How Activists Are Both Born and Made:
An Analysis of Users on Change.org

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ABSTRACT

E-petitioning has become one of the most important and popular forms of online activism. Although e-petition success is driven by user behavior, users have received relatively little study by e-petition researchers. Drawing from theoretical and empirical work in analogous social computing systems, we identify two potentially competing theories about the trajectories of users in e-petition platforms: (1) "power" users in social computing systems are born, not made; and (2) users mature into "power" user roles. In a quantitative analysis of data from Change.org, one of the largest online e-petition platforms, we test and find support for both theories. A follow-up qualitative analysis shows that not only do users learn from their experience, systems also "learn" from users to make better recommendations. In this sense, we find that although power users are "born," they are also "made" through both processes of personal growth and improved support from the system.

Author Keywords

online activism, civic engagement, e-petition, power user, contribution, motivation

INTRODUCTION

In November 2013, 15-year-old high school student Sarah Kavanagh found out that brominated vegetable oil (BVO), a controversial flame retardant chemical, is an ingredient in some Gatorade drinks. She decided to go to Change.org – one of the largest e-petition platforms – to start a petition to ask Gatorade to remove the harmful ingredient. In less than two months, the petition received more than 200,000 signatures from people around the world and was widely discussed in the press. As a result, Gatorade executives agreed to remove the ingredient. Although her petition's wild success is not typical, Kavanagh's experience is not unique. In September 2014, there were hundreds of thousands of peti-
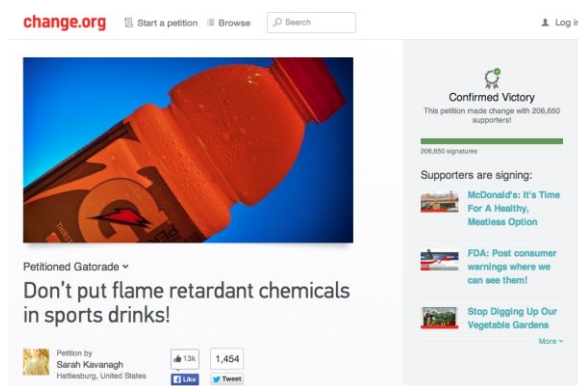
Figure 1. The petition about removing flame retardant chemicals in Gatorade on Change.org. The campaign was a huge success with more than 200,000 signatures.

tions on Change.org, and many successful stories like Kavanagh's.

Despite this potential for impact, the vast majority of petitions on Change.org have few signatures and more than 99% of petitions are never marked as "victorious." To be successful, e-petitions need signatures – our data shows that victorious petitions on Change.org receive, on average, 20 times more signatures than non-victorious petitions. Because these signatures come from users, it becomes critical for designers and petitioners to understand user behavior in these platforms.

Although e-petitioning has received relatively little study by HCI and social computing researchers, e-petition platforms share many features and qualities with other social computing systems. Users have accounts, profiles, and can create and share content. Like many other social computing systems (e.g., Wikipedia [9]), the most active users are responsible for the majority of contributions. Our data shows that the top 5% of Change.org users make more than 50% of all signatures. As a result, understanding these power signers may be a key to building a successful e-petition platform.

An important issue with any discussion of power users is the degree to which users begin as active contributors and the degree to which they learn to grow into these roles. Often, these debates are framed as whether power users are

"born or made" [13, 16]. For example, social computing research on Wikipedia [16] has shown that extremely active users are different from ordinary users in the first days of their lifespans and suggested that these users are inherently different. On the other hand, another body of research suggests that participants in communities learn to become contributors, or even leaders, through situated peripheral participation [11] and can systematically be nurtured by carefully designed systems such as the reader-to-leader framework proposed by Preece and Shneiderman [18].

In this study, we used a mixed analysis to examine these two competing theories. First, we present a quantitative analysis of users' participation in Change.org that aims to test the *born* and *made* theories. In a second study, we present a qualitative analysis of 14 in-depth interviews with Change.org signers that further explores our quantitative findings. Our work makes several theoretical, methodological, and substantive contributions to the literature on social computing and the born or made debate. Our results use qualitative data to reveal previously untheorized mechanisms and extend social computing research to e-petition platforms. Additionally, although previous work on whether users are born or made has focused on the first hypothesis (e.g., [17]), our work tests both and finds support for each. In doing so, we offer a novel approach to the born/made debate and a way to reconcile the apparently contradictory findings.

BACKGROUND

E-petitioning
A classic example of grassroots political activity, petitioning is an act of collective action by citizens where groups place a single-issue request before an authority or organization to undertake or impede certain actions or policies [14]. An online analog, e-petitioning has gained popularity because it features low-commitment action based on easy and convenient tools allowing more people to support causes important to them. From the comfort of their homes, people can quickly and easily sign a petition with a click of a button. E-petition platforms like Change.org, Causes.com, and Moveon.org have rapidly grown and increased in number over the last several years.

Political science researchers have shown a particular interest in e-petition platforms. For example, Hale et al. [7], traced the growth of over 8,000 petitions on the UK Government's No. 10 Downing Street website for two years and found that most successful petitions grow quickly. Jungherr and Jürgens also analyzed 1.5 years worth of data from the German parliament e-petition platform, *epetitionen.bundestag.de* [8] and provided descriptive statistics about its petitions and signers.

Although these studies have explored several characteristics of e-petition platforms, they have been primarily descriptive of how people use the system (e.g., [8] reports the distribution of the number of total petitions and distinct topics sup-

ported by signers) or have focused on questions of what *petition* qualities, rather than *user qualities,* lead to more signatures and petition success. Following lessons from human-centered designs, designers also need to understand *users* – petition signers – to effectively improve these e-petitioning platforms.

Change.org
To obtain a broader understanding of e-petition platforms, we studied petition signers on Change.org. Change.org was founded in 2007 as a social network for non-profits and for project-based giving. Used by more than 70 million users in 196 countries, Change.org is the largest and most widely used e-petition platform and has been widely adopted by social movement organizations working on a wide variety of issues. Although it does not substitute for other forms of civic engagement, there are many examples of successful Change.org petitions like Kavanagh's that have led to meaningful social change in the real world. Unlike other e-petition platforms (e.g., We the People, UK No. 10 Downing Street), a *victorious* petition on Change.org does not mean the petition's signature count exceeds a certain threshold. On Change.org, a petition's goal for signatures can be changed once it reaches its original goal and petitioners can declare victory at any point.

Are Power Signers Born or Made
Because the goal of a petition is to accumulate signatures, the success of an e-petition platform requires significant user participation. Reviews suggest that a small portion of users make up a major of the contributors in typical online communities [10]. Our data of Change.org shows that the top 4.6% of users (i.e., "power signers") contribute more than half of all signatures (Table 2). Although increased rates of signing might come at the expense of quality, many signatures point to increased political engagement [7,14] and can be a sign of a system that is effective at helping users find petitions that match their ideals. As a result, understanding user behavior to attract and encourage power signers remains one of the most important questions for e-petition researchers. Research into online participation on other social computing systems offers several competing theories of where "power users" come from, and how one might design to support them.

Born
An influential theory of power users suggests that active participants in online communities are born and not made. For example, research has shown that the most active contributors to Wikipedia are different from other contributors on their first day [16]. Similarly, Panciera et al. [17] find support for the "born" hypothesis in a study of power editors in a Geowiki. Additionally, Muller [13] found that the engagement level of users on enterprise social media is related to stable personal traits. Pal et al. [15] found the experts in a Q&A community contribute significantly more

than others at the beginning of their lifespans within the community.

Laboratory experiments have attempted to model individual decisions to participate in petitioning by focusing on qualities of individuals that are unlikely to change with time. For example, Margetts et al. found that more extraverted individuals and people with higher locus of control are more likely to be "starters" – those who sign when petitions are first initiated [12]. In addition, Cruickshank et al. [6] found that petition participation is related to individuals' intrinsic psychological characteristics. This body of work suggests that e-petition signers' behavior may be driven by stable individual characteristics. As a result, we would predict that, like other social computing domains, power signers will be "born," and that users' initial engagement with the platform will predict their long-term activity:

H1: Initial levels of engagement with an e-petition platform will strongly predict users' subsequent levels of engagement.

Made
Another perspective is that power users grow and mature over time. Lave & Wenger discuss the idea of legitimate peripheral participation in their work on general communities of practice and suggest that through interaction and engagement with a community, individuals learn to become experts and core members [11]. Building on this idea, Preece and Shneiderman offer the reader-to-leader framework [18] characterizing online users' participation behavior in terms of four categories that participants move through as they develop in their use of a site: reader (e.g., browsing, searching, returning), contributor (e.g., rating, tagging, reviewing, posting, uploading), collaborator (e.g., developing relationships, working together, setting goals), and leader (e.g., promoting participation, mentoring novices, setting and upholding policies).

In a broader sense, the idea that users' behavior is shaped and driven by their experience over time is central to social computing research, which has frequently focused on ways that users develop identity and commitment over time and respond to social influence [10]. Additionally, a rich literature on organizations points to organizational learning and planned behavior as two of many ways that individual action is shaped, and supports the idea that users of social computing systems learn to be power users.

This perspective suggests that users become more actively involved with communities and more committed to platforms over time and, as a result, participate more often:

H2a: Signers will participate more often as their experience with the platform increases.

Research in other social computing domains also provides support for the idea that learning improves the *effectiveness* of contributors. In their study of Q&A, Ahn et al.'s study of Stack Exchange found that receiving feedback (e.g., votes and favorites) predicts a marginal increase in the quality of question askers' subsequent questions [1]. In a controlled experiment to test donation behavior in crowdfunding sites, Wash & Solomon [19] found that participants could learn to coordinate their efforts and not contribute to high-risk or unfundable projects. In the e-petition context, an improvement in *effectiveness* would mean that signers become better at assessing petitions over time. For example, this might mean that users are more likely to sign petitions that are later declared victorious:

H2b: As their experience with the platform increases, signers will be more likely to sign victorious petitions.

A creator's decision to mark a petition as victorious is a potentially noisy measure of petition quality. A second measure of petition quality is the raw number of signatures that the petition will end up receiving:

H2c: As their experience with the platform increases, signers will sign petitions that eventually get more signatures.

Finally, it is worth noting that it is possible the users are "made" in social computing systems in more than one sense. Users may become more engaged and/or more effective over time not only because they have learned but, rather, because the system has grown to be "better" at supporting them. For example, Cosley et al. [4] utilized the edit history of Wikipedia users to recommend Wiki pages that users might be interested in editing. Others have shown that the same technique is useful in increasing users' contribution in an online movie review forum [5]. In addition, An et al. [2] showed that it is possible to use users' tweets to invite potential investors to fund crowdfunding projects that might interest them. This thread of research demonstrates that social computing systems can use user data to encourage contribution and users can be "made" in the sense that they are supported to become more effective by a system.

STUDY 1: QUANTITATIVE ANALYSIS
The first step in our research seeks to test our hypotheses using public "digital trace" data on users of Change.org published on its website and made available through a publicly accessible API.[1]

Data and Empirical Setting
To build a representative sample of Change.org users, we took advantage of the fact that Change.org user ID numbers increase sequentially. By selecting numbers sequentially, we built a 1% sample of users who created their accounts during the 16-month period between January 2010 and April 2011. From an original sample of 23,000 users, we removed 648 with malformed data (*e.g.*, some users put both city and state information in the city field) and 1,072 users who hadn't signed any petitions. We focused on the

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[1] https://www.change.org/developers

Data field	Description
User ID	The unique ID of the user.
User Name	The name of the user.
User location	Comprised of city, state (province), and country.
User Activities	A list of IDs of the petitions the user signed and created.
Petition ID	The unique ID of the petition.
Petition category	The topic (e.g., Animals or Environment) of the petition.
Petition duration	The start date and end date of the petition.
Petition status	A status that shows if the petition is still running (open), has finished but is not successful (closed), or if the creator finished the petition and declared victory (victory).
Petition signatures	The information (name and location) of the signers of the petition and the timestamps of the signatures

Table 1. A summary of the user and petition data retrieved through Change.org API.

remaining 21,280 users in our analysis. Next, we collected information on the 140,866 petitions that these users signed. A description of the data collected is shown in Table 1. Because many users sign petitions in batches, we grouped signatures into "sessions" when the elapsed time between signatures is less than one hour.

Like many measures of social media activity, our continuous measures are highly skewed. For example, about one third of users only sign once in their lifespans, and more than half of the users sign less than 3 times. In contrast, the power users (top 4.6%) on average sign 205 times and contribute more than 50% of all signatures (Table 2). Toward that end, we log transform each of the continuous measures before using them in regression analyses.

Study 1a: Using the First Session to Predict the Level of Activeness of the User

Measures
Testing **H1** requires cross-sessional data with users as the unit of analysis and measures of long term and initial engagement. To capture the level of a user's long term engagement, we use the total number of signing sessions (i.e., groups of signatures separated by less than one hour) that a user engages in between the time they join the site and the point of data collection (September 2014). To measure ini-

# of Signatures	Users (%)	Accumulated Users (%)	Contributions (%)	Accumulated Contributions (%)
1	33.2%	33.2%	1.7%	1.7%
2-3	17.0%	50.2%	1.9%	3.6%
4-5	10.2%	60.4%	2.2%	5.9%
6-10	11.6%	72.0%	4.3%	10.1%
11-25	11.7%	83.7%	9.5%	19.6%
26-50	6.6%	90.3%	11.4%	30.9%
50-100	5.1%	95.4%	18.3%	49.2%
Over 100	4.6%	100%	50.7%	100%

Table 2. The distribution of users by their signature count. It shows most users contribute only a few signatures on the platform, while, the top 4.6% of the users contribute more than half of the total signatures.

tial levels of engagement, we use the number of petitions that users sign in their first session.[2]

We also constructed a series of control variables to capture other reasons that might influence users' level of engagement with Change.org. Because users attracted by different types of petitions might have different trajectories, we include stable qualities of the initial petitions signed by users in the form of dummy variables indicating whether initial petitions were created by organizations and whether they were declared victorious. We also include continuous measures of the total signatures received by the first petition signed by each user. To control for other observable qualities of users, we also measure the number of signatures and the age of the first petition signed in days at the point when it was signed by the user in question. Because different issues might attract users who are more or less driven to participate in the future, and because users who join Change.org earlier had more time to engage, we also include fixed effects for both the category of the user's first signed petition (e.g., Animal Rights, Criminal Justice, or Education) and for the month in which the user first signed a petition in a second model.

Methods and Analysis
To test our hypotheses that power signers are born, we first follow Panciera et al.'s approach to studying power editors of Wikipedia [16]. We begin with descriptive statistics of the likelihood the signers will become power signers by looking at the different number of petitions signed in their first session. Although defining levels of activity that constitute "power signing" is necessarily arbitrary, our analysis

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[2] We used the first session for our analysis to be consistent with Study 1b. Results using signers' first day instead of their first session were similar.

Signatures in 1st session	Count	Proportion of users	Likelihood of > 1 Session	Likelihood of > 5 sessions	Likelihood of > 20 sessions
1	16336	77%	52%	22%	8%
2	1696	8%	62%	31%	13%
3	1099	5%	69%	35%	13%
4	1580	7%	71%	43%	18%
>=5	569	3%	76%	50%	22%

Table 3. Likelihood of signers becoming active based on the number of signatures in their first session. We report results for > 1 session (50th percentile), > 5 sessions (75th percentile), and > 20 sessions (90th percentile).

suggests, as in previous work [16], that our pattern of results are not sensitive to the threshold we choose.

Beyond these descriptive statistics, we also try to formally test **H1** using a series of fitted regression models. Poisson models are frequently used for counts like the total number of sessions a user makes on Change.org. Like many counts, over-dispersion is a concern in our data so we estimate a quasi-Poisson model. In analyses not reported here, we also estimate negative binomial count models and we find the results are similar.

Results
Table 3 reproduces a table used by Panciera et al. [16] to argue that Wikipedia power users are born, not made. Our results match Panciera et al.'s results from Wikipedia and provide descriptive evidence in support of the claim that users are born. For example, the far right column shows that a larger proportion of users who sign at least 5 petitions will go on to have more than 20 sessions (the 90th percentile) than those who only sign only one petition. This pattern is repeated across all columns which capture the number of sessions users go on to have.

Regression results demonstrate strong support for the born hypothesis as well. Table 4 includes two models with and without controls in the form of fixed effects for first petition category and month of first engagement. Because these are Poisson models, we estimate that, in the model without fixed effects, a log unit increase in the number of signatures in a users' first session will be associated with a 1.5 (or $e^{0.42}$) times increase in the total number of sessions.

To further assist with the interpretation, we fit a series of linear probability models using the right side of the full fixed effects model to describe the model-predicted probability of a user falling into one of the categories described in Table 3. Predicted probabilities from these models with all controls held at their sample medians are shown in Figure 2 and describe a similar pattern of results shown in Tables 3 and 4. They show that users who are more engaged in their very first session are much more engaged in the site over the long term. These analyses provide strong support

for H1 and the idea that power signers on Change.org are born.

Study 1b: A Longitudinal Analysis of Users' Petition Signing Behaviors

Measures
Because testing **H2** involves looking for changes in user behavior over time, we construct a longitudinal dataset where the unit of analysis is the user-session. To test **H2a** that users will participate more frequently over time, we construct a measure of time since the previous session.[3] To test **H2b** and **H2c** that users become more effective at assessing petitions, we construct a dummy variable to measure whether a session includes a signature to a petition that will eventually be declared victorious and a measure of the mean number of signatures that petitions in a given session will ultimately receive. Because all three **H2** hypotheses involve looking for change as a user gains experience, our primary independent variable is the session number or sequence for the user in question (i.e., 5 for a user's fifth session).

As we hypothesize, systems may drive what appears to be learning by presenting users with more popular materials over time. To address this in **H2b** and **H2c**, we include our measure of the average number of signatures a petition has at the time the user signed it. In the case of **H2c**, this is a very strong control because this measure is highly correlated with the dependent variable (i.e., the average total number of signatures that petitions in the session receive).

Methods and Analysis
Testing **H2** in our longitudinal dataset includes repeated measures of the same user, which leads to concerns of a lack of independence between observations. To address this, we estimate fixed effects models that are equivalent to fitting a dummy variable for every single user in the dataset. This reflects a very strong test because these fixed effects control for any observed or unobserved quality that

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[3] We necessarily omit the first session from this analysis.

	w/o Fixed Effect	w Fixed Effect
(Intercept)	1.57***	1.68***
	(0.12)	(0.19)
# of Signatures in 1st Session	0.44***	0.42***
	(0.03)	(0.03)
1st Pet. By Organization	0.31***	0.26***
	(0.04)	(0.04)
1st Pet. Victory	-0.19***	-0.04
	(0.05)	(0.05)
1st Pet. Popularity	0.04	0.02
	(0.02)	(0.02)
1st Pet. Popularity when Signed	0.01	0.02
	(0.02)	(0.02)
1st Pet. Age	0.00	-0.01
	(0.00)	(0.01)
Fixed Effects		
1st Sig. Category	No	Yes
1st Sig. Month	No	Yes
Deviance	476220	461086
Num. obs.	21280	21280

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, All the continuous measures were logged.

Table 4. Quasi-Poisson regression models that predict the number of total sessions with and without fixed effects for petition category and the month of users' first activity.

has a consistent user-level effect on our outcomes. As a result, our estimates rely entirely on within-person variation over time.

Results
Parameter estimates for our fitted regression models for our three sub-hypotheses for **H2** are shown in Table 5. **H2a** (that users will contribute more frequently as they gain experience) is tested in $M_{Elapsed}$ and finds strong support. Because both our dependent and independent variables are log transformed in $M_{Elapsed}$, we estimate that a 1% change in the session sequence number is associated with a 0.12% decrease in the time between the session in question and the previous session. We also find that our control for the number of petitions signed in a session is related to larger spans of time between sessions.
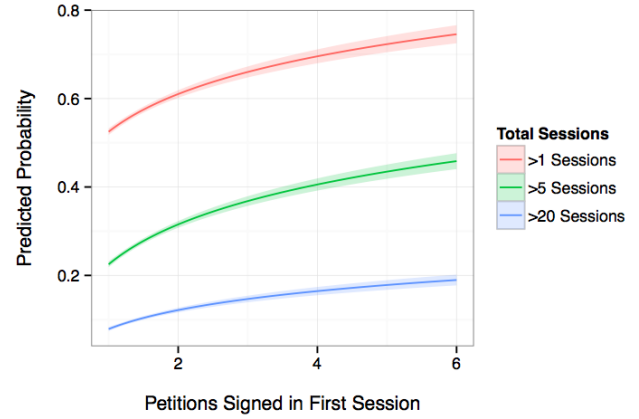

Figure 2. Predicted probability of various level of total sessions based on the number of petition signed in the first session.

In $M_{Victorious}$, we test **H2b** that users become more effective with experience and sign petitions that are more likely to be declared victorious. Our results are contradictory to our prediction. $M_{Victorious}$ suggests that controlling for the number of petitions signed and the number of signatures already on a petition when a user signs it, users are *less* likely to sign a victorious petition in a given session as they gain experience on Change.org. Using a linear probability model, we can interpret that a 1% change in session sequence number is associated with a 2% decrease in the likelihood of the session including one petition that will eventually be declared victorious. This finding provides disconfirming evidence for **H2b**.

$M_{Popularity}$ tests **H2c** that users will sign petitions that will eventually accumulate more signatures. The results provide support for **H2c** in favor of increased user effectiveness. In $M_{Popularity}$, we estimate that a 1% increase in the session sequence number is associated with a 0.04% increase in the total number of signatures. Although this effect is small, it is worth keeping in mind that this reflects the marginal effect after controlling for the number of signatures at the time that the petition was signed. Controlling for when users sign, and given that they are signing more frequently over time, users sign petitions that end up with more signatures as they gain experience with the site.

Although we find evidence that users are both born and made, the relative importance of these effects is an important question. We can begin to answer this by considering whether stable individual characteristics or changes in behavior over time explain more of the variation in our longitudinal models. Although the models used in Study 1b use within-person fixed effects to offer a strong test of the made hypotheses, this means that we cannot simply add dispositional covariates. Instead, we estimate a series of random effects models otherwise identical to the models in Study 1b that allow us to estimate the intra-class correlation, which reflects the proportion of variance in our dependent

	$M_{Elapsed}$	$M_{Victorious}$	$M_{popularity}$
Session sequence number	-0.12***	-0.02***	0.04***
	(0.00)	(0.00)	(0.00)
# of petitions in session	0.05***	0.07***	-0.07***
	(0.01)	(0.00)	(0.00)
Avg. petition popularity when signed		0.04***	0.74***
		(0.00)	(0.00)
R^2	0.01	0.03	0.72
Adj. R^2	0.01	0.03	0.67
Num. obs.	171282	183091	183091
Num. users	11810	11810	11810

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, All the continuous measures were logged.

Table 5. Three regression models where the dependent variables are elapsed time from previous session ($M_{Elapsed}$), # of victorious petitions in session ($M_{Victorious}$), and the Avg. petition popularity in session ($M_{popularity}$)

variables that comes from stable individual characteristics. Our results are mixed and suggest that the importance of stable characteristics varies enormously across our three models. We find that 43% of the variance in time between sessions, 3% of the variance in the proportion of editing sessions with at least one victorious petition, and 21% of the variance in average petition popularity is associated with characteristics that are stable across individuals.

Discussion
Our results echo previous research on Wikipedia and show that power signers on Change.org can also be predicted using engagement level in their first session. This supports **H1** that power signers are *born*. We also find the signers sign more frequently and target more popular petitions when they have more experience on the site. Although our test of **H2b** points in an unanticipated direction, it also shows change over time. This provides broad support for **H2** that the power signers are also *made*. Going beyond Panciera et al. [16,17] who tested only whether users were born, our results show that power users can be both born and made, and to varying degrees, along different and important measures of activity. These results have important theoretical implications to social computing researchers used to presenting "born" and "made" as competing hypotheses.

Our results for our test of **H2b** – that users are *less* likely to sign victorious petitions over time – is both surprising and

at odds with our finding for **H2c**. That said, the relative infrequency of victorious petitions and the subjective nature of creator-defined "victory" suggests that more complex dynamics may be at play than our quantitative results can uncover.

Even our more intuitive results raise questions that are difficult to answer using only observational data from the Change.org website. For example, although our results show that signers sign more frequently as they gain experience on Change.org, we cannot know whether this is because signers learn to contribute more or because the system learns to better target them.

STUDY2: INTERVIEW OF SIGNERS
In a follow-up qualitative study, we aim to answer two questions raised by our quantitative analyses:

1. Why do people select more popular petitions over time?
2. Does the Change.org system play a role in signers' behavior change?

We conducted semi-structured interviews with a number of individuals who have signed more than one petition on Change.org.

Methods
Interviewees were recruited from Facebook and Craigslist in 10 major cities in the U.S. Potential interviewees completed a short demographic and Change.org usage screening survey. Based on the survey answers, we reached out to 20 people through email, and 14 were willing to be interviewed. All interviews were conducted over the phone or Skype, audio recorded, and transcribed. Interviews lasted about 50 minute on average. As compensation, interviewees could choose between $20 in Amazon gift cards or donating the same amount of money to a charity of their choice. All of the participants joined Change.org over one year ago, four of them signed less than five petitions, five of them signed more than five but less than 50, and five of them signed more than 50 petitions. Eight of the participants were between 20-39 years old, three of them were between 40-59, and three of them were 60 years or older. Ten of the participants were female and four were male. The overrepresentation of women among our interviewees is in line with the distribution of women in the population of Change.org users.[4]

In interviews, we asked users about their first and most recently signed petitions on Change.org, and explored how their motivation and signing behavior has changed over time. Some example lead-in questions were:

- What triggers you to sign petitions on Change.org?

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[4] https://chartio.com/blog/2013/12/the-data-behind-online-activism

- How do you search/decide which petition to sign?

- Has your signing behavior on Change.org changed since you first signed? How?

Each of the interviews was coded with inductive codes using Dedoose qualitative data analysis software by two members of our team. Codes were discussed, combined, and interpreted to create themes using a grounded theory approach [3]. Coded responses were analyzed based on categories related to how interviewees responded to the questions.

Results

Signers Become More Selective

In line with our results in **H2c** that users become more effective, interviewees frequently explained that they felt they had become more careful about choosing the petitions they sign as they gained experience with Change.org. First, they explained a growing recognition that some petitions on Change.org are of low quality:

> You can tell that some are just put up there as a joke, or maybe not a serious petition. And, you know, it has to be something I believe very strongly before I even take the time to sign it. (P14)

Also, we found that as signers become more aware of their presence on the site, they choose the petitions more carefully. For example:

> In the beginning, I used to sign in all the time and … displaying my signature was okay. Now … I really don't want to put my name on everything. It's a bit overwhelming. I'm careful where I put my name on petitions. (P7)

This provides support for our hypotheses that signers become more selective as they become more experienced on Change.org.

Raising Awareness as Petition Success

The results in our quantitative analyses were surprising in the sense that they suggest that users are selecting more popular petitions but not the ones that are more likely to be declared as victories. Although we did not describe this finding to interviewees, many participants suggested petition success might not only be through a petition accomplishing its stated goal. For example, users found that raising awareness of an issue could be equally, or even more, important:

> I guess the success of a petition, there are two definitions. It would be either bringing more awareness to people on a situation or actually getting a goal accomplished because sometimes, petitions may not be as successful as we want them to but it does bring awareness to people. Sometimes, when I sign it, it may say maybe 10,000 signatures but then when I get an update, it might say 20,000 signatures. Although that isn't a lot, it's still 10,000 people you're reaching out to. (P13)

Another interviewee echoed a similar sentiment:

> If you're getting people thinking about an issue or you're making them feel like it's a passionate issue and you're changing somebody's approach to something … they're more aware of issues that may be around them. (P2)

In further explanation of our finding in **H2b**, signers emphasized that petition victory is something that is outside of the petitioners' control:

> It doesn't seem like very many petitions are truly successful, maybe they are, but it seems like you'll get all these supporters and still nothing's been changed. But at least you know that you're not the only person that thinks that way. Maybe there's 3,000,000 people who think that GMOs are wrong, but the government's still not listening. (P1)

These explanations suggest that many active signers do not target the petitions based on how likely it is to accomplish its goal (i.e., victory) but rather to find issues that are important and that help them raise awareness. To the extent that this position, common in our interviews of experienced Change.org users, develops in users over time, it may provide an explanation to why our quantitative analysis finds disconfirming evidence for **H2b** but in support of **H2c**.

Signers Are Being Made By the System

Finally, our results in **H2a** suggest that signers sign more frequently over time. As we suggested in our background, it can be difficult to unpack the way that users are made through personal growth and learning or through increased support from a system.

To unpack this issue, we asked all interviewees what prompted them to sign petitions on Change.org. Interestingly, unlike many social computing systems where users actively go to the site to make contributions, our interviewees rarely went to Change.org unprompted. Instead, they returned to the platform when receiving invitations to sign a petition. For many interviewees, this was over email:

> Well, they send me an e-mail. That's the only time I [sign petitions on Change.org]. It's an e-mail about one specific issue and if you want to sign it you click a thing and if you say skip to the next one it skips to another one. Then you read it and if it's something I want to sign, I sign it. (P9)

Other interviewees cited Facebook as the primary prompt for engagement but the pattern of interaction was nearly identical:

> Facebook is actually the quickest way because once you say, "Oh I like it" you get the updates that you want. So that's actually a quicker way, if I don't have patience to just go scroll through the "bajillion" things, I can go through Facebook. (P7)

To the extent that users' engagement is driven by these targeted prompts sent through channels managed by the Change.org platform (i.e., emails from the site and its peti-

tioners and from Facebook channels), this provides evidence that users are not only learning but that their signing behaviors may be shaped by the site.

In further support of this conclusion, signers mentioned that they think Change.org does a good job of modeling their interests and provides useful recommendations to them:

> They must know the topics that I respond to because I will not sign every one. I must read the petition first to make sure it agrees with my principles. (P5)

A common response suggested that, although they did not understand how Change.org worked, users felt it did a good job of recommending petitions to them based on their previous use of the system:

> I don't know how Change.org actually, how the system runs but … I always get petition for animals. That's the number one thing that I always receive. I guess because it's saved, I guess your likes or your recent signing and petitions, it brings up recommendations of what you're interested in. (P13)

Several interviewees explicitly suggested that many emails for petitions they sign come not from Change.org but from organizations using Change.org as a platform. To the extent that these organizations are also learning, they provide a larger concept of the platform that can effectively target users. For example, one user explained:

> I get a lot of messages from, like, the Freedom from Religion Foundation, for example. I get, you know, e-mails from them, and sometimes they do include links to petitions on Change.org. (P14)

Of course, many other forms of engagement were driven by prompts outside the control of Change.org and petition creators. Many other interviewees suggested that they received petition information from other social media platforms like Twitter and Reddit. That said, these interviews suggested that not only were users learning to be more selective and effective, but that the Change.org system, and the broader ecosystem of petitioners using the system, was also learning to make better recommendations as it collected more data about signers. In this sense, Change.org activists are not only "made" themselves, but also "made" by the system.

DISCUSSION
By examining the born and made hypotheses in a mixed method analysis of Change.org users, our study advances our understanding of user behavior in e-petition systems. Our results also add to the larger theoretical debate about whether users are born or made in social computing systems in general, and suggest that these theories may not be in conflict.

First, in our study on Change.org signers, we found similar results to prior studies that the likelihood of a user becoming a power user can be estimated using initial engagement. Although this provides strong evidence in favor of the claim that power users are born, we found that this is not the full story. A longitudinal analysis of Change.org signers shows that user behavior also changes over time and suggests that both "born" and" made" theories help explain user behavior on Change.org.

This research is an observational study of users. As a result, more research is needed to understand how systems can use both theories to elicit more contributions from users. That said, several implications for design are immediately clear. For example, even though one might be able to identify power users after their initial engagement, a system might still effectively nurture these users.

In strong support of this approach, our in-depth interviews uncovered evidence that the behavior of signers on Change.org changes not only because signers are learning from their own experience in the community, as proposed in research on situated learning and the reader-to-leader framework [10, 18], but also because signers are being "made" into more active and engaged users by the system as the platform itself learns from the history of signers and engages them more effectively. This provides strong support for the idea that social computing systems that utilize intelligent task routing to encourage contributions, like those created for Wikipedia [4] and MovieLens [5], might play an important role for users who were born as active contributors. For instance, a system might actively send out requests to users to better understand their interests by their responses. Then, the system might send requests to users based on their interests to solicit additional contributions.

Limitations
In this study, we analyzed data from 21,280 users who joined Change.org between January 2010 and April 2011 and all the petitions they signed. Although we sampled randomly over this period, this random sample is unlikely to contain extreme outliers that may be of interest to a studies of power users. Because we rely on a random sample, our study is limited to average effects.

Additionally, we cannot be confident in our findings' generalizability to other social computing platforms or even to other e-petition systems. Although it is important to note that general user interaction on e-petition sites are quite similar, and although we have also found that patterns of use on Change.org are similar to what other scholars of e-petition platforms have reported, it is impossible to know how findings gleaned from Change.org can inform our understanding of user behavior on other platforms. This is particularly the case for social computing systems that operate very differently than Change.org. For instance, our "made" effect might be weaker in a platform such as Wikipedia which does not send out emails or systematically recommend that users edit particular pages.

CONCLUSION
In this study, we analyzed petitions and users on one of the most popular e-petition platforms. In particular, we asked

whether power signers on Change.org are born or made. Our results found support for both the born and made hypotheses. We found that users who contribute more frequently initially are more likely to be active over their lifespan on the site. We also found that signers' behavior changes over time and that as signers gain experience, they contribute more frequently, sign petitions that are more likely to be popular, and are less likely to sign victorious petitions.

Using data from interviews of Change.org users, we unpack this final finding in ways that lead us to be more confident in our hypothesis that users learn. Additionally, this interview data suggests signers' activity on the site is often prompted by email and social media in ways that suggest that learning is also happening within the system. As signers sign more petitions, the Change.org platform can better model signers' interest to recommend petitions that the signers are more likely to sign. These findings suggest that administrators of e-petition platforms should both find ways to identify power signers early in their lifespans, and devote more resources to encourage users to develop and grow in their activity.

There are many possible directions for future work. One interesting finding from this study is that email and social media seem like important drivers of Change.org signing. Therefore, in the future, we hope to measure activity around petitions outside of e-petition platforms.

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