Socioeconomic Inequalities in the Non/use of Facebook

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ABSTRACT
Use and non-use of technology can occur in a variety of forms. This paper analyzes data from a probabilistic sample of 1000 US households to identify predictors for four different types of use and non-use of the social media site Facebook. The results make three important contributions. First, they demonstrate that many demographic and socioeconomic predictors of social media use and non-use identified in prior studies hold with a larger, more diverse sample. Second, they show how going beyond a binary distinction between use and non-use reveals inequalities in social media use and non-use not identified in prior work. Third, they contribute to ongoing discussions about the representativeness of social media data by showing which populations are, and are not, represented in samples drawn from social media.

Author Keywords
Social media; Facebook; non-use; demographics; socioeconomic status.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
A growing line of research emphasizes that not everyone uses social media. Most such work compares users and non-users, noting a variety of differences [1,3,35,54,64,68]. Some of these differences arise from individual traits, such as personality [54,64] or privacy attitudes and experiences [6,54,68]. In other cases, differences emerge from categories related to demographics or socioeconomics, such as gender, race, or parents' level of education [20,30,35,68]. Put differently, despite their general popularity [20,30], social media use is not equally distributed.

At the same time, social media provide numerous benefits. Users of social networking sites generally have greater social capital [22,39,40]. Many use Facebook and other social media as a means of maintaining social ties [37]. These social ties provide varied types of support, especially in times of crisis [25,71,73]. Communication with social ties online can also provide assistance after job loss, including an increased likelihood of finding a new job [15]. Those who do not use social media do not have access to these same benefits.

An emerging consensus, though, suggests that a binary distinction between users and non-users hides more than it reveals [7]. In early, influential pieces on non-use, both Wyatt [74] and Satchell and Dourish [56] offer typologies distinguishing different kinds of non-use, with four and six different types, respectively. Lampe et al. [41] compare both light and heavy Facebook users against non-users. Hargittai and Hseih [36] categorize social media users according both to their intensity of usage and to the number of different sites they use.

Despite these developments, most prior work on non-use simply compares users against non-users [1,3,35,54,64,68]. Thus, this paper makes a unique contribution by considering different types of non/use[1]. Specifically, it examines demographic and socioeconomic differences among four different types of Facebook non/use:

- *current user*, who currently has and uses a Facebook account;
- *deactivated*, who has temporarily deactivated her/his account but could technically reactivate at any time;
- *considered deactivating*, who has considered deactivating her/his account but never actually done so; and
- *never used*, who has never had a Facebook account.

This typology, despite being informed by prior work [6,56,74], is not exhaustive. For instance, it does not account for those who have "taken a break" from Facebook [51] or those who have explored more creative mechanisms of avoidance [6]. Instead, it focuses on forms of use and non-use enabled by Facebook's technical affordance of account deactivation.

The data for this study come from a probabilistic sample of 1,000 U.S. households conducted by Cornell University's Survey Research Institute [https://www.sri.cornell.edu/sri/]. These data are analyzed using multinomial logistic regression to determine which factors increase or decrease

1 As elsewhere [7], the term "non/use" is meant as a shorthand for the phrase "use and non-use."

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the likelihood that an individual will belong to any one of the types of use and non-use listed above. An iterative model selection process tests a series of hypotheses, informed by prior work, about which factors likely influence a respondent's type of non/use. Results show that demographics and socioeconomic status (SES) play an important role. Thus, the paper both replicates and expands on several prior findings [1,3,35,68] with a more diverse, representative sample. Furthermore, the results show factor's varying impacts on different forms of non/use.

Taken together, these findings provide three major contributions. First, they show which factors identified in previous binary analyses also have predictive power when accounting for different types of non/use. That is, the results show *that* social media non/use is unequally distributed.

Second, by accounting for different types of non/use, the results also show *how* social media use is unequally distributed. Understanding the nature of these inequalities elucidates the disparate impacts that technology can have, especially along existing inequalities, such as around socioeconomic status [65,67]. The results presented here provide an important complement to findings about the various benefits gained from social media use [15,22,25,37,39,40,71,73]. Namely, since social media use is unequally distributed, the benefits it confers are likely to be unequally distributed, as well.

Finally, these findings contribute to the growing body of research showing just how representative (or unrepresentative) data drawn from social media are [12,33]. That is, these results help illuminate exactly what and whom we are actually studying when we analyze social media data.

RELATED WORK

Prior work has shown that non-use of social media can be impacted by a variety of individual attributes. These personality [54,64], frequency or intensity [22] of prior use [6,54,68], privacy attitudes and experiences [6,51,64,68], proclivity towards addictive behaviors [64], and others.

Rather than providing a comprehensive inventory of such possible factors, this paper instead focuses specifically on demographic and socioeconomic factors. Much rhetoric depicts social media, and communication technologies more broadly, as a democratizing force that can overcome existing social inequalities [e.g., 52,61]. However, some evidence suggests that such technologies, rather than mitigate inequalities, instead perpetuate or exacerbate them [65,67]. Focusing on demographics allows for empirically investigating these questions: how do demographic and socioeconomic factors relate to social media non/use? This focus also speaks to the questions raised above about the representativeness of data drawn from social media. Put differently, while much prior work suggests *that* demographic disparities exist, this paper demonstrates *how* such inequalities occur in use of social media.

Hypotheses and Research Questions

Prior work has identified several demographic and socioeconomic factors related to social media non/use. For each, this paper examines one hypothesis and one research question.

The hypotheses state that each category (age, gender, employment status, etc.) will have a significant impact on a respondent's type of non/use. Since most prior work treats use and non-use as a binary, this paper offers a novel contribution by testing whether those same predictors matter when different categories of non/use are considered.

The research questions deal with what impact the category will have when these different types of non/use are taken into account. That is, the hypotheses ask *if* each predictor matters, while the research questions ask *how* each predictor matters.

Age

H1. Age will predict type of non/use.

Prior work has found that younger people are more likely to be Facebook users and that older people are less likely to be Facebook users [1,3,20,30,35]. This paper tests the hypothesis that age will also significantly predict a respondents type of non/use. Due to a lack of testing in prior work, there are not clear expectations about the exact nature of the impact that age will have on each of the different categories of non/use examined here.

RQ1. How will the impact of Age vary by non/use type?

Gender

H2. Gender will predict type of non/use.

Hargittai [35] and Tufekci [68] find that females are more likely to use social networking sites. This effect is most pronounced for MySpace and for Friendster [35]. US national surveys have also found that, compared to men, a greater proportion of women use Facebook [20,30]. Some have argued that this imbalance may arise in part from stereotypical gender roles around emotional labor and care work (sharing and liking photos, organizing social events, keeping apprised of family news, etc.) [48]. One question becomes how this imbalance will play out when accounting for multiple different types of non/use.

RQ2. How will the impact of Gender vary by non/use type?

Phone Access

H3. Phone Access will predict type of non/use.

A combination of internet access and overall technology proficiency can influence an individual's use of social media [35]. Although prior work has documented cases of intermediaries who use a technology on behalf of others [55,75], someone who does not have internet access would likely find it difficult to have, let alone to use, a Facebook account. Furthermore, a small but growing contingent of Americans rely on their phone as their only means of internet access, and a growing proportion of cell phones are smartphones [62,63]. Also, households that can be reached via more phone numbers have by some measure greater access to, and may also have greater proficiency with, communication technology. The question becomes how phone access relates with social media non/use.

RQ3. How will the impact of Phone Access vary by non/use type?

Employment

H4. Employment Status will predict type of non/use.

Some work has suggested a link between social media usage and employment. Finding a job is often cited as an important use of social capital. However, prior work on social capital and social media has not specifically examined employment seeking [21,22,41]. Burke and Kraut [15] found that individuals who had lost their job were more likely to find a new job within three months when they communicated with strong ties on Facebook. Thus, while some evidence links employment and social media usage, prior work provides little expectation about the nature of this relationship.

RQ4. How will the impact of Employment Status vary by non/use type?

Income

H5. Household Income will predict type of non/use.

Prior work has shown that individuals with lower incomes are less likely to have internet access [47]. However, less worked has examined the connection between income and social media usage. Some studies have found certain sites, such as Twitter and LinkedIn, more common among those with higher incomes, while others, such as Facebook, are more common among those with lower incomes [20,30]. In a survey of college students, Hargittai [35] used parental level of education as a proxy for SES, since students may not have knowledge of their parents' incomes and because the term "household" has some ambiguity, especially for those living in dormitories. That analysis showed that students whose parents had a college degree were more likely to use Facebook, while those whose parents had a graduate degree were less likely to use MySpace.

RQ5. How will the impact of Household Income vary by non/use type?

Race

H6. Race will predict type of non/use.

In a study of college students, Hargittai [35] found that race predicted the probability that an individual used a social networking site. However, this relationship only held when the broader concept of social networking was disaggregated to ask about individual sites. For instance, self-identified Hispanic respondents were less likely to use Facebook but more likely to use MySpace. However, such effects did not occur for the broader umbrella of using any social networking site. In contrast to binary distinctions between use and non-use, this work expands the analysis to ask:

RQ6. How will the impact of Race vary by non/use type?

Finally, other factors not identified in prior literature may predict use and non-use of social media. Examples might include marital status, political party, social ideology, physical characteristics (such as height or weight), homeownership, parental status, and others.

RQ7. What additional factors impact a respondent's type of non/use?

METHODS

Survey Materials and Data

The data analyzed here come from the Cornell National Social Survey conducted by Cornell's Survey Research Institute (SRI) in 2015. Sampling was conducted using Using random digit dialing (RDD). Initially, 9895 numbers were called. For 1887 of these, someone answered, yielding a response rate of 19%. Of these, 534 were not viable as respondents (business number, language barrier, etc.). Of the 1353 viable responses, 1000 completed the survey and 353 refused, yielding a moderately high cooperation rate of 74%. Within each household, a single member was selected by asking for the person who was at least 18 years of age and had the most recent birthday. The survey protocol included an omnibus of 52 questions on varied topics, as well as demographics such as age, gender (F/M), marital status, social ideology (liberal to conservative), level of education, income, race, and others. Interviews averaged no more than 20 minutes in length[2]. Incomplete responses (52) were removed, leaving N=948 for the main analysis.

The data set includes a diverse battery of demographic questions: age, gender, height (in feet and inches), weight (in pounds), the age respondent feels, the age respondent wants to be, race, whether the respondent was born in the US, employment status, job type (full time, part time, temp, etc.), whether the respondent looked for work in the past four weeks, household income, level of education, whether respondent owns or rents her/his home, marital status, number of adults in the household, number of children in the household, the number of phone numbers that can be used to reach the household, whether the respondent was reached on a landline or cell phone, political party, social ideology, religious affiliation/preference, and how often respondent attends religious services.

Some of these variables were recoded, either during collection by SRI or for this analysis. *Marital status* was converted during this analysis to a binary variable for currently married or not, where not married included single, widowed, divorced, etc. Other variants were tested, but treating marital status as a binary yielded the best results in terms of model diagnostics (described further below).

2 For more details about this data set, please see https://www.sri.cornell.edu/sri/cnss.reports.cfm.

Following categories used on the US census [70], *race* was collected as a series of binary variables, one for each of Asian or Pacific Islander; Black or African American; Native American, American Indian, Aleut, or Eskimo; White or Caucasian; and Other. A separate binary question asked whether the respondent was of Hispanic origin or descent. The analysis treats race as a single categorical variable, with White as the reference level since it is the most common in these data [46]. Those respondents who selected more than one race are labeled as Multiracial. Implications of, and alternatives to, this approach are considered further both in the Results and in the Discussion sections. *Education* was collected as an ordinal variable with seven levels, from eighth grade or less, to post-graduate school or professional training after college. *Household income* was collected as an ordinal variable with nine levels. The first five levels correspond to US$10,000 increments from US$0 to US$50,000. The last four levels represent incomes from US$50,000 to US$75,000, US$75,000 to US$100,000, US$100,000 to US$150,000, and US$150,000 or more. Respondents who did not know their exact income but knew whether it was more than US$50,000 were coded as level six, and those who knew it was less than US$50,000 were coded as level five. Finally, both *social ideology* (collected as a seven-point ordinal scale from extremely liberal to extremely conservative) and household income were median-centered prior to analysis.

For inclusion in this survey, the authors formulated three questions directly addressing Facebook use and non-use:

- Do you currently or have you ever had a Facebook account?
- Have you ever deactivated your primary account?
- Have you ever considered deactivating your Facebook account?

The second question was only asked of respondents who replied Yes to the first question. In this question, the word "primary" is included in case respondents have more than one Facebook account. The third question was only asked of respondents who replied No to the second question.

These questions are informed by prior typologies of non-use. For instance, the *never used* resembles Wyatt's [74] "resister," who has never adopted a given technology, as well as Satchell and Dourish's "active resistance" [56]. The *deactivated* respondents resemble Wyatt's "rejecter," who previously used a given technology but no longer does. Respondents who *considered deactivating* exhibit what Baumer et al. [6] term "lagging resistance."

This series of yes/no questions provides a decision tree by which to classify four different types of users and non-users (see Figure 1). Those respondents who replied No to the first question are labeled *never used*, since they have never had a Facebook account. Those who responded Yes to the second question are labeled *deactivated*. A deactivated account still technically exists and can be reactivated at any time, but all information posted on that account is invisible to other Facebook users [24]. Those who responded Yes to the third question are labeled *considered deactivating*, since they currently use the site but report having some reservations about doing so. Finally, those who respond No to the third question are labeled *current user*, since they currently have and use an active Facebook account.

As noted above, other forms of non/use exist, such as taking an intentionally temporary break [6,8,51,58], or having a friend change one's password [6]. This analysis focuses specifically on one form of non-use that is relatively common [6] and has a technical manifestation on Facebook.

Analysis

As described above, the data analyzed provide four different classes of Facebook users and non-users (current user, deactivated, considered deactivating, and never used). Although it might be tempting to see these as an ordinal scale, this analysis forgoes any *a priori* assumptions about the relative intensity of use or non-use represented by any of these. Thus, the analysis instead treats the type of non/use as a categorical variable. As such, it employs multinomial logistic regression to determine which factors best predict the type of non/use in which an individual engages. Current user is treated as the reference level, primarily because it is the largest single category [46].

Model selection began by testing all models with only one variable to find the single variable with the most explanatory power, using two model diagnostics. First, Akaike's Information Criterion (AIC) [2] compares the complexity of a model, in terms of the number of variables it includes, against the model's fit, in terms of its ability to account for observed variance. Second, log-likelihood, i.e., a likelihood ratio test (LRT), provides a means of comparing how significantly two models differ in terms of their residuals. When these two diagnostics diverged, LRT was given preference. Keeping that single variable in the model, all other options of a second variable were tested.

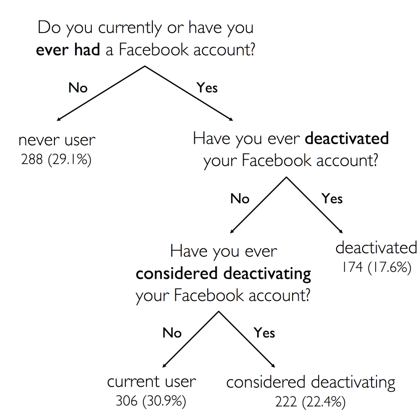

Figure 1: Each respondent's type of non/use was determined via this decision tree using answers to the three survey questions shown here. Numbers show how many respondents were of each type, with percentages in parentheses.

		Non/use Type			
Predictor		Current User	Cons. Deact.	Deactiv.	Never Used
gender	female	151	108	78	120
	male	140	107	91	153
married	no	110	110	110	113
	yes	181	105	59	160
social ideology	extremely liberal	27	16	9	12
	liberal	40	39	30	33
	slightly liberal	29	18	29	19
	moderate	102	55	59	93
	slightly conservative	30	27	15	38
	conservative	49	42	18	54
	extremely conserv.	17	18	9	24
household income	$0 - $9,999	5	5	1	9
	$10,000 - $19,999	10	8	12	19
	$20,000 - $29,999	12	15	11	20
	$30,000 - $39,999	17	13	13	20
	$40,000 - $49,999	39	24	20	47
	$50,000 - $74,999	82	60	42	56
	$75,000 - $99,999	37	20	24	26
	$100,000 - $149,999	44	33	19	33
	$150,000 or more	37	35	25	37
work	not looked (no)	270	160	120	272
	looked for (yes)	34	58	54	17
race	White	236	165	121	237
	Asian	16	5	8	3
	Black	23	23	21	34
	Multiracial	22	19	17	7
	Native American	3	1	3	5
	Other	4	5	4	3

Table 1: Cross tabulation of the four types of non/use (current user, considered deactivating, deactivated, never user) with each categorical predictor.

This process was repeated to find the model with the best trade off between explanatory power and model complexity, i.e., the lowest AIC and the highest log-likelihood. Once this model was identified, variance inflation factors (VIF) were calculated for each predictor. All variance inflation factors were between 1.0 and 1.3, indicating no presence of multicollinearity among predictors; i.e., none of the predictors was linearly correlated with any of the other predictors. The final resulting model is presented below.

Hypothesis Testing

This model selection process serves as a means of testing the hypotheses enumerated above. Each hypothesis suggests one or more variables that should significantly predict a respondent's non/use type. For each hypothesis, inclusion of the relevant variable represents confirmation of the hypothesis (i.e., rejection of the null), while exclusion of the variable indicates a failure to reject the null hypothesis. For example, if a respondent's age significantly predicts her/his type of non/use, then we confirm H1, i.e., we reject the corresponding null hypothesis.

This process also tests factors that may significantly predict types of non/use without being mentioned in prior work. In addition to the specific hypotheses listed above, the model selection process also considers as possible predictors the full array of demographic and socioeconomic variables provided by this data set (see above).

RESULTS

The analysis process above resulted in a model with eight predictors: age (continuous), gender (binary), household income (ordinal), whether the respondent has looked for work in the past four weeks (binary), whether the respondent is married (binary), the respondent's political ideology (ordinal), the respondent's race (categorical), and the respondent's weight (continuous). Table 1 cross tabulates respondents by non/use type and each of the six categorical, binary, or ordinal predictors in the model. These proportions roughly align with prior responses to the question, "Do you use Facebook?" [20,30]. In our sample, this question would solicit a "yes" response not only from Current Users but also from Considered Deactivating and Deactivated respondents, since all these types of respondents have a Facebook account. Thus, our sample includes a total of 675 Facebook users (71%), in line with prior findings of 68% [20,30]. This point demonstrates both the utility and importance of teasing out different types of use and non-use.

The details of this final model are presented in two complementary formats. First, following standard conventions, for each predictor in the model, we present the odds ratio for each type of non/use, a 95% confidence interval for each odds ratio, and p-values (Table 2). This format shows how each predictor impacts the probability that a respondent will have deactivated their account, have considered deactivating, or have never had an account, each in comparison with the probability of being a current user.

	Current User versus...		
Predictor	Cons. Deact.	Deactivated	Never Used
Age	0.982 *** (0.970, 0.994)	0.944 *** (0.929, 0.959)	1.046 *** (1.033, 1.059)
Gender Male	1.325 (0.873, 2.011)	1.127 (0.714, 1.779)	2.656 *** (1.730, 4.076)
Married	0.682 (0.448, 1.039)	0.568 * (0.350, 0.924)	0.901 (0.596, 1.363)
Looked for Work	2.276 ** (1.385, 3.742)	2.030 ** (1.197, 3.443)	0.709 (0.360, 1.393)
Household Income	1.068 (0.968, 1.179)	1.100, (0.985, 1.228)	0.894 * (0.812, 0.985)
Social Ideology	1.082 (0.967, 1.211)	0.966 (0.848, 1.099)	1.152 * (1.032, 1.286)
Asian	0.278 * (0.096, 0.803)	0.561 (0.215, 1.465)	0.238 * (0.984, 3.301)
Black	1.252 (0.657, 2.386)	1.394 (0.692, 2.810)	1.911 * (1.030.3.547)
Multi-racial	0.985 (0.488, 1.990)	1.120 (0.525, 2.386)	0.389 (0.148, 1.023)
Native American	0.401 (0.040, 4.034)	1.264 (0.239, 6.669)	3.779 (0.773, 18.49)
Other Race	3.274 (0.608, 17.64)	1.706 (0.210, 13.85)	1.419 (0.213, 9.455)
Weight	0.994 * (0.989, 0.999)	1.002 (0.997, 1.007)	0.990 *** (0.985, 0.995)

Table 2: Multinomial logistic model describing how each predictor impacts the probability of different types of non/use. Right three columns show impacts on the probability of considering deactivation, of actually deactivating, or of never having an account, as compared to a current user. Each cell lists an odds ratio with a 95% confidence interval in parentheses. *p<0.05, **p<0.01, ***p<0.001.

This presentation format has a significant limitation, in that it only provides pairwise odds ratios between the probability of being a current Facebook user and each of the other types of non/use. That is, it shows how each predictor influences the chance that a respondent deviates from the reference category of current user. To address this limitation, this section provides effects plots showing the simultaneous impact of each predictor on each different type of non/use examined here. Doing so helps address in more detail RQ1. through RQ6.

Before discussing the details of the final selected model, several points should be made about alternative models that were tested. First, including respondent's level of education results in a slightly better fit. However, the difference in not significant (log-likelihood -1074.3 > -1076.7, p=0.181), and the model's AIC is slightly higher, i.e., worse (2232.6 > 2231.5). Second, including the binary Hispanic variable has a similar effect, providing a slightly (but not significantly) better model fit (log-likelihood -1074.4 > -1076.7, p=0.201) and a higher AIC (2338 > 2336). Third, excluding race entirely results in a lower, i.e., better, AIC (2229.2 < 2231.5), but it also results in a lower, i.e., worse, log-likelihood (-1090.6 < -1076.7, p=0.023). Finally, alternative models were tested that treated race as a series of binary variables, rather than as a single categorical. Although the differences are not statistically significant, doing so results in a poorer model, both in terms of fit (log-likelihood -1076.9 > -1076.7, p=0.958) and in terms of AIC (2237.8 > 2231.5). Furthermore, in all these alternative models that include additional predictors, the effects reported below remain virtually unchanged. Thus, the final model provides the best explanatory power using the fewest predictors.

Hypothesis Test Results

For each of the six hypotheses, the results in Table 2 provide either full, partial, or no confirmation.

*H1. Age **Predicts** Non/use Type*

The results provide clear evidence to *confirm H1.* Older respondents were more likely to have never had a Facebook account (OR=1.046, p<0.001). Older respondents who did have an account were less likely to have deactivated (OR=0.944, p<0.001) or to have considered deactivating (OR=0.982, p<0.001). These odds ratios are interpreted in terms of reported age. For example, the odds ratio of 1.046 above means that every one-year increase in age increased the odds of having never had a Facebook account by 4.6%. Younger respondents are more likely to have either deactivated or considered deactivating their Facebook account, while they are simultaneously less likely to be a current user (Figure 2). The probability of deactivation, considered or actual, drops as age increases, while the probability of never having had an account goes up. These findings both build on prior results [1,3] and help address RQ1. Specifically, rather than try Facebook and leave, older respondents never had an account in the first place.

*H2. Gender **Partially** Predicts Non/use Type*

The odds of a male respondent having never been a Facebook user are 2.656 times higher than those of a female respondent. Put differently, female respondents were 2.656 times more likely than male respondents to be a current user rather than never having used Facebook (p<0.001). However, gender did not significantly predict deactivation, either considered or actual, in comparison to current use (see Figure 3), which partially confirms H2.

This result aligns with prior findings that social media use is more common among female respondents [20,30,35,68]. These results show that this difference occurs not because male users try and then leave Facebook, but because they never create an account in the first place, addressing RQ2.

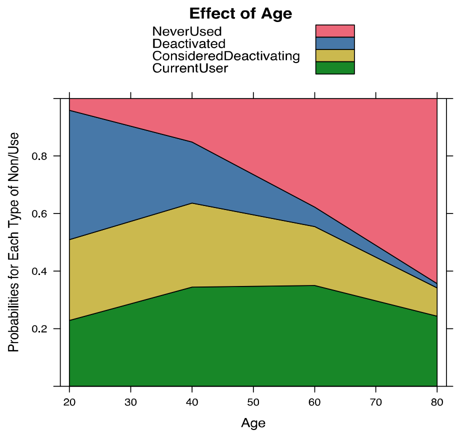

Figure 2: How age impacts the probabilities of each type of non/use.

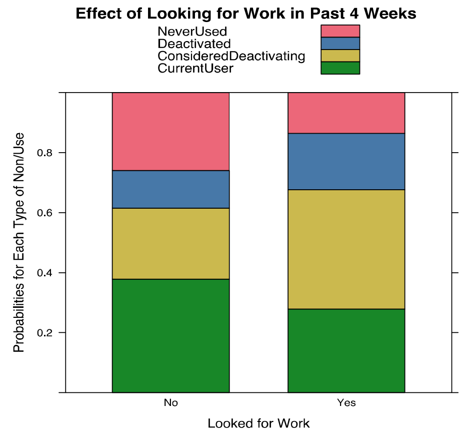

Figure 4: How looking for work impacts the probabilities of each type of non/use.

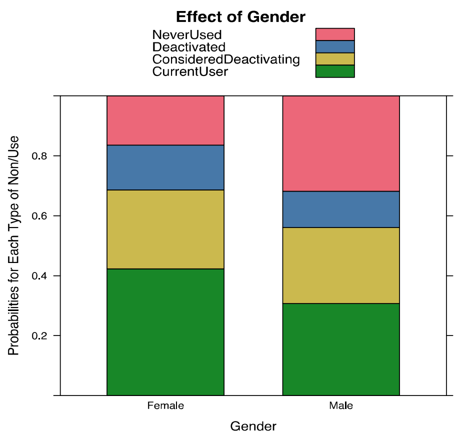

Figure 3: How gender impacts the probabilities of each type of non/use.

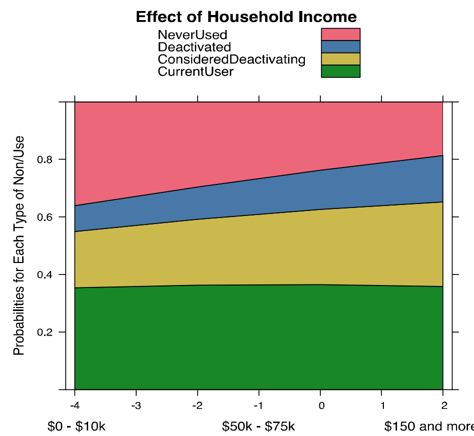

Figure 5: How household income impacts the probabilities of each type of non/use.

*H3. Phone Access Does **Not** Predict Non/use Type*

The analysis process included two potential predictors related to phone use: whether the respondent was reached using a landline or a cell phone, and the number of phone numbers that could be used to reach the respondent's household. Neither of these emerged as significant predictors in the final model in Table 2. Thus, the results *do not confirm H3.,* and they do not speak to RQ3.

*H4. Employment **Partially** Predicts Non/use Type*

A respondent's current employment status did not emerge as a significant predictor. However, the model does include whether the respondent looked for work in the past four weeks, thus *partially confirming H4.* Respondents who had looked for work were 2.030 times more likely to have deactivated their account (p=0.008) and 2.276 times more likely to have considered deactivating (p=0.001) (Figure 4).

Of the 161 respondents who had looked for work, most (118) were currently employed. These respondents may have already been employed and were seeking a different job, or perhaps respondents who sought employment some time in the preceding four weeks obtained it. Either way, *seeking* employment more significantly impacted non/use than *being* employed, but only in terms of deactivation, either considered or actual, addressing RQ4.

*H5. Household Income **Partially** Predicts Non/use Type*

A respondent's household income had no significant effect on deactivation, either considered or actual. However, respondents with lower household incomes were more likely to have never had a Facebook account (OR=0.894, p=0.024). As income increases, the probabilities for deactivated and considered deactivating increase slightly, but neither is as significant as the decrease in the probably of having never had an account (Figure 5). Thus, income does impact non/use, but only in terms of never having an account, *partially confirming H5.* and addressing RQ5.

*H6. Race **Partially** Predicts Non/use Type*

In the final model, only two racial categories have a significant impact, and each of those only significantly impacts a single type of non/use. First, respondents who identify as Asian are only 0.278 times as likely (i.e., 3.597 times less likely) to have considered deactivating their account (p=0.018). These respondents are also 0.238 times as likely (i.e., 4.202 times less likely) to have never had a Facebook account (p=0.035). This point offers a novel

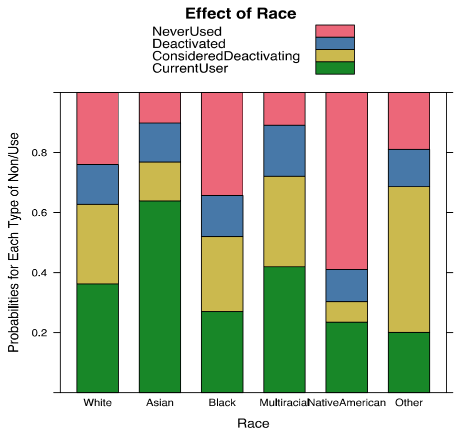

Figure 6: How race impacts the probabilities of each type of non/use.

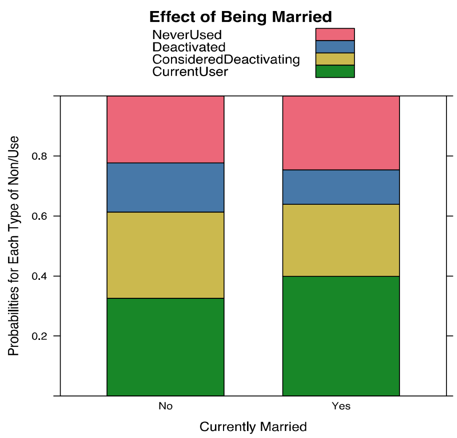

Figure 7: How currently being married impacts the probabilities of each type of non/use.

contribution. Prior analyses found that identifying as Asian had a non-significant impact on use of either Facebook or social networking generally [35,68], although some Asian respondents were less likely to use MySpace and more likely to use Xanga [35].

Second, respondents who identified as Black more likely to have never had a Facebook account (OR=1.911, p=0.040). This finding contrasts with prior results, which found limited differences in the proportion of Black or African American respondents who used Facebook [20,35,68]. Instead, it aligns with findings suggesting Facebook use as relatively less common among African Americans [10]. These findings help address RQ6.

Figure 6 shows that many of the racial categories considered here had a large, though not statistically significant, effect on a respondent's type of non/use. As discussed further below in the Limitations section, the sample included relatively small numbers of multiracial, Native American, or other race respondents, limiting the ability to detect statistically significant differences for these groups. However, the analysis above indicates that the model still provides an overall better fit when accounting for race, thus *partially confirming H6.*

Research Questions

This analysis also identified three significant predictors not mentioned in prior work.

Marital Status

Being married (as opposed to single, divorced, widowed, etc.) decreases the chance of considering deactivation (OR=0.665, p<0.05) and reduces the odds of actually deactivating almost by half (OR=0.522, p<0.01). Figure 7 depicts this impact, showing also that the probability of never having had an account remains nearly unchanged.

Social Ideology

Self-identified conservative respondents were more likely never to have had a Facebook account. Each move toward the conservative end of the Likert scale corresponded to being 1.152 times more likely to have never had an account (p=0.012). Figure 8 depicts this effect, also showing that social ideology has only a slight impact on the probability of deactivation, either considered or actual.

Weight

Heavier respondents were less likely to have considered deactivating their account (OR=0.994, p=0.018) and to have never had an account (OR=0.990, p<0.001). As weight increases, the combined probability of either considering or actually deactivating is fairly consistent (Figure 9). However, lower weight respondents are more likely only to consider deactivating, while higher weight respondents are more likely actually to have deactivated. This effect, though, is not significant when compared with a similar increase in current use among heavier respondents (OR=1.002, p=0.511).

As expected, average weight varies by gender (M=195.2 > F=158.3, t=14.41, p<0.001). However, the model already controls for the impact of gender. Including an interaction term results in a model with an equivalently good fit (log-likelihood -1076.1 > -1076.7, p=0.729) and a higher, i.e., worse, AIC (2236.2 > 2231.5). Furthermore, the variance inflation factors indicate no multicollinearity, as described above. These analyses provide good evidence for including both gender and weight as separate factors in the model.

DISCUSSION

To summarize, these results show that *current Facebook use* is more common among respondents who are: middle aged (40 to 60) (H1.), female (H2.), not seeking employment (H4.), of Asian descent (H6.), or currently married (RQ7.). *Deactivation*, either actual or considered, is more common among respondents who are: younger (H1.), seeking employment (H4.), or not married (RQ7.). Respondents most likely to have *never had an account* are: older (H1.), male (H2.), from a lower income household (H5.), racially of Black or African-American descent (H6.), more socially conservative (RQ7.), or weigh less (RQ7.).

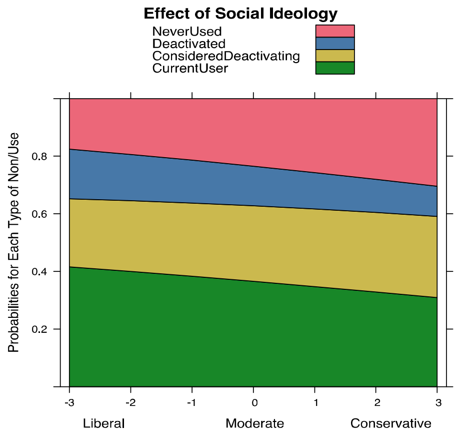

Figure 8: How social ideology impacts the probabilities of each type of non/use.

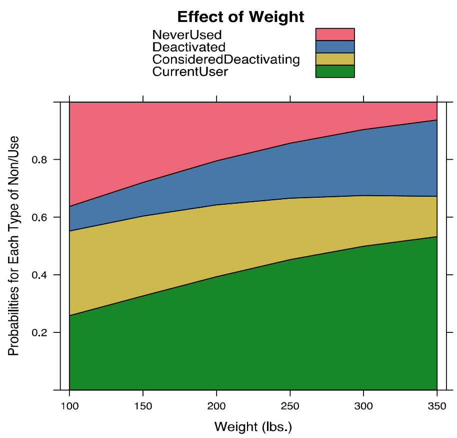

Figure 9: How weight impacts the probabilities of each type of non/use.

Interpretation and Comparison with Prior Work

Age

These results confirm prior findings that older individuals are less likely to have a Facebook account [1,3]. The finding that younger users are far more likely to have deactivated their account confirms prior work suggesting that certain groups, especially students, deactivate for intentionally brief periods of time [6,11,58]. The results also contribute to the assertion that Facebook's user base is aging as younger individuals choose not to sign up for an account [13,38,42]. The data analyzed here suggest that having a Facebook account is in fact most common among younger individuals [cf. 20,30]. However, the higher rates of deactivation among younger respondents suggests that they are not keeping active the Facebook accounts they create. That is, they are not resisters but rejecters [74].

Gender

Prior studies found social media use more common among female respondents [20,30,35,68]. The above results both confirm that finding and add further detail. The difference between female and male respondents stems entirely from the proportions of each that have never used Facebook.

Prior work has found gender differences in topics and language use on social media [4,72]. Gender differences in non/use may arise in part from social expectations based on these gendered use patterns, such as around care work [48]. The labor involved to "plan the get-togethers, send the birthday and holiday greetings, transmit the family gossip, and just generally stay present in everyone else's lives" [48] tends to be performed by women. Much of this work now occurs via social media, especially Facebook. Thus, to fulfill these gender normative roles, women may feel obligated to participate in social networking sites. Men, meanwhile, may not feel the same obligations, despite often benefitting from this affective labor. The findings about marriage corroborate this interpretation. Married individuals, who have a larger network of relations in which to perform care work, are also less likely to have deactivated their account. Prior work has argued that men may feel freer to walk away from Facebook than do women [48]. The above results suggest instead that men are less likely to have an account in the first place.

Weight

Prior work gives little direct expectation about how an individual's weight might impact Facebook non/use. One possibility is that weight relates to issues of self-perception, self-presentation, and self-esteem [26,32,66]. Rather than leverage selective self presentation that improves their self-perception, heavier individuals seem to deactivate to avoid reduced self-esteem from comparison with others.

Two important caveats must be added. First, the effects of weight may vary by gender [cf. 32]. Second, these effects may be non-linear. For example, deviation from the mean may matter more than absolute weight. Thus, significant future work is required to understand this effect more fully.

Socioeconomic Status and Seeking Employment

Finally, these results suggest how socioeconomic factors may work in concert. Social networks provide important means of fostering social capital [21,22,27,41], which can be put to a variety of uses [27,45]. An individual with lesser economic resources could thus leverage her or his social capital for accomplishing particular tasks.

Improved ability to find employment is often touted as a benefit of social capital, but the use of social media can become a double edged sword. Social networks provide important resources for job seekers [15,21,27]. However, an increasing number of employers search social media sites and the Internet for information about job applicants [5,28], despite the ambiguous legality of this activity [23,31,59]. Such situations may place job seekers in a double bind, where having a social media account can simultaneously both help and hurt their job prospects.

The findings here complicate this issue further. First, those respondents who had recently sought work were also more likely to have deactivated their account or to have considered doing so. These individuals may be responding to the trends noted above in which employers use internet searches for background checks [5,28]. Second, those with lower incomes are also more likely never to have had a Facebook account, meaning that they have reduced access to both economic and social capital [21,22]. At the same time, individuals with higher incomes were slightly more likely to have deactivated their account or considered doing so. One possible explanation is that individuals with higher incomes may be more technologically literate [34] and thus more aware that deactivation is even an option. It is also possible that, because these individuals have more economic capital, they are (or perhaps feel) less in need of the social capital that social networking sites can provide. Alternatively, job seekers who only consider deactivating their account may make more extensive or complex use of privacy settings, while those who actually deactivate take an arguably simpler but more drastic approach [16,18].

Thus, these results suggest, but do not prove, a poor-get-poorer paradox. Facebook, rather than acting as a democratizer [52,61], may be perpetuating existing social inequalities [65,67]. Future work should attend much more closely to how such factors influence social media non/use.

The (un)Representativeness of Social Media Data

Prior work has shown that data sampled from social media are unlikely to be representative of any population other than social media users [33]. However, researchers also leverage analysis of social media to develop understandings of more general social phenomena [43], such as group formation and dissolution [19,69], how newcomers join and influence existing groups [17,49], and others. Rather than gaining insights into some underlying social phenomenon, such work instead illuminates how those phenomena manifest in online social interaction. While the latter is certainly an interesting question, we should not mistake it for the former [cf. 53]. The analysis above helps explicate the particular ways that data from social media, specifically Facebook, are not representative of a broader population: Facebook users are more likely older, female, higher income earners, married, and ideologically liberal.

LIMITATIONS AND FUTURE WORK

The data set analyzed here provides a larger, more diverse sample than prior studies of non-use [3,6,35,41,54,64,68]. That said, these data also carry some important limitations.

First, only four types of non/use were considered. These data do not indicate, for example, whether the respondents who deactivated their account subsequently returned to Facebook [6,8,14,58]. Similarly, the data provide little insight into respondents' motivations for *why* they do or do not use Facebook in various ways. Due to the constraints of the survey format, a very limited number of questions were included on each topic. Future work should examine relationships between different forms of technology non/use and different types of motivations.

Second, despite the sample's diversity, it includes relatively few respondents from some racial categories. Table 1 shows that, out of 948 respondents, only 32 (3.4%) identified as Asian, 12 (1.3%) as Native American, and 16 (1.7%) as some Other race. The dearth of such respondents impacts both the lack of statistical significance and the large size of the confidence intervals for results related to race (Table 2).

Relatedly, many potential demographic variables were not collected, such as duration of current residence, disabilities, sexual orientation, net worth, etc. The data set also excludes minors, preventing analysis of teen non/use [cf. 44].

Moreover, these data use (and perhaps reinforce) existing demographic categories. Recent work has pointed out how analyzing only one category at a time, e.g., using race and gender separately, limits the ability to examine more nuanced, intersectional identities [57]. A related issue in these data can be seen it the fairly coarse-grained treatment of race and ethnicity. Subjectively experienced cultural distinctions may not reflect authoritative racial categories [cf. 9] historically defined by, e.g., the US Census Bureau [70]. Similar points could be made about gender, employment, housing status, etc. In conducting a large scale, quantitative survey, well-established categories provide a pragmatic approach. However, we should be aware of the subtle, nuanced distinctions they may obscure.

Third, at the time of writing, these data are roughly two years old. Thus, they may not account for the impacts of such developments as Facebook Live [77] or the US Federal Bureau of Investigation (FBI)'s request that Apple unlock the phone of a suspected terrorist [50,60,76]. However, the data would still reflect ongoing discussions, such as the Black Lives Matter movement [78] or government surveillance programs illuminated by Edward Snowden [29].

Finally, the data analyzed here only pertain to Facebook. Prior work has shown that social media use varies among different demographics [20,30,35]. Future work should examine how the factors influencing the types of non/use identified here play out with different social media sites.

CONCLUSION

This paper provides three unique contributions. First, it moves beyond a dichotomous distinction between use and non-use to consider other types of relationships with social media. Second, the results show how this finer-grained approach reveals socioeconomic inequalities not identified in previous work. Third, it provides specific details about the types of populations we are, and are not, studying when we analyze data from social media.

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