All Users are (Not) Created Equal: Predictors Vary for Different Forms of Facebook Non/use

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Relatively little work has empirically examined use and non-use of social technologies as more than a dichotomous binary, despite increasing calls to do so. This paper compares three different forms of non/use that might otherwise fall under the single umbrella of Facebook "user": (1) those who have a *current* active account; (2) those who have *deactivated* their account; and (3) those who have *considered* deactivating but not actually done so. A subset of respondents (N=256) from a larger, demographically representative sample of internet users completed measures for usage and perceptions of Facebook, Facebook addiction, privacy experiences and behaviors, and demographics. Multinomial logistic regression modeling shows four specific variables as most predictive of a respondent's type: negative effects from "addictive" use, subjective intensity of Facebook usage, number of Facebook friends, and familiarity with or use of Facebook's privacy settings. These findings both fill gaps left by, and help resolve conflicting expectations from, prior work. Furthermore, they demonstrate how valuable insights can be gained by disaggregating "users" based on different forms of engagement with a given technology.

CCS Concepts: • **Human-centered computing**;

Additional Key Words and Phrases: Facebook, non-use, social media, technology refusal, addiction, privacy, demographics

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1 INTRODUCTION

Every day, over 1.5 billion unique users log in to Facebook [29]. In the US, 71% of online adults use Facebook; among those age 18-29, 87% use Facebook [25]. If each daily active account represents one person, then Facebook users comprise over 20% of the people on the planet.

But should *all* these people should be equally called "users" of Facebook? While almost half of US users report visiting the site several times per day, around 10% log in less than once per week [25, 39]. Rainie et al. [81:2] found that "61% of current Facebook users [...] have voluntarily taken a

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break," while "27% of Facebook users say they plan to spend less time on the site in the coming year."

Indeed, much research has highlighted the need to attend to different forms of engagement with computing systems [13]. Examples include intermediated use [13, 84], throw-away accounts [62], disenfranchisement [85, 94, 95], rejection [77, 93], being used by a technology [9], oscillating among different forms of engagement and disengagement [11, 15, 49], and others.

Prior work on social media, especially Facebook, has examined differences between users and non-users [3, 45, 60, 82, 88, 89]. Results have shown that such factors as demographics (e.g., age, gender, race, and parents' level of education) [3, 6, 45], privacy concerns [3, 11, 88], levels of addiction [88], and perceptions about using social networking sites [89] each have varying impacts on whether or not an individual uses social media.

However, less work has moved beyond such a binary distinction. While different forms of non-use have been examined [e.g., 20, 85, 86, 93], only a few studies have examined predictors for different forms of social media *use* [10, 60]. That is, what happens when the monolithic "user" is disaggregated into different forms of non/use[1]? As noted elsewhere, "there is not one prototypical kind of Facebook quitter" [88:623], and "comparing non-users of the site to users as a single block may miss some subtleties" [60:810].

This paper helps to fill that gap. It analyzes data from two different samples, a demographically representative sample of 515 US internet users, and a convenience sample of 1,000 internet users. Incorporating the above arguments, it assess the impact of various predictors on three different types of non/use that might typically fall under the single umbrella of Facebook users:

- *Active* - An individual who currently has and uses a Facebook account.
- *Considered Deactivation* - An individual who currently has a Facebook account and has considered deactivating but has not actually done so [11].
- *Deactivated* - An individual who has temporarily deactivated her or his Facebook account but can technically return to the site at any time [15, 86].

Numerous other forms of non/use exist, from asking a friend to change one's password [11], to computational tools that limit one's access [77], to a slow "fading away" due to loss of interest [20]. In the interest of simplicity, this paper focuses on actual or considered use of one technical mechanism that Facebook provides: account deactivation. Doing so enables this paper, as the title suggests, to focus squarely on various types of Facebook *users*, that is, those who currently have an account.

Facebook provides a valuable context in which to perform this disaggregation among types of users, for at least three reasons. First, several social media platforms, including Twitter[2], Instagram[3], and Pinterest[4], offer various forms of account deactivation as an intermediate step between usage and deletion. Thus, findings from this work may apply to such other platforms. Second, Facebook account deactivation is a somewhat common form of non-use. Prior work has found between 17.8% [10] and 26.8% [11] of respondents had deactivated their account. In these studies, another 22.7% [10] and 21.2% [11] reported considering deactivating their account. Not only is deactivation more common than deletion [11], but deactivation is more interesting, in that it signals a dissatisfaction with the platform but a hesitance to leave entirely. Furthermore, the group who considered deactivation allows for examining differences between current Facebook users and what might be termed

[1]The notation "non/use" serves as a shorthand for "use and non-use" or for "use or non-use." This notation differs from "non-use," which, though prevalent, has been noted as potentially problematic due to its oppositional nature [12, 14, 85].
[2]https://help.twitter.com/en/managing-your-account/how-to-deactivate-twitter-account
[3]https://help.instagram.com/728869160569983
[4]https://help.pinterest.com/en/article/deactivate-or-close-your-account

"reluctant" users [11]. Finally, understanding who takes advantage, or considers taking advantage, of in-built mechanisms for limiting one's social media use can provide implications for designers who develop and implement the details of such mechanisms.

The analysis considers how each of the above categories is predicted by different factors, selected based on prior related work, including Facebook intensity (FBI) [27], Facebook addiction [5], privacy-related behaviors and experiences [91], and demographics [10].

The results show that higher Facebook intensity [27] predicts decreased probability of deactivation. Also, increases in a respondent's number of Facebook friends or their responses to questions about Facebook use prompting conflicts in other areas of their lives [5] predict increased probability of deactivation. Finally, greater familiarity with and use of Facebook's privacy settings [19] predicted increased probability of actually deactivating but decreased probability of only considering deactivation. The discussion also briefly describe alternative possible analyses, including

These findings confirm the existence of significant differences among individuals who would typically be categorized as social media "users." Thus, these results contribute to the growing body of work on Facebook non/use. They also provide insights that may generalize to other social media platforms that provide an account deactivation mechanism. Finally, this analysis provides broader implications about the importance of considering different possible categorizations with respect to how an individual or group might use or not use a technology.

2 RELATED WORK AND RESEARCH QUESTIONS

Significant prior work has emphasized the importance of studying who do *not* communicate using computational technologies, such as social media [14, 85, 93]. Understanding how and why particular communication technologies are refused [78] or avoided [77] can provide a more nuanced understanding of both the perceived benefits and the potential drawbacks of such technology [e.g., 45, 82, 88, 89]. This paper draws on that work to help analytically disaggregate the traditional category of social media "user."

Such prior work has illuminated a variety of different forms and styles of technology non-use. Non-use may or may not be a willful choice [85, 93–95], a political identity statement [78], an instrumental attempt to retain privacy [11, 81, 88], an intentionally short-term break [15, 86], or perhaps even a desirable but unavailable option [11]. This variety suggests, among other things, that a given factor documented in prior literature may have differing predictions for different forms of non/use.

This study examines four categories of factors that have been identified as informative in prior work making a binary distinction between users and non-users. This paper then tests whether and how each type of factor differently predicts three different forms of what might otherwise be called Facebook use.

2.1 Perceptions and Use of Facebook

Prior work has found a variety of motivations for using, perceptions of, and relationships with Facebook [27, 52, 58, 59, 67, 92]. Such differences may also impact non-use. Tufekci [89] finds that people who are more disparaging of social grooming (small-talk, gossip, non-functional social interaction, etc.) are less likely to use social networking sites. Portwood-Stacer [78] argues that Facebook abstainers reject the practice of identity construction through conspicuous consumption. Baumer et al. [11] and Rainie et al. [81] both provide lists of reasons for Facebook non-use, some of which deal with perceptions about, and use of, the site (e.g., its banality, its impacts on productivity).

One means of assessing an individual's perceptions and use of Facebook comes from the Facebook Intensity (FBI) [27] scale. This scale combines aspects such as frequency and duration of use, number of friends, and perceived importance of the site (see Methods for details). Few studies, however, have examined how FBI may relate to non/use, providing limited expectations about the exact nature of these relationships. On one hand, people with with greater Facebook intensity might be more likely to consider or actually take advantage of deactivation, in an attempt to curtail their (over)usage. On the other, people with higher Facebook intensity may feel that the site is more important to them and thus may be less likely to leave or even to consider doing so.

RQ1 How does intensity of Facebook usage (FBI) (Ellison et al., 2007) influence the likelihood of different types of Facebook non/use?

2.2 Addiction

Prior work has also suggested relationships between feelings of addiction to social media and non-use of social media. Stieger et al. [88:631] found that those who left Facebook "had higher Internet addiction scores [...] than Facebook users," though with a small effect size. Roughly one tenth of respondents from another study described experiences related to addiction [11]. In a recent study, people who left Facebook and reported experiences consistent with addiction, such as withdrawal or compulsive behavior, were more likely to return [15].

That said, the very notion of technology addiction is a contested concept [5, 22, 40, 41, 51, 96]. Some argue that problematic Facebook usage resembles many aspects of other behavioral addictions [37, 38], such as problem gambling. Others, though, suggest significant differences, such as an absence of the physical and medical withdrawal symptoms seen in chemical dependence [22, 40]. Furthermore, questions arise about to what people are addicted. Facebook has numerous functions – instant messaging, games, viewing photos, etc. – and it is not clear whether an individual should be seen as addicted to the site as a whole or to certain aspects thereof. Furthermore, prior work on addiction and non-use used a scale that was not rigorously psychometrically validated [88].

To mitigate potential issues, the present study uses a previously validated measure of Facebook addiction, the Bergen Facebook Addiction Scale (BFAS) [5], described further below. The discussion further considers, based on the results, the extent to which the notion of "addiction" applies in this context.

One might expect addiction scores to predict increased rates of deactivation, as addicts attempt to curb or to break their habit. However, standard addiction measures also ask questions about desires to, or unsuccessful attempts to, reduce usage [5, 38, 51]. Thus, addiction scores may predict lower rates of deactivation but greater consideration of doing so.

RQ2 How do standard measures of addiction (BFAS) [5] influence the likelihood of different types of Facebook non/use?

2.3 Privacy

Significant amounts of prior work have pointed to the relationships between Facebook non/use and privacy concerns. Among a sample of US college students, Tufekci [89] found increased privacy concerns were linked with decreased likelihood of using social networking sites. Archambault and Grudin [6] found that, from 2008 to 2011, increasing numbers of Microsoft employees made "many" changes (as opposed to "a few" or "none") to social network sites' access control settings. Both Rainie et al. [81] and Baumer et al. [11] identified privacy as a significant motivation for non-use of Facebook. In an earlier study, Acquisti and Gross [3] found that privacy concerns decreased the likelihood of Facebook membership, except among undergraduate students, for whom privacy concerns had no effect on non-use.

However, the single term "privacy" belies significant underlying complexity [2, 87]. Boundary negotiation [76], social surveillance [68], corporate data mining [11], conspicuous non/consumption [78], regretful experiences [42, 91], and other practices all relate to the higher-level concept of privacy. Furthermore, the social desirability of caring about one's own privacy can lead to an apparent "privacy paradox" between stated attitudes and observed behaviors [8, 72].

Thus, rather than asking directly about "privacy" concerns, examining specific behaviors and experiences [79, 91] can prove more informative. One might expect that, e.g., changing one's Facebook's privacy settings [19] would help a user feel more in control and more comfortable using Facebook, and thus less likely to deactive their account. However, it could also indicate an overall greater concern with privacy, which prior work has linked with non-use.

RQ3 How do privacy-related behaviors and experiences (PBE) [68, 76, 91] influence different types of Facebook non/use?

2.4 Demographics

Several studies have found that older individuals are less likely to use Facebook [3, 6, 45, 60, 88]. Others have found that race [45], gender [45, 89], parents' education [45], personality traits [82, 88], and frequency of Internet use [45, 60] also significantly influence non/use. Such work rarely disaggregates among various possible forms of non/use, with two exceptions.

First, demographic factors were used to distinguish between occasional and frequent SNS use, and between use of one SNS and use of multiple SNSs [47]. This valuable analysis shows that, for instance, "women are only more likely to be Omnivores [heavy users of multiple social media platforms] than are men," but other gender differences are not significant [47:156]. However, gender does not significantly predict omnivores vs. samplers (those who use multiple SNSs occasionally). The survey instrument from that study distinguished among different types of non-users, such as those who have never used Facebook and those who used it in the past but no longer do. However, the analysis treated each of these non-users for a given site as a single group, limiting the ability to see differences in the impact of various factors on different types of non-use. Second, In more recent work, men were about two and a half times more likely than women to have never had a Facebook account [10]. That analysis also found that attributes such as marital status and recently seeking employment were related, respectively, with decreased or increased probability of Facebook account deactivation [10]. That analysis, however, only considered demographic and socioeconomic factors alone, without comparing their explanatory power against that of the other predictors examined here.

RQ4 How do demographics, such as age, gender, or socioeconomic status [10, 45, 47], influence the likelihood of different types of Facebook non/use?

2.5 Expectations

Collectively, this prior work provides some expectations for how various factors might predict different types of Facebook non/use, as summarized in Table 1. These are not presented as hypotheses, especially since in several cases different previous studies provide either conflicting expectations (indicated by ± in Table 1) or no expectations (indicated by ? in Table 1). In the interest of concision, Table 1 only includes continuous demographic variables, i.e., age and socioeconomic status (SES).

In drawing these expectations, though, we must consider that most prior work did not differentiate among various types of non/use. Acquisti and Gross [3] mention "former members" of Facebook, but only 7 respondents (2.4% of their sample) belonged to this category. Similarly, the sample from Hargittai [45] included 74 respondents (8.0%) who had previously used Facebook, but the analysis combines these non-users with the larger set of respondents who had never used FB (151 respondents, 14.2% of the sample). Lampe et al. [60:816] differentiate among heavy users, light users, and non-users. However, as those authors note, they "were unable to distinguish [respondents]

Factor	Active	Considered	Deactivated	Prior Work
Facebook Intensity (FBI) [27]	+	?	±	[11, 82, 89]
Facebook Addiction (BFAS) [5]	?	+	±	[11, 88]
Privacy Behaviors & Experiences (PBE) [68, 76, 91]	-	?	±	[11, 81, 88, 89]
Age	-	-	-	[3, 6, 10]
Socioeconomic Status (SES)	+	?	?	[10, 45, 47]

Table 1. Expectations for how each predictor (left column) will influence the likelihood of each type of non/use (top row), based on prior work (right column). For each pair of one predictor and one non/use type (i.e., each cell), + indicates increased probability, - indicates decreased probability, ± indicates mixed expectations, and ? indicates no expectation from prior work.

who used the site and then stopped from those who never tried the site." Thus, prior work both provides important guidance and indicates unexplored areas.

3 METHODS

3.1 Instrument Design

The survey included three groups of questions. First, a series of questions determined the type of non/user for each respondent. Second, existing scales were used to measure the four constructs described above (perceptions and use of Facebook, addiction, privacy behaviors and experiences, and demographics) that may influence types of non/use. Third, the survey included several open-ended questions not analyzed here. The full survey protocol, along with a complete, anonymized data set, are available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/8GRBRZ.

3.1.1 Types of Non/use. To assess each respondent's type of non/use, we used four nested yes/no questions, as depicted in Figure 1. Per this paper's focus on different types of "users," the analysis considers only those respondents who currently have a Facebook account. Doing so leaves the three non/use types analyzed here.

Two important caveats should be noted about this typology. First, it is not ordinal. We do not suggest that, e.g., respondents who Deactivated their account engaged in a more intense form of non-use than those who Considered deactivating. While conceivable, our analysis instead treats these as three unordered categories. Second, this typology is not exhaustive. For instance, it does not include the notion of "taking a break" (Rainie et al., 2013) from Facebook without technically deactivating or deleting one's account. Similarly, it treats differences in intensity of Facebook usage [27] not as different types of non/use, but as a predictor for the types enumerated here. As noted above, rather than trying to be exhaustive, this typology instead focuses on one technical mechanism that Facebook provides to manage non/use, i.e., account deactivation.

3.1.2 Facebook Intensity Scale (FBI). This simple, well known, and widely used scale assess the overall "intensity" of Facebook use [27]. It includes "two self-reported assessments of Facebook behavior," total number of friends and total time spent on Facebook, as well as "a series of [six] Likert-type attitudinal questions designed to gauge the extent to which the participant was emotionally connected to Facebook and the extent to which Facebook was integrated into her daily activities" [27:1150]. Examples include "Facebook is part of my everyday activity," and "I feel out of touch when

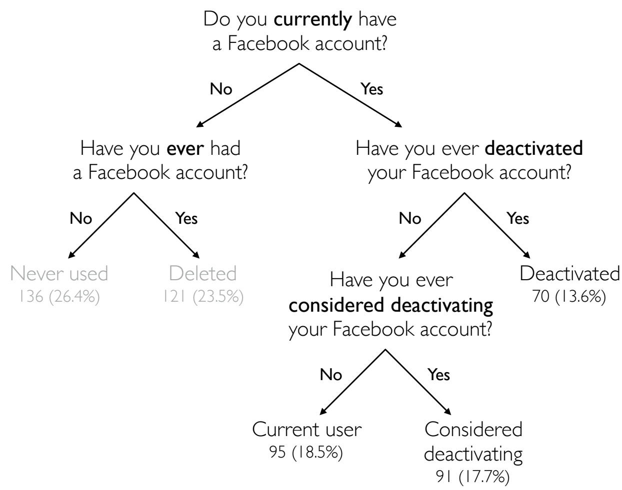

Fig. 1. Decision tree assigning the type of non/use for each respondent, including number of respondents for each type with percentages in parentheses. Respondents who do not currently have a Facebook account are greyed-out, since the analysis here focuses only on those respondents who could conceivably be called "users" since they currently have an account.

I haven't logged onto Facebook for a while." The scale has high internal consistency (Cronbach's $\alpha = 0.83$) with an apparent single factor structure. See [27] for full details.

3.1.3 Bergen Facebook Addiction Scale (BFAS). Clinically, addiction involves six main components: salience, tolerance, mood modification, withdrawal, conflict, and relapse. Andreassen et al. [5] composed an 18 item scale with three questions for each component. The wording of questions resembles that of a validated measure for gambling and gaming addiction [63].

Other measures of Facebook addiction similarly adapt the wording of existing scales for, e.g., alcohol dependence [51]. As described above, though, if Facebook usage can be considered as an addiction, it more closely resembles behavioral addictions [22, 37, 38, 40]. Thus, this paper uses a measure based on behavioral, rather than substance, addiction.

All questions on the BFAS ask how often in the last year the respondent had certain experiences, with each question related to one aspect of addiction. Examples include: "Felt bad if you, for different reasons, could not log on to Facebook for some time?" (withdrawal), "Used Facebook so much that it has had a negative impact on your job/studies" (conflict), and "Tried to cut down on the use of Facebook without success?" (relapse).

Andreassen et al. [5] validated their scale on a sample of 423 college students. Their results show high internal consistency (Cronbach's $\alpha = 0.83$) and high 3-week test-retest correlation (Pearson's $r = 0.82$).

3.1.4 Privacy Behaviors and Experiences (PBE). As argued above, a respondent's stated concerns about "privacy" likely do not provide as much insight as specific behaviors and experiences [2, 8, 72, 87]. Thus, we asked respondents (1) whether they were familiar with Facebook's privacy settings and, if so, (2) whether there had ever changed their privacy settings [19].

Many privacy concerns fall under the umbrella of interpersonal privacy, that is, an individual's privacy from other users of the site [68, 76]. Specifically, we focus on regret, as it offers a specific privacy-related experience about which to ask without using the term "privacy." Wang et al. [91] combined an interview protocol, a diary study, and an online survey to investigate different types of embarrassing, regretful, or privacy concerning situations that Facebook users might encounter. This prior work does not provide a validated measure of experiences around regret, but it does provide meaningful language that we can use to ask respondents about regretful experiences.

Other privacy concerns are more institutional in nature, that is, what Facebook as a corporate entity (or perhaps national governments) do with an individual's information on the site [11, 15, 80]. Kang et al. [53] examined mental models of data surveillance. While those with expertise in computer science tended to have more sophisticated mental models, their privacy-related actions did not significantly differ from lay persons'. Other work has suggested that, given the limited control most individuals perceive over their data, many become apathetic about maintaining their privacy [48]. Again, while prior work does not provide validated measures, it does indicate the kinds of concerns that emerge related to institutional surveillance and privacy.

Synthesizing across this prior work, we assembled two sets of questions. The first set (six questions) asked about the respondent's general experiences pertaining to privacy, e.g., "Have you ever posted something that you later regretted?", "Have you ever had your personal information misused?", or "Have you ever received targeted advertisements that felt very personal?" The second set (five questions) included all but one of the same experiences as the first set, but the question asked whether the respondent knew anyone else who had such experiences.

Put differently, the first and second set of questions ask about the *respondent's* own privacy experiences. The third set asks about their knowledge of *others'* privacy experiences, since knowledge of others' experiences can influence an individual's own privacy behaviors [cf. 79, 87]. Together, these questions help draw out privacy behaviors and experiences related both to interpersonal privacy and to privacy from large institutions.

3.1.5 Demographics. The survey also asked for several demographic details, many of which were identified as important in prior work. These included age [3, 6], gender [45, 89], race and ethnicity (using standard census categories) [45], marital status, and political views. Socioeconomic status was operationalized as household income (in $10,000 increments) and education level (7-point Likert from "Less than 8th grade" to "Graduate degree").

3.2 Participants

To acquire a representative sample of US Internet users, we contracted with a survey and sampling agency, Qualtrics, whose recruitment and sampling procedure is outlined on their website (https://www.qualtrics.com/online-sample/).

Qualtrics' staff assembled a web panel of participants using demographic criteria derived in part from Pew's omnibus Internet survey (http://www.pewinternet.org/datasets/january-2014-25th-anniversary-of-the-web-omnibus/). Qualtrics generally incentivizes participation by providing gift cards to survey respondents. Respondents were screened at the beginning of the survey using gender, race/ethnicity, age, and income. For example, once we received 89 respondents age 25-34 (i.e., 17.8% of our target sample size of 500 respondents), subsequent respondents in the age 25-34 did not pass the age criterion. Respondents who did not pass any of the demographic screening criteria were excluded.

Ultimately, we collected a web panel of 515 participants, for which we paid $2,750. Of them, N=256 currently had a Facebook account. Age and household income, as continuous variables, are described in the appendix (Table 6) with the standard five-point summary. The remaining categorical demographics are cross tabulated by gender in the appendix (Table 7).

This Qualtrics panel provides a useful, demographically representative sample. However, it still allows for the possibility of over fitting to this data set. Thus, we also collected a convenience sample of 1000 Amazon Mechanical Turk (MTurk) workers. Workers were paid $1.50, with most completing the survey in 10 to 15 minutes for an effective pay rate of $6/hr to $9/hr. This convenience sample served as a validation data set, as described below.

For both Qualtrics and MTurk, the survey included an attention check roughly three quarters of the way through. The BFAS asks participants, "How often during the last year have you..." had certain experiences about Facebook. One of the questions ended the sentence, "been to visit the planet Mars?" Since humans have not yet visited Mars, any respondents who answered anything other than Very Rarely were screened out.

All data were collected during early summer of 2015. All data were anonymous, and no personally-identifying information was collected about any respondent; Qualtrics provides no such information about its panelists, and MTurk worker IDs were dissociated from survey data after compensation. Informed consent was obtained before any data were collected, and all study procedures were approved by Cornell University's and by Lehigh University's Institutional Review Boards.

3.3 Extraction of Possible Features

To identify predictors for each type of non/use, we created several individual features that each captured many conceptually related survey items. Six features were derived from the PBE items discussed above: three binary features for the items regarding regretful experiences, one ordinal feature for the number of privacy-related experiences of the user, one ordinal feature for the number of privacy-related experienced that they witnessed others having, and one ordinal feature for familiarity and use of Facebook's privacy settings (0 - no familiarity, 1 - familiar, but did not change, 2 - familiar and changed).

Exploratory factor analysis using all respondents (N = 515, which includes those who do not currently have an account) was used to extract features from the FBI [27] and BFAS [5] scales. In FBI, questions about a respondent's number of friends and time spent on Facebook were "designed to measure the extent to which the participant was actively engaged in Facebook activities" [27:1150]. In contrast, the Likert question were "designed to tap the extent to which the participant was emotionally connected to Facebook and the extent to which Facebook was integrated into her daily activities" [27:1150]. Thus, only the six Likert questions were subject to factor analysis. The factor analysis shows that FBI (Table 2) was best represented by a single factor for Facebook Intensity, which explained 83% of the variance.

For BFAS, a three factor model (Table 3) was selected that explained 73% of the variance. The first factor includes all the items associated with Salience, Tolerance, and Mood Modification, and one item from Relapse. The second factor includes the Conflict items, and one Relapse item, and the third factor is identical to the Withdrawal factor in [5]. Item 11, "Tried to cut down on the use of Facebook without success," did not load significantly on any factor.

These features, plus seven demographic items, brought the total number of predictors in our full model to seventeen. The next step was to use model selection to reduce the number of predictors to only those relevant for classifying the three types of Facebook users described above.

3.4 Model Selection

As described above, the three types of non/use analyzed here were treated as possible values of a single categorical, rather than ordinal, variable. While other approaches were considered, a

Question	Loading
I feel out of touch when I haven't logged onto FB for a while	0.94
I feel I am part of the FB community	0.88
I would be sorry if FB shut down	0.96
FB is part of my everyday activity	0.88
FB has become part of my daily routine	0.92
I am proud to tell people I am or was on FB	0.90

Table 2. FBI: Factor analysis

Question	STM	Conflict & Failure to Quit	Withdrawal
Thought about FB use	0.82		
More free time for FB	0.77		
Thought about events on FB	0.81		
Spent more time than intended	0.81		
Urge to use more	0.84		
More use to get pleasure	0.78		
Forget about personal problems	0.68		
Reduce negative feelings	0.68		
Reduce restlessness	0.76		
Ignored others who suggest reducing use	0.60		
Decided to use less frequently, but failed		0.51	
Negative impact on work/life		0.75	
Given less priority to other activities		0.77	
Ignored others because of use		0.76	
Became restless if prohibited			0.72
Become irritable if prohibited			0.83
Felt bad if prohibited			0.55
Tried to cut down use, but failed			

Table 3. BFAS: Factor analysis. "STM" is an abbreviation for "Salience, Tolerance, and Mood," the factors described in [5]

multinomial logistic model was chosen as providing the best combination of interpretability and generalizability.

The primary, demographically representative sample from Qualtrics was first used to select which features should be included in the model to predict a respondent's non/use type. This dataset contained 256 respondents with roughly balanced proportions across the three non/use type: Active - 95 (37.1%), Considered - 91 (35.5%), and Deactivated - 70 (27.3%). The decision to include or exclude a given predictor was based primarily on relative Akaike Information Criterion (AIC) [4]. Significance values and other goodness of fit statistics (e.g., Likelihood ratio test) were also used as secondary checks. A backwards, stepwise regression procedure was used which began with all seventeen predictors and iteratively excluded features whose removal caused the greatest reduction in AIC. The procedure was halted when further exclusion of predictors would not cause a significant reduction in AIC. Four predictors were retained for the reduced model: BFAS Conflict (the second factor in Table 3), FB Intensity (the single factor in Table 2), FB Friends (self-reported number of Facebook friends on an ordinal Likert scale), and Facebook Privacy Settings (familiarity with and/or use of Facebook privacy settings). Facebook privacy and FB Friends were significant at $p < 0.05$, and BFAS Conflict and FB Intensity at $p < 0.01$.

		Observed			
		Active	Cons. Deact.	Deactivated	Total
Predicted	Active	*61*	34	15	110
	Cons. Deact.	25	*33*	23	81
	Deactivated	9	24	*32*	65
	Total	(37.1%) 95	(35.5%) 91	(27.3%) 70	256

Table 4. Confusion matrix from primary Qualtrics sample for final fitted model after cross validation. Numbers on the diagonal (in *italics*) show the number of respondents whose type of use was correctly predicted by the model. Accuracy is 49.2%, which is higher than the no information rate of 37.6% (p = 0.003).

Next, five-fold cross validation was used to estimate the coefficients, as well as to generate confusion matrices and fit statistics on the held-out test sets. The coefficients were averaged across the five folds to arrive at a final model. Across the five folds, coefficient estimates differed by less than 0.5%, indicating a stable model.

Finally, we validated the final model against a separate convenience sample of Amazon Mechanical Turk (MTurk) workers, which the trained model had never seen before. Doing so helped avoid over fitting and ensured that the predictions from this final model still held for other datasets.

4 RESULTS

This section summarizes results from the model selection process described above. The following Discussion section provides an interpretation of these results, as well as compares them with related prior literature.

4.1 Model Fit

Overall, the results show an acceptable level of model fit. Table 4 shows the confusion matrix from the cross-fold validation, which sums across the five held-out test sets. This table indicates the relationship between the model's prediction and the observed category of use for each respondent. The model achieves a test accuracy of 49.2%, which is significantly ($p = 0.003$) above the no information rate of 37.6%. These metrics align relatively well with diagnostic metrics in similar work involving social media [17, 83], thus providing a sufficient degree of confidence about our methodological approach.

Accuracy on the validation dataset from MTurk was comparable at 54.8%. However, this validation accuracy was not statistically significantly better than the no information rate of 58.4%. This result arises in part because the MTurk dataset has a significant class imbalance, with 405 (58.4%) Active users, 120 (17.3%) who Considered deactivation, and 168 (24.2%) who actually Deactivated. Contrasting these proportions with the more balanced proportions from the Qualtrics dataset (in the bottom row of Table 4) shows why the no information rate is higher for the MTurk validation dataset: it includes a much greater proportion of Active users.

Furthermore, the final resulting model was trained on a more demographically representative dataset. The MTurk data skewed significantly younger (mean age 24 vs 32 for the Qualtrics dataset) and more highly educated (59% with at least a bachelor's, vs 44%). It also had a much higher proportion of Asian respondents (25% vs 5%) and lower proportions of black and Hispanic respondents (5% vs 14% and 4% vs 21%, respectively). Because it is more demographically representative, the remainder of this paper only discusses results obtained from the Qualtrics dataset.

	BFAS Conflict	FB Intensity	FB Friends	FB Privacy Settings
Cons. Deact.	1.12 **	0.85 **	1.16 *	0.86 *
Deactivated	1.28 **	0.77 **	1.21 *	1.49 *

Table 5. Odds ratios for the final model. Values indicate how a one-unit change in each predictor increases or decreases the probability of a respondent having Considered Deactivation or having Deactivated vs. having a currently Active account. * is $p < 0.05$, ** is $p < 0.01$.

4.2 Model Summary and Main Findings

The final multinomial logistic regression model indicates how each predictor impacts the relative probability of a respondent belonging to each class of non/use. This is typically reported through the use of odds ratios, which represent how a one-unit increase in each predictor affects the relative probability of being in one class versus a reference class. In this case, the reference class is Active users, so odds ratios represent the relative probability of being in the Considered Deactivating and Deactivated classes. Table 5 shows the odds ratios averaged across five folds. For each unit increase in BFAS Conflict, likelihood of being in class Cons. Deact or Deactivated increase relative to to Active by 12% and 28% (both $p < 0.01$), respectively. Number of Facebook friends shows a similar trend: relative increases of 16% and 21% for Cons. Deact and Deactivated. Facebook Intensity, on the other hand, has the opposite association: a *reduction* in likelihood relative to Active for both Cons Deact (15%) and Deactivated (23%) for each unit increase in FB Friends. Finally, a one-unit increase in FB Privacy (which represents familiarity with and use of Facebook's privacy settings) results in a 14% reduction in likeilhood of being in class Cons. Deact versus Active, but a 49% *increase* for Deactivated.

At times, it can be difficult to interpret and visualize odds ratios. So, inspired by prior computational work [32, 33], we also include effects plots, which use marginal probabilities rather than relative odds. Figure 2 illustrates the simultaneous effects of each predictor on the probability of a respondent being in each of the three classes of non/use. As suggested by the odds ratios, increases in BFAS Conflict and FB Friends are associated with decreased probability of being in the Active class, and increased probability of being in the Considered Deactivation and Deactivated classes. In other words, people who have experienced conflict (such as distraction from work/life activities, or interpersonal trouble) as a result of their Facebook use are more likely to Deactivate their accounts or to Consider deactivating. Respondents who report having a higher number of friends on Facebook are also more likely to have Considered or actually to have Deactivate their accounts.

The effects plots also show that respondents who report higher Facebook intensity are more likely to be Active users, and less likely to Deactivate or Consider deactivating.

Familiarity with and use of Facebook privacy settings was the only PBE feature retained in the final model. It is most informative in distinguishing those who have Deactivated from those who have only Considered doing so. This feature has very little effect on the probability of being an Active user, but has significant, and opposite effects on the other two classes. Those who are more familiar with Facebook's privacy settings are more likely to actually Deactivate their accounts and less likely only to Consider doing so.

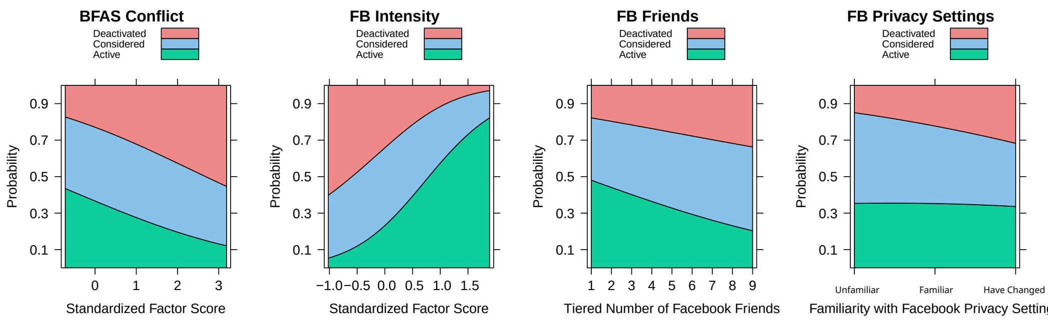

Fig. 2. Effects plots for the final model showing how different values of each predictor influence the marginal probabilities that a given respondent belongs to each class of non/use. The first and second plots display the values for BFAS Conflict and FB Intensity factors after mean centering (so 0 is the mean) and standardization (such that a one unit corresponds to one standard deviation). In the third plot, the x-axis represents the range of number of friends. 1 is '10 or less', 2 is '11-50,' 3 through 7 represent fifty-friend buckets, and 8 is '400 or more.' The fourth plot displays familiarity with and use of Facebook privacy settings.

5 DISCUSSION

This section first considers how the findings contribute to the growing understandings about various forms of non/use. It then offers implications from this work for more general studies of social technology.

5.1 Interpretation of Findings and Comparison with Prior Work

As noted above, a main goal of this paper is to identify differences among individuals who might otherwise all be referred to as Facebook "users." The differences in predictors in the above results advance our understanding of how users leverage, or consider leveraging, the in-built mechanisms provided by such platforms to limit their use. This subsection considers each of the predictors in the above model in light of prior work, showing how the results advance our understanding not only of Facebook non/use but of social technology more broadly.

5.1.1 Privacy Behaviors Show Varying Effects. Most predictors included in the final model have a similar impact on actual Deactivation and on Consideration thereof. However, our privacy measure had opposite impacts. That is, respondents who reported being familiar with or changing their Facebook privacy settings were less likely to have Considered deactivating their account, but they were more likely to have actually Deactivated (see Table 5).

Interestingly, none of the questions about privacy-related *experiences*, such as regretful experiences [42, 91] or perceived misuse of personal information, were selected for inclusion in the model. Prior work has found that privacy-related experiences, both one's own and others', may influence mental models of privacy and security threats [79]. However, this analysis does not provide evidence to suggest that such experiences predict Considering or actually Deactivating one's Facebook account. Future work would need to examine whether any such relationship occurs with other platforms that provide the option to deactivate one's account.

Intuitively, one might expect that people who change their privacy settings would be more comfortable with using Facebook, since they have exercised greater control over their privacy. Instead, these results suggest that such individuals may be more sensitive to privacy issues. It is also possible that such respondents are more attuned to the frequent changes in Facebook's privacy policy and default settings [70, 73].

However, causality cannot be claimed here. It is possible that respondents try to change their privacy settings, find that unsatisfying, then deactivate. On the other hand, it is possible that respondents previously deactivated their account, then came back but changed their privacy settings. As yet another possibility, both privacy behaviors and deactivation may arise from a shared underlying, but unobserved, predictor (e.g., managing social tensions [cf. 11]). Finally, the option to deactivate one's Facebook account has, at times, been located alongside Facebook privacy settings. Thus, respondents may be interpreting account deactivation as a type of privacy setting. Due to this study's approach of sampling at a single point in time, rather than longitudinally, these data do not provide such fine grained details. However, they do show how the same predictor – awareness and changing of Facebook privacy settings – has an opposite effect on the probability of a respondent Considering vs. actually Deactivating. Thus, our privacy measure arguably provides the most support for this paper's central claim, that so-called "users" differ from each other in informative ways.

5.1.2 Conflict as the Key Element of Addiction. As described above, prior work suggests potential relationships between experiences commonly associated with addiction and forms of Facebook non/use [5, 11, 40, 41, 51, 88]. The analysis here suggests that the Conflict dimension of addiction is most predictive of deactivation. That is, those respondents who experienced negative impacts on their work, their personal relationships, or other aspects of their lives due to voluminous time and attention spent on Facebook were more 11.7% more likely to consider deactivating their account and 28.1% more likely actually to do so (see Table 5).

Interestingly, this aspect of behavioral addiction has not been highlighted previously. Other work has found, e.g., that habitual Facebook usage is associated with relapse [15], and that colloquial "addiction" is often cited as a reason that individuals leave the site [11, 81]. Other work has also examined how individuals at times engage in selective non/use across either individual or multiple platforms [23, 43]. However, such work suggests negotiation of identity presentation, rather than negative consequences from excessive use, as a main driver. Thus, this finding represents an important contribution in terms of deepening our understanding about which aspects of behavioral addiction are most closely linked with account deactivation.

That said, two important caveats must be made. First, this result is based a factor structure that differs from the original BFAS [5]. That scale was developed and validated on a sample of college students, and the factors thus identified may not hold for a more diverse or representative population. Similarly, despite the demographically representative sample analyzed here, the conflict-oriented factor identified in this analysis (which includes deciding to use Facebook less frequently but failing to do so) may not hold for all populations.

Second, this analysis does not enable testing the direction of causality. That is, it may be that the negative consequences of excessive Facebook usage drive users to deactivate their account or at least consider doing so. Alternatively, it may be that deactivation, actual or considered, draws users' attention to these negative consequences. As another option, both these effects may stem from another, unmeasured underlying cause. Regardless of interpretation, this result shows how disaggregating among different types of Facebook "users" reveals an informative relationship. Further work would be necessary to determine the extent to which the conflict component of addiction predicts account deactivation on other social media platforms.

5.1.3 Varying Impacts of Facebook Intensity. Ellison et al. [27] developed the FBI scale as a general measure of the intensity of an individual's Facebook usage. Thus, it is perhaps unsurprising that higher Facebook intensity predicts increased probability of Active use and decreased probability of Considering or actually Deactivating. Indeed, prior work has suggested a relationship between intensity of social media use and its importance to a respondent [6, 82, 88].

One component of that scale, though, has the opposite effect. A respondent's number of Facebook friends is meant to capture one aspect of their Facebook usage intensity [27]. However, the results show that increasing numbers of friends has the opposite effect as self-report questions about the importance of Facebook. That is, the more Facebook friends a respondent has, the less likely they are to be an Active user and the more likely they are to have Deactivated or to have Considered doing so.

This difference might be explained by the wording of the FBI questions. These items emphasize a combination of regular, routine use (e.g., Facebook as "part of my everyday activity") and emotional salience (e.g., "I feel out of touch when I haven't logged onto Facebook for a while"). These subjective experiences may be orthogonal to a user's number of friends.

This finding is particularly surprising given the importance of having numerous but weak social ties, both generally [36] and specifically in social media [21, 26, 35]. A higher number of Facebook friends may be associated with greater overall social capital [27], perhaps reducing the need to rely exclusively on Facebook as a social medium. Alternatively, perhaps those with increasing numbers of friends also experience increasing difficulties with boundary negotiation [76] due in part to context collapse [64, 69]. As above, the analysis here does not allow us to establish causal linkages among these patterns. However, it does demonstrate how self-reported subjective intensity and objective usage measures (such as number of friends) can predict opposite trends in terms of non/use behaviors. Furthermore, such differences between self-reported perceptions and logs of usage data could easily arise with almost any social media platform.

5.1.4 Lack of Demographic Predictors. Prior studies have also consistently found demographics, especially age, to be effective predictors of Facebook non/use [3, 6, 10, 45, 47]. However, no demographic variables were included in the final model. At least two possible explanations could account for this finding.

First, this sample may lack representativeness. As described above, the sample was collected to match the demographic make-up of general internet users according to gender, race/ethnicity, age, and income. That said, the sample may still lack evidence of relationships between these predictors and forms of Facebook non/use that could occur in a broader population.

Second, the predictive power of demographics might not hold when attempting to disaggregate among different types of Facebook "users." Most prior analyses of demographic differences offer a binary comparison between users and non-users. In one exception, Baumer [10] found that age was a significant predictor of deactivation, but that result was not replicated in the present analysis. Thus, future work should likely examine more closely potential demographic predictors among different forms of non/use.

5.2 Broader Implications for Studying Non/use of Social Technologies

Although based on analysis of data pertaining to Facebook, this work has two broader implications more generally for the study of social technologies.

5.2.1 Defining Categorizations and Classifications. To reiterate, our data included five classes of non/use (see Figure 1). However, for respondents who had never had a Facebook account, the FBI [27] and BFAS [5] questions would have been nonsensical or meaningless, so those respondents did not answer these questions. Thus, we were left with four classes of respondents who saw all survey questions.

Why, then, should the analysis use Current User, Deactivated, and Considered Deactivating as the three types into which respondents are categorized? Above, we make conceptual arguments, informed by prior work [10, 11], in support of this typology. However, one could just as easily make a data-driven argument.

For comparison, we tried repeating the above analysis but with a two-class model, comparing those respondents who had deleted their account vs. all others who currently had an account. Such a comparison would more closely resemble prior work comparing users against non-users [3, 45, 82, 88, 89]. This binary model achieved high accuracy (78.4% vs. a no information rate of 68.1%). However, the only predictors included in the model were FB Intensity and BFAS Conflict. That is, such a model would reveal neither the effects identified here of a respondent's number of Facebook friends, nor those of their familiarity with or use of Facebook's privacy settings. Put differently, this result demonstrates how disaggregating among types of so-called "users," rather than conducting binary comparisons of users vs. non-users, can illuminate more nuanced outcomes than could otherwise be found.

As noted above, a variety of other social media platforms provide users the ability to deactivate their account, including Twitter, Instagram, and Pinterest. It is possible that some of the findings here may apply to usage of the deactivation mechanisms provided by those sites, as well. Such tests provide a valuable direction for future work. Furthermore, other social media platforms, such as YouTube, LinkedIn, and Snapchat, provide no deactivation mechanism, only the possibility of deleting one's account. These differences provide opportunities to perform comparative analyses of use and non-use across these various platforms.

That said, a variety of different typologies of non/use could be formulated, both for Facebook and for other platforms. We describe further below how future work may benefit from a data-driven approach to categorizing or classifying individuals as different types of non/users.

5.2.2 Using Validated Predictors and Changing Platform Dynamics. A second methodological implication relates with our approach to feature selection and predictor handling (described in Sections 3.3 and 3.4). Potential predictors were selected that were either well validated or frequently cited [5, 19, 27, 91]. However, for FBI [27] and BFAS [5], i.e., our validated scales, dimension reduction through factor analysis yielded factors that were different from those in the literature establishing these scales. As noted above, these differences may arise from a variety of causes, e.g., differences in sample demographics.

This difference, between the factor structure of these scales in our data and their factor structure in the original work from which these scales came, raises two implications. First, validated scales for measuring specific types of constructs should likely be updated, tested, and replicated as the body of knowledge advances in the area. For instance, scales developed and used for distinguishing among heavy, light, and non-users of Facebook [60] might not apply well to other classes of non/use, either on the same technological platform or on a different platform. Second, as noted above, such platforms are highly dynamic – user interfaces, feature availability, and core functionalities change appreciably over time. Thus, well validated scales that have a consistent factor structure on a single sample or even multiple temporal samples may not hold for other samples drawn at a later time period, even if they come from the same underlying population. Thus, future work would benefit from analyzing the factor structure of prior instruments or scales that they use, comparing that structure with the original, and potentially revisiting or updating those scales over time [cf. 44, 46].

Indeed, this point includes not only the factor structure of previously validated scales, but also the results themselves about different forms of non/use. As noted above, platforms such as Facebook are not inert substances that people simply use or not. Instead, these platforms are actively designed to encourage sustained and even increasing engagement [65]. Not only were the functionalities afforded by Facebook different in 2015, when these data were collected, but the site used different mechanisms to promote user engagement. For example, the privacy checkup and its associated "privacy dinosaur" of 2014 [28, 74] take an arguably different approach to assuaging Facebook users' concerns about privacy than the company's response to targeted political advertising in 2016 [1].

Thus, the relationship between privacy settings and account deactivation may likely have been different in 2015 (the time of data collection) than in 2019 (the time of publication). These findings, then, can serve as a point of comparison for subsequent analyses of patterns in different forms of non/use.

6 LIMITATIONS AND FUTURE WORK

6.1 Types of Non/use and Sites of Non/use

As noted throughout, this paper examines Facebook deactivation, as well as consideration thereof. Some other social media platforms (Twitter, Instagram, Pinterest, etc.) offer users the ability to deactivate their account. However, patterns in who makes use of such functionality may differ across different platforms based on, e.g., the purposes for which one uses the platform, the specific technical implementation of how deactivation works, or the purposes and motivations for which people deactivate. Similarly, different predictors may not be entirely comparable. For example, the privacy settings available on Facebook differ from the privacy settings available on other platforms. It will be important for future work to examine,

Furthermore, this paper only compared current use, deactivation, and consideration of deactivation. As noted above, these were chosen because of their prominence identified in prior work [10, 11] and because they are forms of use and non-use that might otherwise fall under the umbrella of "use," since all such respondents currently have a Facebook account. Future work should examine different forms of non/use – intentionally short-term breaks [81, 86], asking a friend to change one's password [11], gradual loss of interest [20, 85], blocking software [77], and others – to determine similarities and differences among predictive factors. It may also be fruitful, rather than choosing categories of use and/or non-use *a prior*, to instead allow a non/use typology to emerge in a bottom-up, data-driven manner. Doing so can help determine not only which particular forms of non/use are most common but also which forms occur across multiple social technologies.

Relatedly, the survey did not ask explicitly about (perceived) volitionality. Most recent work has focused on instances of volitional non-use, where an individual makes a willful choice to forgo use of a communication technology [15, 77, 78, 82, 86, 88, 89]. However, some work has highlighted the importance of analyzing situations where the individual may feel that s/he does not have a choice about her or his own technology use [14, 85, 93–95]. Such non-volitionality may stem from socio-economic disparities [45]; from "disenfranchisement" [85] due to infrastructural, economic, or other limitations [e.g., 95]; from institutional constraints, pressures, or obligations [e.g., 11]; or from other sources. Our results about the relationship between deactivation and the conflict-related aspects of the BFAS [5] align with recent work how an individual's perceived sense of their own agency [30, 31, 71, 75] relates with their technology non/use [16]. Future work should examine more extensively the role of perceived volitionality in non/use, both of Facebook and of other social technologies.

6.2 Data Included and Not Included

The sample analyzed here was both moderately large (515 respondents, with N = 256 for the main analysis) and demographically representative. However, a probabilistic sample using, say, random digit dialing may technically be more representative. That said, the model achieved comparable accuracy in the primary Qualtrics dataset and the MTurk validation dataset. This consistent accuracy boosts our confidence that the results identified here will likely hold for other populations.

That said, there are three major limitations to the survey data that were collected. First, as noted above, these data were collected during early summer of 2015. Noting such collection dates is important for studying social media platforms in general, as they tend to change quite rapidly.

However, that date is particularly significant for Facebook, as it precedes a series of high-attention events around privacy and misinformation that unfolded during 2016, the full extent of which was not known until sometime later [1]. Thus, as noted above, some of the relationships identified in these results, such as between privacy practices and deactivation, may manifest in different ways in 2019 (i.e., the date of publication) and onward than they did in 2015.

Building on the above points about types of non/use, it is also important that future work look beyond the specific technical mechanisms that a platform provides for non/use. Recent work has identified a variety of technology curtailment practices, such as unfriending, self-censorship, self-enforced respites, blocking software, and others [11, 15, 34, 43, 66, 77, 86]. Future work should consider whether the predictors identified here, such as privacy experiences or aspects of (Facebook) addiction [5], may be associated with such forms of non/use given the evolving dynamics of trust in the mechanisms provided by technology platforms themselves.

Second, all data pertained only to the individual. That is, the data do not deal with respondents' interactions or relationships with others, either or Facebook or elsewhere. Prior work has shown that the structure of social connections can predict the formation and dissolution of online groups and social ties [24, 54, 57, 90]. Thus, future work should examine how various forms of non/use are predicted not only by psychometric attributes of a given respondent but also by sociometric attributes of that respondent's social connections, both online and offline.

Second, this survey relied entirely on self-report. Additional insights might be gained by directly collecting Facebook usage data, such as frequency and duration of use, number of friends, patterns of interaction, etc. Recent computational developments open numerous intriguing lines of inquiry using such data [cf. 61]. For instance, one could analyze the entire Facebook social graph [a la 7] combined with a history of account deactivation and techniques that infer individual traits based on social media data [50, 55, 97]. Doing so would enable a study similar to that presented here but encompassing the entirety of Facebook or other similar social media platforms. Such data could also be analyzed for qualitative insights about how and why people deactivate their account. Do they feel more drawn by the social connections that Facebook and similar platforms enable, or are they more driven by the habitual nature of social media usage [15]. While such data could enable more sophisticated modeling approaches that may add greater precision to the results, they would also raise complex ethical concerns about consent and algorithmic inference [cf. 56].

Questions also emerge around who has access to such data [cf. 18]. A single, static snapshot, like that studied here, can be obtained by independent researchers. However, longitudinal data, especially usage data, are only available to social media platforms themselves. More generally, the rapidly changing dynamics of social media platforms present one of the most difficult challenges to researchers studying them. While longitudinal, high-granularity data might be helpful, the next best things is for researchers to provide details about when and how data were collected, as done here. This approach provides the opportunity for retrospective analyses to understand how phenomena around social media use and non-use evolve over time.

7 CONCLUSION

Increasing attention has been paid to the myriad ways that people engage with, and disengage from, social technologies [9, 13, 14, 20, 49, 60, 62, 84–86, 93]. The results presented here demonstrate empirically that we should not, and perhaps cannot, treat all technology use as a single, monolithic category.

This paper focuses on one technical mechanism (deactivation) to identify different types of non/use among Facebook "users." It shows how various predictors (Facebook intensity [27], Facebook addiction [5], and privacy behaviors [19, 76, 91]) have different associations with each form of non/use. These findings build on prior work to advance our understanding of how each of these factors may predict increased or decreased likelihood of the forms of non/use considered here. Future work will likely benefit similarly by disaggregating among different types of people who might otherwise be grouped under the label of "user" [cf. 47, 60] to provide a more thorough understanding of our engagements with, and disengagements from, social technology.

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A SURVEY INSTRUMENT

This appendix lists all questions used in the survey instrument.

This appendix lists all questions used in the survey instrument. Names of specific constructs are presented in **bold** typeface.

A.1 Demographics

Demog.1 What is your age?

Demog.2 What is your gender?

Demog.3 For statistical purposes, last year (that is in 2014), what was your total household income from all sources before taxes?

Demog.4 Please enter the zip code of the mailing address for your primary residence.

Demog.5 What is your marital status?
- Single
- Married
- Divorced
- Separated
- Widowed
- Other

Demog.6 How would you describe yourself?
- Asian (including Indian Subcontinent)
- Black or African American
- Hispanic
- Mixed or Multi-ethnic
- Native American
- Pacific Islander
- White

Demog.7 Which of the following best describes your highest achieved education level?
- Less than 8th grade
- Some high school
- High school graduate
- Some college, no degree
- Associates degree
- Bachelors degree
- Graduate degree (Masters, Doctorate, etc.)

Demog.8 Please identify your political views on the scale below:
- Very liberal
- Liberal
- Slightly liberal

- Independent
- Slightly conservative
- Conservative
- Very conservative

A.2 Facebook Usage

FBUse.1 Do you currently have a Facebook account? (answer "yes" if you have an active account, or have deactivated / suspended your account. Answer "no" if you have permanently deleted your account, or have never had Facebook)
If No, skip to FBUse.8.

FBUse.2 When did you first sign up for Facebook?
- 2004
- 2005
- 2006
- 2007
- 2008
- 2009
- 2010
- 2011
- 2012
- 2013
- 2014
- 2015

FBUse.3 Why did you first sign up for Facebook? *<open-ended free-text response>*

FBUse.4 Do you have multiple accounts on Facebook *<Yes/No>*
If Yes...
- How many Facebook accounts do you have? *<whole number>*
- Please describe why you use multiple Facebook accounts. *<open-ended free-text response>*

FBUse.5 How do you access Facebook? Please check all that apply.
- Web browser
- Mobile phone Facebook app
- Facebook chat client
- Through other apps and services

FBUse.6 Why did / do you have a Facebook account? *<open-ended free-text response>*

FBUse.7 Have you ever deactivated your Facebook account? (Deactivation means your account disappears from Facebook, but your information is saved and can be reactivated later) *<Yes/No>*
If Yes...
- Why did you deactivate your Facebook account? *<open-ended free-text response>*
- How happy were you with your decision to deactivate your Facebook account? *<Five-point Likert from Very Unhappy to Very Happy>*

If No...
- Have you ever considered deactivating your Facebook account? *<Five-point Likert from "No, I would never consider it" to "I think about it all the time">*

FBUse.8 Have you ever had a Facebook account? *<Yes/No>*
If Yes...
- Why do you no longer have a Facebook account? *<open-ended free-text response>*
- How happy were you with your decision to delete your Facebook account? *<Five-point Likert from Very Unhappy to Very Happy>*

If No...

- Why have you never had a Facebook account? <*open-ended free-text response*>
- Please describe a time that you questioned your choice not to have a Facebook account or felt pressured to sign up for an account. <*open-ended free-text response*>

Facebook Intensity [27] (only asked of respondents who had a Facebook account)
How do you feel about the following statements?

FBI.1 Facebook is part of my everyday activity. <*Five-point Likert from Strongly Disagree to Strongly Agree*>
FBI.2 I am proud to tell people I am or was on Facebook. <*Five-point Likert from Strongly Disagree to Strongly Agree*>
FBI.3 Facebook has become part of my daily routine. <*Five-point Likert from Strongly Disagree to Strongly Agree*>
FBI.4 I feel out of touch when I haven't logged onto Facebook for a while. <*Five-point Likert from Strongly Disagree to Strongly Agree*>
FBI.5 I feel I am part of the Facebook community. <*Five-point Likert from Strongly Disagree to Strongly Agree*>
FBI.6 I would be sorry if Facebook shut down. <*Five-point Likert from Strongly Disagree to Strongly Agree*>
FBI.7 Approximately how many TOTAL Facebook friends do or did you have?

- 10 or less
- 11-50
- 51-100
- 101-150
- 151-200
- 201-250
- 251-300
- 301-400
- More than 400

FBI.8 In the past week, on average, approximately how much time PER DAY have you spent actively using Facebook?

- Less than 10 minutes
- 10 to 30 minutes
- 31 to 60 minutes
- 1 to 2 hours
- 2 to 3 hours
- More than 3 hours

Bergen Facebook Addiction Scale [5] How often during the last year have you ...

BFAS.1 Spent a lot of time thinking about Facebook or planned use of Facebook? <*Five-point Likert from Very Rarely to Very Often*>
BFAS.2 Thought about how you could be free to spend more time on Facebook? <*Five-point Likert from Very Rarely to Very Often*>
BFAS.3 Thought a lot about what has happened on Facebook recently? <*Five-point Likert from Very Rarely to Very Often*>
BFAS.4 Spent more time on Facebook than initially intended?
BFAS.5 Felt an urge to use Facebook more and more?
BFAS.6 Felt that you had to use Facebook more and more in order to get the same pleasure from it?
BFAS.7 Used Facebook in order to forget about personal problems?

BFAS.8 Used Facebook to reduce feelings of guilt, anxiety, helplessness, and depression?
BFAS.9 Used Facebook in order to reduce restlessness?
BFAS.10 Experienced that others have told you to reduce your use of Facebook but not listened to them?
BFAS.11 Tried to cut down on the use of Facebook without success?
BFAS.12 Decided to use Facebook less frequently, but not managed to do so?
BFAS.13 Become restless or troubled if you have been prohibited from using Facebook?
BFAS.14 Become irritable if you have been prohibited from using Facebook?
BFAS.15 Felt bad if you, for different reasons, could not log on to Facebook for some time?
BFAS.16 Used Facebook so much that it has had a negative impact on your job/studies?
BFAS.17 Given less priority to hobbies, leisure activities, and exercise because of Facebook?
BFAS.18 Ignored your partner, family members, or friends because of Facebook?

A.3 Privacy Behaviors and Experiences (PBE)

PBE.1 Are you familiar with Facebook privacy settings? <*Y/N*>
If Yes...

PBE.2 Have you ever changed your Facebook privacy settings? <*Y/N*>
- If Yes: Please describe when you last changed these privacy settings and why? <*open-ended free-text response*>

PBE.3 Have you ever experienced any of these kinds of situations on Facebook? Please select all that apply:
- Have you ever posted something that you later regretted?
- Has someone ever posted something about you that they later regretted?
- Had something found out about you that you didn't want known
- Received targeted advertisements that felt very personal
- Had your personal information misused
- Had information posted about you that you wish hadn't been posted

  If Yes to any: Tell us a story about any of these experiences <*open-ended free-text response*>

PBE.4 Have any other people that you know ever experienced these kinds of situations on Facebook? Please select all that apply:
- Posted something they later regretted
- Had something found out that she or he didn't want known
- Received targeted advertisements that felt very personal
- Had her or his personal information misused
- Had information posted about her or him that she or he wish hadn't been posted

  If Yes to any: Tell us a story about any of these experiences <*open-ended free-text response*>

B PARTICIPANT DEMOGRAPHIC CROSS TABULATION

This appendix, containing Tables 6 and 7, cross tabulates demographic variables, both continuous (age and income) and categorical (non/use type, marital status, ethnicity/race, education, and political views).

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Table 6. Continuous Demographic Variable Cross Tabulation

Variable	Minimum	Maximum	Mean	Std. Dev.	Median
Age (years)	18	84	47.60	17.28	46
Household Income (US$)	1,000	1,000,000	72,220.35	98,406.63	50,000

Summary of continuous demographics for main sample (Qualtrics Panel).

Table 7. Categorical Demographic Variable Cross Tabulation

Variable	Categories	Gender Female	Male	Other	Total
Facebook Non/use Type	Current User	29	30	1	60
	Considered Deact.	59	69	0	128
	Deactivated Account	41	29	0	70
	Deleted Account	77	44	0	121
	Never had an Account	56	80	0	136
Marital Status	Single	96	99	1	196
	Divorced	23	17	0	40
	Separated	3	3	0	6
	Married	125	122	0	247
	Widowed	11	7	0	18
	Other	4	4	0	8
Ethnicity / Race	Native American	2	2	1	5
	White	165	165	0	300
	Asian or Indian subcontnt.	13	11	0	24
	Black or African American	43	20	0	63
	Hispanic	31	50	0	81
	Pacific Islander	0	1	0	1
	Mixed Multi-ethnic	8	3	0	11
Education	Less than 8th grade	0	0	0	0
	Some high school	3	4	0	7
	High school graduate	58	35	1	94
	Some college, no degree	76	58	0	134
	Associate's degree	29	29	0	58
	Bachelor's degree	59	79	0	138
	Graduate degree	37	47	0	84
Political Views	Very Liberal	26	25	1	52
	Liberal	48	38	0	86
	Slightly Liberal	31	31	0	62
	Independent	68	63	0	131
	Slightly Conservative	35	38	0	73
	Conservative	36	33	0	69
	Very Conservative	18	24	0	42

Summary of categorical demographics for main sample (Qualtrics Panel).