutch school teacher named after that teacher: Hanny's Voorwerp (Keel et al., 2012). In another Zooniverse project, Seafloor Explorer, volunteers coalesced around a “stripey tube-dwelling creature" after volunteers asked, “what are the tube shape and the stripey creature”? The discovery was that the images displayed a new species, named convict worm by the citizen scientists[5]. In the Stardust @Home project, when a user discovers a dust grain, he or she receives co-authorship on the article announcing the discovery and also receives the privilege of naming the dust grain. Indeed, it is feasible that volunteers may be driven to contribute by the potential for making a scientific discovery. Others include

[5] http://blog.seafloorexplorer.org/tag/convict-worm/

Galaxy Zoo ``green peas" (Cardamone et al., 2009; Masters et al., 2009) and quasar light echoes (Keel et al., 2012; Lintott et al., 2009) were discovered by citizen scientists.

The potential to make a scientific discovery may drive some volunteers to take part. In the projects studied here the potential for scientific discovery is unclear. In Asteroid Zoo, training materials explicitly promote scientific discovery, a few sentences on the site reads, “Your goal is to find the moving dots in the images. These could be asteroids no one has ever seen before…” In Asteroid Zoo, while the project lists several scientific goals – identify near-earth asteroids, catalog objects for asteroid mining, study the solar system, and collect training images for future machine classification, in FAQs it is stated, “You might be the one to find the next Asteroid! With every image set that gets analyzed you could find an actual asteroid”. In Higgs Hunters, scientists project website does note the potential for discovering new particles called baby bosons, however, no detection of such volunteer led discoveries have occurred.

While scientific discovery is an extrinsic motivator, alerting volunteers to novel data objects could be motivating for volunteers driven by discovery. If scientific discovery is a motivator, novelty pushes both intrinsic (i.e., curiosity) and extrinsic motives (i.e., scientific discovery). This move from intrinsic (excitement by novelty) to extrinsic (potential to make achieve notoriety associated with being the first to make and record observations of astronomical phenomenon) motivation may define volunteers’ participation as it evolves. In any case, novelty cues and scientific discovery do share a relationship. For volunteers motivated by scientific discovery, knowing which data objects have not been analyzed by any other volunteer means a greater chance of discovery if a volunteer uncovers a phenomenon. In short, novelty intertwines with other motives like discovery.

Task and workflow differences. Another potential source of differences are the embedded motivational elements already existing in the task and workflow design (TWD). Scholars point to growing needs to design tasks, which volunteers find motivational considering cognitive demand, feedback, system usability, etc. (Cartwright, Dove, Méndez & Bello, 2019; Houghton et al., 2019; Rosser & Wiggins, 2018; Sprinks et al., 2017; Tinati et al., 2015). For instance, several studies on TWD note the linkages between task design and motivation (Hutt et al., 2015; Sprinks et al., 2017). For instance, Sprinks et al. (2017) changed the Planet Four workflow to allow volunteers to make judgments sequentially, batched, or full. The results of the study revealed volunteers prefer greater variety and having batch jobs lead to more data classification.

Projects place different cognitive and time demands on volunteers, which might influence how long people continue contributing. All project researched here showed very different response times with Higgs Hunters at 38 seconds, Asteroid Zoo more than one minute, and Gravity Spy 17.4 seconds. The differences in the attention required to execute a classification might also influence how much time and effort a volunteer will spend during a session.

The task or workflow design itself might also reinforce motivation implicitly, which further obfuscate novelty cues. For instance, many scholars argued, and experimental studies find feedback plays a crucial role in encouraging people to stay in projects (Zhu et al., 2013). As volunteers are promoted to added levels, they may come in contact with novel glitch types that they haven't seen previously but are not necessarily new to the project. Thus, different attributes of the environment could be driving exploration (and responses) of the site. The of novelty to other salient task motivators could have caused different outcomes.

Timing. The periods during which motivational reinforcers appear on a platform might also affect people's responsiveness to them. A reasonable assumption is that most visitors to a project during the first days of a project's launch are testing out the project to determine if they want to contribute. The literature on contribution patterns suggested that most visitors to citizen science projects make a few contributions and never return (Eveleigh et al., 2014). During this period, projects might expect people to dropout quickly as they evaluate the project's scientific goals against their desire to contribute to those goals. Therefore, it may not be beneficial for projects to supply motivational reinforcers during preliminary stages of a project. Additionally, projects may need to balance the effectiveness of utilizing certain motivation reinforcers if they are scarce (projects may run out of new data for long gaps) since they may be better used for volunteers who may eventually contribute more; returns could be marginal when compared to later stages when interest in the project might be dissipating.

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6.3 Methodological Insights

The next sections discuss the methodological implications discovered during the course of this research

6.3.1 An Intention to Treat (ITT) Approach to Experiment Analysis

A methodological contribution of this research was the use of an intention to treat approach to analyzing the data (Gerber & Green (2013). The approach was necessary because not all the sessions selected for the treatment group received the treatment. Experimental studies facing similar limitations might look to intention to treat to analyze their datasets. This too might open the door for experimental studies on platforms where researchers cannot control every aspect of the treatment's administration.

6.3.2 Designing, implementing, and evaluating online field experiments.

Beyond its applicability for determining the motivational characteristics of novelty messages in citizen science, this research speaks broadly to experimental approaches to designing and evaluating features on digital platforms. While experimental studies are single setting and single period evaluations of a treatment, a benefit of this study is that the evaluation occurred across several platforms, during different periods which speak to issues of generalizability and maturation, which are often overlooked in other field experiments conducted on digital platforms. One would expect similar experimental findings given the similar project foci (all are citizen science projects) and sociotechnical assemblages (all have routine classification tasks and spaces for volunteers to socialized). It also gives evidence that homogenous settings may result in very different outcomes. These suggest when we conduct online field experiments our ability to generalize to other settings might be limited by factors not considered relevant in the early setting in which the experiment was conducted.

Few experimental studies advocating for platforms to implement their designs have conducted analysis about the habituation potential of their designs. This suggests the need for rigorous evaluation of design proposals to determine their true outcomes over longer periods of time.

6.3.3 The experimental apparatus

A growing number of scholars point to the limitations of digital trace data for researching human behaviors in digital platform (Jackson, Crowston, & Østerlund, 2018; Østerlund, Crowston, & Jackson, 2019). The source of data used in this research. Scholars argue that some data collection efforts might results in incomplete volunteer histories resulting in misleading findings. Since some digital platforms do not require people to login data may be missing about a volunteer's history. For instance, a person might tryout the project making classifications before deciding to register for an account on the system. Only after creating an account are participants provided a unique identifier in the database and subsequent interactions recorded using that identifier. In such cases, events recorded by the system prior to a person registering for an account are anonymous and thus, omitted from being aggregated in evaluations of a person's behavior on the system. Omitted events are problematic as they represent an incomplete picture of a participant's interaction on the system. For this research, it is conceivable that a volunteer classified anonymously prior to signing in to their account and being exposed to novelty cues, essentially miscalculating their contribution behaviors.

6.4 Designing for novelty

Academic research in computer supported cooperative work (CSCW) and human computer interaction (HCI) could benefit from additional studies on novelty. Given the prevalence of information on the internet, efforts to direct people's attention to new information and experiences researchers of social computing systems, communications researchers, etc. are uniquely positioned to consider the novelty's role, how a platform's features support or limit novelty and how humans react to such experiences online. There are several recommendations and applications. First, it may be beneficial for platforms to build motivational profiles for its contributors. Mao, Kamar, and Horvitz (2013) designed an algorithm that predicts when volunteers are likely to drop out of the Galaxy Zoo project. A more useful design for motivational reinforcers would be to implement the model described by Mao et al. (2013) and deliver personalized motivational reinforcers when the model has a high confidence that a person will soon dropout. This requires prior knowledge about which motivators are most salient to whom.

In many ways existing new sites, social media platforms, social networking systems make novelty a central part of the system. In open source software communities, designers of projects might highlight novel coding challenges and encourage potential contributors to be the first to solve a certain problem. WordPress pages encourage authors to publish posts that include a "Be the first to comment" script at the end, to encourage readers to start a conversation. In Q&A communities, being the first to respond to a post holds the promise of increased attention to one's comment, i.e., that others after the first poster will see their responses. The first person to post also sets the topic of conversation or is the first individual to point out a novel feature. For example, in a study of *Answerbag*, a Q&A site, Gazan (2014) found the first submitted answers accumulate 17% more rating points than subsequent responses. In Q&A where the value of answers are being the first to post might make a comment more prominent to readers; in communities where, social voting is a feature, it might increase the number of up-votes. Systems designers on other crowdsourcing and peer production platforms could draw on this motivation in varying ways including novel cues when possible.

One also finds opportunity sites like Facebook, Instagram, YouTube etc. where people receive encouragement to create and consume novel content. Newsfeed algorithms tend to serve up novelty context. Knowing when and how people become habituated to novelty in these contexts might contribute to research on human behaviors online.

6.5 Limitations and Future Work

Limitations in this study include:

The experimental design for Higgs Hunters and Asteroid Zoo (chapters 3 and 4): a quasi-experiment. Given the indiscriminate administration of the treatment to volunteers, this design was the only workable way to analyze the data from the system. A true randomized controlled experiment would have been preferential in all projects, but the system was not able to support randomized assignment. The analysis presented in chapter 5, which focuses on habituation to the novelty treatment from a single message, also has limitations. While the explanation of the results suggests different response decrements for prior and post exposure to the treatment, task learning could also explain the results. As volunteers execute more classifications, they are likely to execute the classifications faster. Future work might account for generalized learning effects for classifications over time.

While the experiments in chapters 3 and 4 gives convincing evidence for a causal relationship between a treatment and an outcome, there is a trade-off for the richness of data. For example, our analysis does not include all differences in volunteers that were uncapturable by the system (e.g., demographics or education). Nor does it give the rich data needed to illuminate the mechanism of the effect, that is, why volunteers found novelty to be motivating. Prior research found that volunteers report being so motivated by novelty but understanding in more detail exactly why is a question for further in-depth investigation. To mitigate this limitation, future research may explore how people's personalities and baseline preferences for novelty will influence their likelihood to be influenced by novelty. The literature described in Chapter 2 notes personalities differences might drive people's susceptibility to novelty cues. Scholars argue for the presence of a novelty seeking trait guiding people's behaviors. This suggested genetic variations affect the brain's regulation of dopamine, which could cause some volunteers to differ in their baseline for rewards from engaging with stimuli possessing novel characteristics. These variations could lead to differences in approach and avoidance behaviors. Several studies in psychology attest to these differences suggesting: a small percentage (15%) of the population possesses the trait (Gallagher, 2011), age moderates curiosity levels (Camp, Rodrigue, & Olson, 1984), and lifestyle choices factor into behaviors (Schweizer, 2006). These individual personality differences suggest novelty's behavioral affects may not be seen uniformly and individual variation between volunteers and even within individuals persist. For instance, the appearance of the novelty seeking trait could have an impact on an individual's baseline for susceptibility to novelty stimuli manipulation. Alerting an individual with low curiosity drive might actually induce avoidance behaviors (Glanzer, 1958). Cloninger, Przybeck, Svrakic, and Wetzel (1994) argued for a classification of novelty drives into neophobes (those tending to avoid the novelty), neophiles and, at the most extreme, neophiliacs. Accounting for baseline novelty preferences may help determine heterogeneous treatment effects across volunteers.

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Wiggins, A., & Crowston, K. (2010a). Developing a conceptual model of virtual organisations for citizen science. *International Journal of Organisational Design and Engineering, 1*(1), 148–162.

Wiggins, A., & Crowston, K. (2010b). From Conservation to Crowdsourcing: A Typology of Citizen Science. In *Proceedings of the Hawaii International Conference on System Sciences*, 1–10.

Wiggins, A., & Crowston, K. (2012). Describing public participation in scientific research. In *Proceedings of the 2012 iConference*.

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Yadav, P., & Darlington, J. (2016). Conceptual Frameworks for Building Online Citizen Science Projects. *Human Computation, 3*(1), 1–9.

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Yuen, M.-C., King, I., & Leung, K.-S. (2011). A Survey of Crowdsourcing Systems (pp. 766–773). In *Proceedings of the Privacy, Security, Risk and Trust (PASSAT)*, IEEE.

Zhang, F., Yuan, N. J., Lian, D., & Xie, X. (2014, April). Mining novelty-seeking trait across heterogeneous domains. In *Proceedings of the 23rd international conference on World wide web* (pp. 373-384). ACM.

Zhu, H., Zhang, A., He, J., Kraut, R. E., & Kittur, A. (2013, April). Effects of peer feedback on contribution: a field experiment in Wikipedia. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2253-2262). ACM.

Zuchowski, O., Schlagwein, D., & Fischbach, K. (2016). “Open Calls” Rather than “Fixed Assignments”: A Longitudinal Field Study of the Nature and Consequences of Internal Crowdsourcing. In *Proceedings of the Thirty Seventh International Conference on Information Systems* (pp. 373-383). ACM

CURRICULUM VITA

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RESEARCH FOCUS

My research centers on two areas: human behavior in socio-technical systems i.e., online crowd-based citizen science communities and the impact of crowd-based socio-technical systems on the organizing behaviors of individuals, groups, and organizations.

keywords: computer supported cooperative work (CSCW), social computing, crowdsourcing, citizen science, human- computer interaction (HCI), data science

EDUCATION

Syracuse University, School of Information Studies, Syracuse, New York, USA
Ph.D., Information Science & Technology, May 2019
Thesis Title: Characterizing Novelty as a Motivator in Web-based Citizen Science

University of Illinois Urbana-Champaign, Urbana, Illinois, USA
Master of Science in Library & Information Science, May 2012
Bachelor of Arts in Political Science, 2010

RESEARCH and WORK EXPERIENCE

Syracuse University, School of Information Studies, Syracuse, New York, USA
Research Assistant, May 2012 – Present

IBM, Almaden Research Center, San Jose, California, USA
Research Intern, May 2016 – August 2016
Mentors: Laura Anderson and Cheryl Kieliszewski

Allstate Insurance, Northbrook, Illinois, USA
Systems Analyst Intern, May 2011– August 2011

University of Illinois Urbana–Champaign, iSchool, Urbana, Illinois, USA
Research Assistant, May 2010 – 2012

One Laptop Per Child (OLPC), São Tomé, São Tomé and Príncipe
Project Coordinator, April 2009–August 2009

University of Illinois Urbana-Champaign, Office of Minority Student Affairs, Urbana, IL, USA
Graduate Coordinator for Information Systems and Security, 2008 – 2014

TEACHING EXPERIENCE

University of California Berkeley, School of Information, Berkeley, California, USA
Lecturer, 2018-present, W201 Research Design and Applications for Data and Analysis

Syracuse University, School of Information Studies, Syracuse, New York, USA

Adjunct, 2018-present, IST 687 Applied Data Science
Teaching Assistant, 2012, IST 687 Applied Data Science
Teaching Assistant, 2013-14, IST 755 Strategic Information Management
Teaching Assistant, 2015, IST 444 Information Reporting and Presentation

University of Pittsburgh, iSchool Inclusion Institute (i3), Pittsburgh, Pennsylvania, USA
Teaching Fellow, Jun-July 2015, Programming in Python

PUBLICATIONS

Manuscripts Under Review

[R4.] Coughlin, S., Bahaadini, S., Rohani, N., Zevin, M., Patane, O., Harandi, M., **Jackson, C.B.**, Noroozi V., Allen,S., Areeda, J., Coughlin, M., Ruiz, P., Berry, C P L., Crowston,K., Østerlund,C., Smith,J.R., Trouille,L., Kalogera, V. (Submitted). Classifying the unknown: Discovering novel gravitational-wave detector glitches using similarity learning.

[R3.] **Jackson, C.B.**, Anderson, L., Kieliszewski, C. (Submitted). Methodological Reinforcements: Investigating Work through Trace Data and Text.

[R2.] Crowston, K., Østerlund, C., Lee, T., **Jackson, C.B.**, Harandi, M., Allen,S., Bahaadini,S., Coughlin,S., Kat- saggelos,A., Larson,S., Rohani,N., Smith,J., Trouille,L., Zevin,M. (Submitted). Knowledge Tracing to Model Learning in Online Citizen Science Projects.

[R1.] **Jackson, C.B.**, Østerlund, C., Crowston, K., Harandi, M., Allen, S., Bahaadini,S., Coughlin,S., Katsagge- los,A., Larson,S., Rohani,N., Smith,J., Trouille,L., Zevin,M. (Submitted). Making High-Performing Contributors: An Experiment with Training in an Online Production Community.

Journal Papers, Peer-Reviewed

[J5.] Østerlund, C., Crowston, K., **Jackson, C.B.** (In Press). Building an apparatus: Refractive, reflective and diffractive readings of trace data. Journal of the Association for Information Systems.

[J4.] **Jackson, C.B.**, Crowston, K., Østerlund, C. (2018). Did they login? Patterns of Anonymous Contributions in Online Communities. Proc. ACM Hum.-Comput. Interact. 2, CSCW, Article 77 (November 2018), 16 pages.

[J3.] **Jackson, C.B.**, Crowston, K., Østerlund,C., Harandi,M. (2018). Folksonomies to Support Coordination and Coordination of Folksonomies. Computer Supported Cooperative Work (CSCW), vol. 27, no. 3-6, pp. 647–678.

[J2.] **Jackson, C.B.**, Wang, Y. (2018). Addressing Privacy Discrepancy through Personalized Notifications. In Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT), vol. 2, no. 2.

[J1.] **Jackson, C.B.**, Huang, Y., Kasowitz-Scheer, A.S.(2015). Face-to-Face Matters: Inspirations from the Human Library. International Journal of Mobile Human Computer Interaction. Special Issue on the Collection of Best Papers from Selected MobileHCI'2014 Workshops: Toronto, Canada, 2014, vol. 7, no. 3.

Conference Proceedings, Peer-Reviewed

[C7.] **Jackson, C.B.**, Crowston, K., Mugar, G., Østerlund,C. "Guess what! You're the first to see this even" Increasing Contribution to Online Production Communities. In Proceedings of the ACM Conference on Supporting Groupwork (GROUP'16). Sanibel Island, FL. New York: ACM [28% acceptance rate]

[C6.] **Jackson, C.B.**, Østerlund, C., Maidel, V., Crowston,K., and Mugar, G. (2016). Which Way Did They Go? Newcomer Movement through the Zooniverse. In Proceedings of the 19th ACM conference on Computer supported cooperative work & social computing (CSCW'16). San Francisco, CA. New York: ACM [25% acceptance rate]

[C5.] Mugar, G., Østerlund, C., **Jackson, C.B.**, and Crowston, K. (2015). Being present in online communities: learning in citizen science. In Proceedings of the 7th International Conference on Communities and Technologies (C& T'15). Limerick, Ireland. New York: ACM

[C4.] **Jackson, C.B.**, Østerlund, C., Crowston,K., Mugar, G., Hassman, K.D. (2014). Motivations for Sustained Participation in Citizen Science: Case Studies on the Role of Talk. Forty-eighth Hawai'i International Conference on System Sciences (HICSS-48).

[C3.] Østerlund, C., Mugar, G., **Jackson, C.B.**, Hassman, K.D., Crowston,K. (2014). Socializing the Crowd: Learning to Talk in Citizen Science. Academy of Management Annual Meeting, Organizational Behaviour Division.

[C2.] Mugar, G., Østerlund, C., Hassman, K.D., Crowston,K., and **Jackson,C.B.** (2014). Planet hunters and seafloor explorers: legitimate peripheral participation through practice proxies in online citizen science. In Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing (CSCW'14). Vancouver, BC, Canada. New York: ACM [27% acceptance rate]

[C1.] Hassman, K.D., Mugar, G., Østerlund, C., **Jackson, C.B.** (2013). Learning at the Seafloor, Looking at the Sky: The Relationship Between Individual Tasks and Collaborative Engagement in Two Citizen Science Projects. In Proceedings of 2013 International Conference on Computer Supported Collaborative Learning (CSCL'13). Madison, WI.

Conference Short Papers, Peer-Reviewed

[S05.] **Jackson, C.B.**, Crowston, K., and Østerlund, C. (2018). Working in the Shadows: A Cross-Case Analysis of Anonymous Contributions in Online Citizen Science Communities. Presented at InfoSocial, Northwestern University, Evanston, Illinois

[S04.] Østerlund, C., Mugar, G., **Jackson, C.B.**, Crowston,K. (2016). Typologies of Learning in Open Online Collaborative Communities. In Thomas Ludwig, Karin Hansson, Michael Muller, Tanja Aitamurto, Neha Gupta (Eds.), International Reports on Socio-Informatics (IRSI), Proceedings of the CSCW 2016 – Work- shop: Toward a Typology of Participation in Crowdwork (Vol. 13, Iss. 1, pp. 15-22)

[S03.] Østerlund, C., Crowston, K., **Jackson,C.B.** (2016). The hermeneutics of trace data: Building an apparatus. Presentation at the IFIP Working Group 8.2 Working Conference (IFIP 8.2), Dublin, Ireland, 9- 10 December.

[S02.] Mugar, G., Østerlund, C., **Jackson, C.B.**, Crowston,K. (2015). Learning and Motivation in the Zooniverse. Presented at workshop on "Advancing an industry/academic partnership model for open collaboration research" 2015 ACM Conference on Computer Supported Cooperative Work (CSCW'15). Vancouver, BC

[S01.] Østerlund, C., Mugar, G., **Jackson, C.B.**, Hassman, K.D., Crowston, K.. (2014) Socializing the Crowd: Learning to Talk in Citizen Science. Academy of Management Annual Meeting, Organizational Behaviour Division.

Conference Posters, Peer-Reviewed

[P06.] **Jackson, C.B.**, Crowston, K., Østerlund, C., Mugar, G. (2016). Encouraging Work in Citizen Science: Experiments in Goal Setting and Anchoring. In Proceedings of the 19th ACM conference on Computer supported cooperative work & social computing (CSCW'16). San Francisco, CA. New York: ACM

[P05.] Hassman, K.D., Østerlund, C., Mugar, G., **Jackson, C.B.**, Crowston, K. (2015). Beyond data management: Exploring new roles for librarians in citizen science projects. Poster presented at Citizen Science 2015 Conference. San Jose, CA.

[P04.] **Jackson, C.B.**, Crowston, K., Østerlund, C., Mugar, G., Hassman, K.D. (2014). Digital Experimentation: Motivating Contribution to Citizen Science. Presented at the 2014 Conference on Digital Experimentation (CODE@MIT). Cambridge, MA

[P03.] **Jackson, C.B.**, Østerlund, C., Mugar, G., Crowston,K., Hassman, K.D. (2014). Networks of Influential Participants: Information Diffusion in Citizen Science. Poster Presentation. In Proceedings of the second ACM conference on Online social networks (COSN'14). Dublin, Ireland. New York: ACM

[P02.] **Jackson, C.B.** (2014). Event Based Analysis of a Citizen Science Community: Are New and Non-Sustained Users Included? In Proceedings of the iConference (iConference 2014). Berlin, Germany

[P01.] Hassman, K.D., Mugar, G., Østerlund, C., **Jackson, C.B.** (2013). Learning at the Seafloor, Looking at the Sky: The Relationship Between Individual Tasks and Collaborative Engagement in Two Citizen Science Projects. In Proceedings of 2013 International Conference on Computer Supported Collaborative Learning (CSCL'13). Madison, WI.

Talks and Other Presentations

[T04.] **Jackson, C.B.** (2015). Voices from the Field. Presented at the GEM GRAD Lab, October 2015, Syracuse, New York.

[T03.] **Jackson, C.B.**, Shankar, K. (2015). Data and Ethics in Citizen Science. 7th Research Data Alliance Plenary, Paris, France.

[T02.] **Jackson, C.B.** (2015). Data and Ethics in Citizen Science. Presented at the 7th Research Data Alliance Plenary, Paris, France.

[T01.] **Jackson,C.B.**, Østerlund,C., Mugar,G., Crowston,K. (2015). Ethnography in Citizen Science. Presented at the 2nd Annual Graduate Research Symposium, Syracuse University, March 20-21, 2015, Syracuse, NY

GRANTS, SCHOLARSHIPS, FELLOWSHIPS and AWARDS

Ubi-Comp Student Travel Grant, $600, 2018
Conference participation cost
RDA/US Fellowship, $5,000, 2015
Research Data Alliance, award to investigate data sharing in citizen science
Teaching Fellow, $1,000, 2015
iSchool Inclusion Institute (i3), stipend to teach students in i3 summer program
National Science Foundation (NSF) Grant, $175,586, 2015-2017
Award# 1464347, PI: Yang Wang (Assisted in the research and the writing of the grant.)
Travel Grant: Conference on Online Social Networks, $1,800, 2014
Award to attend the 2014 Conference on Online Social Networks (COSN)
Science, Technology, Engineering, and Mathematics (STEM) Fellowship, 2013-2015
Full tuition support
Elizabeth Liddy Fellowship, $28,000, 2013–2015
Summer research support
Graduate Assistance in Areas of National Need (GAANN) Fellowship, 2012–2013
Full tuition support and stipend
Midwest Access Program Fellowship, 2010–2012
University of Illinois, full tuition support and stipend
GSLIS Berger Entrepreneurial Promise Award, $200, 2012
Graduation award for entrepreneurial motivated students
Freeman Study Abroad Fellowship, $3,000, 2006
Award to travel abroad China

PROGRAMMING and TOOLS

R for statistical computing for data analysis, data munging, **Python** for data munging, Structure Query Language (**SQL**) for querying relational databases (e.g., MySQL, Oracle), **MongoDB** for back-end data collection and storage, **SPSS** for data analysis, **Gephi** and **Cytoscape** for social network analysis, **WEKA** for simple data mining tasks, **GitHub** for code repository and sharing (https://github.com/cjacks04).

SERVICE

Reviewer

The Journal of Collaborative Computing and Work Practices
(CSCW) – 2017 Conference on Human Factors in Computing
Systems (CHI) – 2016, 2017
Computer-Supported Cooperative Work and Social Computing (CSCW) – 2013, 2014, 2015, 2016,
2017 Symposium on Usable Privacy and Security (SOUPS) – 2013
Hawaii International Conference on System Sciences (HICSS) –
2014, 2018 iConference – 2014, 2019

Committees

2016-2017	Doctoral Committee, School of Information Studies, Syracuse University
2015-2016	Faculty Search Committee, School of Information Studies, Syracuse University
2014-2015	Faculty Committee Rep., School of Information Studies, Syracuse University
2013-2014	Senator, Graduate Student Organization, Syracuse University
2013-2014	University Senator, Syracuse University
2013-2014	University Senate Research Committee, Syracuse University
2013-2013	Doctoral Committee, School of Information Studies, Syracuse University
2007-2008	Dean of Students Search Committee Member, University of Illinois
2006-2009	Senate Sub-Committee on Student Discipline, University of Illinois

Mentees

Undergrad	Philip Lee, Syracuse University Noah David Leiboff, Syracuse University Eddie Huang, University of Illinois Urbana-Champaign Tajanae Harris, Syracuse University
Graduate	Netra Prakash Kayastha, Syracuse University Amruta Bhat, Syracuse University Dhruv Kharwar, Syracuse University Saurabh Patel, Syracuse University Akshay Bagde, Syracuse University Jay Park, Syracuse University

PRESS

2016 *Daily Orange*, “Syracuse University researchers continue to further gravitational wave research"
2016 *Symmetry Magazine*, “Citizen scientists join search for gravitational waves"
2015 *ischool.syr.edu*, "Ph.D. Student Jackson Receives Two Prestigious Fellowships "
2014 *Syracuse.com*, “Student startups win thousands at Emerging Talk event"
2009 *ischool.illinois.edu*, “Grant Awarded to Illinois Students Helps Bring Laptops to São Tomé, Africa"