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Missing Photos, Suffering Withdrawal, or Finding Freedom? How Experiences of Social Media Non-Use Influence the Likelihood of Reversion

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Abstract

This article examines social media reversion, when a user intentionally ceases using a social media site but then later resumes use of the site. We analyze a convenience sample of survey data from people who volunteered to stay off Facebook for 99 days but, in some cases, returned before that time. We conduct three separate analyses to triangulate on the phenomenon of reversion: simple quantitative predictors of reversion, factor analysis of adjectives used by respondents to describe their experiences of not using Facebook, and statistical topic analysis of free-text responses. Significant factors predicting either increased or decreased likelihood of reversion include, among others, prior use of Facebook, experiences associated with perceived addiction, issues of social boundary negotiation such as privacy and surveillance, use of other social media, and friends' reactions to non-use. These findings contribute to the growing literature on technology non-use by demonstrating how social media users negotiate, both with each other and with themselves, among types and degrees of use and non-use.

Introduction

Social media often play an important role in much of modern life, from building social capital (Ellison, Steinfield, & Lampe, 2007) to self-presentation and impression management (Donath & boyd, 2004) to maintaining connections with friends (Joinson, 2008). However, commentators have also voiced various concerns about other, more unseemly repercussions of social media usage. Some have argued that constant connectivity can disrupt the ability to express and experience our authentic selves (e.g., Jurgenson, 2013). Psychological experiments suggest that the format of online information may restructure our brain, making us less able to attend to focused tasks for extended periods of time (Carr, 2010). Some in popular culture even claim that social media use should be treated as addicting (summarized by Portwood-Stacer, 2012). Such examples represent an emerging trend of what has been termed disconnection, technology push-back, "digital detox," or media refusal.

These developments have also drawn interest to technology non-use as a topic of scholarly research. Some of this research examines rhetorical framing, for instance, of non-use as a political identity statement (Portwood-Stacer, 2013), or of the non-user as the epitome of an authentic human being (Harmon & Mazmanian, 2013). Other studies have examined motivations for leaving social media (Baumer et al., 2013), comparisons between users and non-users (Acquisti & Gross, 2006; Hargittai, 2008), or particular instances of non-use, for example, forgoing social media use during Lent (Schoenebeck, 2014). Whether an act of resistance or the result of infrastructural constraints, studying non-use illuminates the myriad factors that influence whether or not individuals use certain technologies.

One important finding emerging from this work is that, in practice, non-use rarely emerges as a clear-cut, binary distinction in opposition to use. Rather, "disconnectors" demonstrate "a desire for selective and reversible disconnection" (Mainwaring, Chang, & Anderson, 2004, p. 425). The discourse around smartphone usage is, in many ways, characterized by fluctuations between extreme use and extreme non-use (Harmon & Mazmanian, 2013). In one study, nearly half the respondents who left Facebook subsequently returned to the site (Baumer et al., 2013). Another study focused on Grinder suggested

departure as a gradual, tenuous, and, moreover, reversible process (Brubaker, Ananny, & Crawford, 2014). Indeed, "research agendas around non-use may benefit from studying returns [and] cyclical adoption and departure" (Brubaker et al., 2014, p. 14).

This article fills that gap by examining one case of departing from, and returning to, social media. Such reversion provides a key moment for understanding, and studying the impact of, various individual and social influences on technology non-/use. We employ a novel combination of methods to examine a group of users who voluntarily left the site Facebook, their reported motivations for and experiences of non-use, as well as whether or not they returned to the site. This particular group of users is analytically interesting largely because they left the site in response to a specific series of events.

The Backstory

In June of 2014, Kramer, Guillory, and Hancock (2014) published a study indicating experimental evidence for emotional contagion on social media. As part of their experimental intervention, the authors adjusted Facebook's automatic curation of news feeds for hundreds of thousands of users, including either fewer posts with positive words or fewer posts with negative words, and then monitored the number of positive and negative words in those users' own posts. People reacted to the study in a variety of ways. To some, it was a promising model for collaboration between a data-rich corporation and university researchers, but to many, it was a distasteful manipulation of users' emotions.

In one response to the study, Merijn Straathof, art director at the Dutch advertising firm, Just, wanted to see if he could stay off of Facebook for 99 days. After describing the plan to his colleagues, they, too, decided to share this commitment. His firm then launched a campaign they dubbed 99 Days of Freedom.[1] Participants were encouraged to change their profile picture to the image shown in Figure 1, post to their friends that they would be back in 99 days, and then try to avoid using both the site itself and any other Facebook-linked product or service. Furthermore, participants were asked to supply their email address and told they would be contacted with information about filling out a survey after 33, 66, and 99 days. At the time of writing, over 40,000 people had taken this pledge.

Figure 1. Logo for 99 Days of Freedom. Facebook users who took the pledge were encouraged to change their profile picture to this image.

Although 99 Days was not designed as a social scientific study, we can nevertheless examine data collected from those 33, 66, and 99 day surveys. The entire 99 Days project, including the surveys, was conceived of and executed by staff at Just. Shortly after the project began, this article's lead author contacted Straathof, who was willing (with each participant's consent) to share anonymized data with the authors. He also solicited from the authors, suggested for questions that might be asked on the survey, though Straathof and his staff were the final arbiters of the survey design. The surveys ultimately included a mix of closed-ended questions, demographics, and open-ended free-text responses. These data present a unique opportunity to study social media reversion, that is, those participants who made the pledge but returned to Facebook before the 99 days were up. This configuration provides a clear means of identifying reverters who did not initially intend to return as early as they did. This arrangement also provides a unique complement to more common approaches such as scraping existing data (e.g., Backstrom, Boldi, Rosa, Ugander, & Vigna, 2012; Schoenebeck, 2014), purposive university-run surveys (e.g., Baumer et al., 2013; Lampe, Vitak, & Ellison, 2013), or qualitative interviews (e.g., Portwood-Stacer, 2013; Schoenebeck, 2014). Analysis of these data, though, may not provide fully generalizable conclusions. People who signed up for 99 Days likely do not resemble a representative of all Facebook users. Similarly, those who reverted may not be representative of all users who left the site and subsequently returned. However, the individuals who joined 99 Days had at least some, potentially significant, personal motivation to stay off of Facebook. Thus, although a convenience sample, this data set is one in which the phenomenon of social media reversion is both conceptually salient and well-defined.

Summary

We analyze these data using a novel mixed-methods approach to examine how three different types of factors influence the likelihood of social media reversion. First, we consider individual traits derived from demographic and Likert-style data. Second, we incorporate self-reported experiences through a factor analysis of the adjectives, drawn from prior work on surveillance in social situations (Robles, Sukumaran, Rickertsen, & Nass, 2006) and on affect (Watson, Clark, & Tellegen, 1988), respondents' use to describe their 99 (or fewer) Days. Third, we leverage topic modeling (Blei, Ng, & Jordan, 2003) to examine free-text descriptions of respondents' experiences of non-use. Synthesizing across these analyses, four themes consistently recur as significantly influencing the likelihood that a respondent returned to Facebook before 99 days had passed. First, experiences consistent with *perceived addiction*, such as withdrawal and limited self-control, increased the likelihood of reversion. Second, concerns around social *boundary negotiation* had mixed effects; respondents who emphasized social surveillance were less likely to revert, while those concerned with impression management were more likely to revert. Third, respondents who reported a better subjective *mood* while off of Facebook were less likely to revert. Finally, use of *other social media* while not using Facebook played a varied role, dependent in part on concomitant shifts in attitudes about, and use of, social media. These findings both contribute to the growing literature on technology non-use and help understand in greater depth the kinds of experiences that occur not merely on but also around social media.

Related Work

Researchers in human-computer interaction (Satchell & Dourish, 2009) and the sociology of technology (Wyatt, 2003) have acknowledged the importance of, and begun to study phenomena around, technology non-use. Examples include resistance to electrification among rural Americans in the early

20th century (Kline, 2003), how an "information society" accounts for those who do not use digital technologies (Uotinen, 2003), or demographic differences in usage of social networking sites (Hargittai, 2008).

Researchers describe non-users with various typologies. For example, Wyatt (2003) suggests a two-by-two typology using the dimensions of volitionality (is non-use the individual's choice?) and temporality (was the individual previously a user?). *Rejecters* previously used a technology but voluntarily gave it up, while *resisters* never used it in the first place. The *excluded* are, against their will, prevented from using a technology, while the *expelled* previously used it but then were forced to stop. Other work suggests potential extensions, such as the "lagging resister" (Baumer et al., 2013) who has strongly considered dis-using some technology but not yet actually done so. In this article, we extend these typologies with the notion of a *reverter*, a rejecter who later becomes a user again.

More recently, researchers have focused specifically on the non-use of social media. In a recent survey, 61% of Facebook users described having "voluntarily taken a break from using Facebook for a period of several weeks or more" (Rainie, Smith, & Duggan, 2013). The social interactions afforded by such technologies precipitate specific concerns, such as who gets to see what about whom. Practices around privacy, surveillance, impression management, and related concerns fall under a broad umbrella of *boundary negotiation* (Palen & Dourish, 2003). In particular, surveillance can be top-down, imposed by governments and corporations (Lyon, 2007), or it can be more social: "*social surveillance* is the ongoing eavesdropping, investigation, gossip, and inquiry that constitutes information gathering by people about their peers, made salient by the social digitization normalized by social media" (Marwick, 2012, p. 382). Some users may continue, reconfigure, or even limit, their usage as a means of managing the costs and benefits of such surveillance (Guha & Birnholtz, 2013; Guha & Wicker, 2015; Humphreys, 2011).

Other factors can also play a role influencing non-use. A comparison among heavy users, light users, and non-users of Facebook found that non-users tend to be older, spend less time on the Internet, perceive Facebook as less useful, and have lower levels of bridging social capital (Lampe, Vitak, & Ellison, 2013). Due to the data collected, that analysis was "unable to distinguish [. . .] between those who used the site and then stopped from those who never tried the site" (Lampe et al., 2013, p. 816). An exploratory study of Facebook non-use found that those who left the site reported being happy with their decision. Of those who deleted their account, very few returned, but of those who deactivated their account, almost half returned to the site (Baumer et al., 2013). Furthermore, a social contagion effect showed "respondents who knew someone that had deactivated were almost three times as likely to deactivate their account" (Baumer et al., 2013, p. 3261). Another analysis focusing on users who gave up Twitter for the Christian period of Lent found that only 64% actually stayed off Twitter for the entire 40 days (Schoenebeck, 2014). Collectively, this prior work hints at the phenomenon of reversion, but none has yet examined it in detail.

Methods

Data Collection and Respondents

Information about 99 Days of Freedom was disseminated by Just on social media, by social diffusion, and through coverage in major news media outlets (e.g., Time, The Huffington Post, USA Today). Interested participants could visit the project landing page, download an image of the project logo, and

upload this logo in place of their regular Facebook profile picture. The pledge to avoid using Facebook for 99 days was voluntary, and perceptions and usage behavior were self-reported in the three different surveys deployed at the 33rd, 66th, and 99th day automatically through an email link to each participant. As questions differed slightly and there was little overlap in users between surveys, we analyze each survey as a separate data set, which we name Day 33, Day 66, and Day 99.

Survey Design and Deployment

The three surveys sent to respondents were developed by the staff at Just. Researchers at the Leiden University and the authors of this article were consulted for suggestions, but Just's staff made the ultimate decisions about the survey design and content. While recommendations were sought from university collaborators, Just made the ultimate decisions about the questions and format of the survey.[2]

The surveys included a mix of closed-ended, Likert-style responses (L) and open-ended, free-text responses (F). Specifically, these items covered (verbatim questions from survey in quotes):

1. Prior experiences with Facebook, including "How often did you check Facebook?" and "On average, how much time did you spend on Facebook each day?" (L), average mood using Facebook (L), the most valuable thing about Facebook (F), adjectives to describe experiences with Facebook (binary choices from a list drawn from Robles et al. (2006) and Watson et al. (1988)), "Have you ever considered taking a break from Facebook?" (L), and motivations for joining the 99 Days pledge.
2. Experiences during the most recent 33 days, including "How did you feel?" (F), "How did your friends react?" (F), best and worst things that happened (F), average mood (L), adjectives to describe experiences during the most recent 33 days (binary choice from a list), if (and if so when) respondent returned to Facebook (L) along with their own feelings (F) and friends' reactions (F), "How hard has not using Facebook been for you so far?" (L), and changes in family and social relationships (F). The final Day 99 survey also asked how respondents felt about the 99 Days pledge ending (L), "Are you going back to Facebook now [the pledge] is over" (Y/N), and whether they considered quitting any other habits (F). We use responses to the question about whether (and when) a respondent returned to Facebook to identify reversion.
3. Some demographics, including age, gender, marital status, education, religion, country of residence, and political ideology, (Day 33 only), and other questions not related directly to Facebook, including questions about personal happiness (L). Demographics were collected only at Day 33, as the staff at Just had expected (and hoped) that the same respondents would complete all three surveys. Using unique, anonymized identifiers for respondents, they planned to extrapolate demographic data from the initial survey. However, the low number of repeat respondents across the three surveys resulted in demographic data only being available for Day 33.

Analysis and Results

This section provides a mixed-methods analysis, using three complementary analytic approaches as a means of triangulation. Specifically, we identify predictors that indicate increased or decreased likelihood of reversion to Facebook use. First, we consider demographic variables and responses to self-reported Likert-style questions. Second, we apply an exploratory factor analysis of adjectives used by

survey respondents to describe their experiences with the 99 Days pledge. In both these cases, we followed a manual process of iterative stepwise model selection. Thus, predictors across the three data sets differ slightly, but the final results presented below represent the best model for each data set. Third, we present a novel approach combining topic modeling with close, qualitative reading to understand how respondents describe their experiences in open-ended, qualitative questions. In each case, we construct logistic regression models to determine which factors best predict reversion in each case. The discussion section synthesizes across these three analyses.

Respondents

Table 1 provides sample sizes and proportions of respondents who reverted, as well as age and gender demographics for the Day 33 data. The sample(s), while relatively large in comparison to similar previous studies, (e.g., Baumer et al., 2013; Lampe et al., 2013), may have been biased in a number of ways. Participants were recruited via traditional news media coverage, social media, and snowball sampling. Also, since 99 Days of Freedom began in response to Facebook's study of emotional contagion (Kramer et al., 2014), certain users may have been more motivated to join. Furthermore, those participants who returned to Facebook may have been less (or perhaps more) likely to complete the three surveys.

Table 1. Number of respondents and descriptive statistics for each survey. Gender includes female, male, and declined to report.

Day	N	F/M/D	Age	Reverted
33	3539	1670/1608/261	33.6(16.9)	800 (22.6%)
66	1266	n/a	n/a	195 (15.4%)
99	440	n/a	n/a	100 (22.7%)

F: Female; M: Male; D: Declined to Report.

However, we do not know how a representative sample of Facebook users would look. Indeed, Backstrom et al. (2012), who analyzed the network structure of the entire Facebook social graph, do not provide descriptive statistics about the Facebook users whose data they analyzed. Furthermore, as argued above, this sample, even if biased, is a prime one in which to analyze the phenomenon of reversion. Although it does not give us the ability to make inferences about all Facebook users who try to leave the site, it does provide needed insight into the processes of transitioning between use, non-use, and back to use (Brubaker et al., 2014).

Demographics and Likert Responses

Prior work has found that such factors as age (Acquisti & Gross, 2006; Lampe et al., 2013; Rainie et al., 2013), previous usage (Lampe et al., 2013), happiness with the decision (Baumer et al., 2013), and others predict various forms of non-use. Here, we consider whether similar factors might predict reversion.

Specifically, we consider several factors measured via Likert, yes/no, or similar style questions, including: prior use of Facebook, mood using Facebook and during the 99 Days pledge, prior consideration of

leaving Facebook, difficulty in not using Facebook, some demographics (age, gender, education, marital status, etc.), and others.[3] Some questions were only asked on specific surveys, for example, prior consideration of leaving Facebook, as well as demographics, were only asked at Day 33 (as described above), while whether the respondent planned to return to Facebook was only asked at Days 66 and 99.

Using these data, we constructed a logistic regression model for whether or not the participant returned to Facebook, considering each of the above as a potential predictor. To develop the most parsimonious models, we conducted a manual process of iterative stepwise model selection, including or excluding single variables based on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), residual deviance, and other model fit diagnostics. To reiterate, this process means that different predictors are included or excluded for different data sets, but that the results reported below represent the best model for each data set. The exclusion of a given predictor for a given data set indicates that it did not explain enough of the variance to warrant inclusion in the model.

Table 2 shows full details of the results, along with model fit statistics.[4] Across all three surveys, those who found not using Facebook harder were more likely to return. *Mood* also emerged as a significant predictor: those who reported better moods were less likely to revert. Self-reported frequent use of Facebook (prior to the 99 Days pledge) predicted increased likelihood of reversion, suggesting habitual use as a key influence in reversion. However, beliefs that others checked very often predicted decreased likelihood of reversion. One might expect that social contagion (Le Bon, 1895) would result in the opposite effect. Instead, we suggest this result indicates how normative beliefs may influence social media (non-)use (cf. Lenhart, 2005). If I see myself as a comparatively highly frequent user, it may be more difficult for me not to log in, and vice versa, if I see myself as a less frequent user. Finally, those who reported using *other social media* more often were less likely to revert. The themes of *mood* and *other social media* use both recur in the following two analyses, though the specific findings for *other social media* use differ. The discussion addresses this tension.

Table 2. Logistic regression results showing self-reported Likert-style factors that significantly predict reversion for each data set.

Predictor	Coefficient	Odds ratio
Day 33 survey		
Intercept	−1.281	.277 *
How often check FB	.500	1.649 ***
How often others check FB	−.970	.378 *
Mood first 33 days	−.195	.822 ***
How hard not using	.415	1.515 ***
AIC = 2529, BIC = 2356		
Day 66 survey		
Intercept	−1.137	.193*
Tempted to login	−.430	.217
How hard not using	−.620	.378 *
Think about pledge	−.267	.435 *
Other social media use	−.543	.424 **
Miss Facebook (N)	−.686	.987 ***
AIC = 2653, BIC = 2421		
Day 99 survey		
Intercept	−1.130	.437 *
Overall mood change	−.428	.139 *
How hard not using	.820	1.213 *
Other social media use	−.496	.605 **
Relieved pledge over	.651	1.34 *
Going back to FB (Y)	.345	1.925 **
AIC = 2153, BIC = 2048		

FB: Facebook; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

Thus, self-reported individual characteristics significantly predicted whether an individual was more or less likely to return to Facebook before 99 days had passed. The next two subsections, "Exploratory Factor Analysis," and "Topic Modeling," explore how the experience of non-use itself may influence the likelihood of reversion.

Exploratory Factor Analysis

On each survey, one question asked participants to select from a list of adjectives the words that they would use to describe their experiences during the 99 Days pledge. Responses were recorded as 45 binary variables indicating whether or not the respondent selected each adjective.

Analyzing each data set separately, we used factor analysis to reduce the dimensionality and to identify underlying commonalties among respondents' experiences. Using the Kaiser-Guttman rule (Jackson, 1993), we retained factors with an eigenvalue greater than 1.0. The direct oblimin rotation method was used based on the assumption that the underlying factors that are produced are correlated with one another. The resulting factor loading matrix produced an output that was interpretable and had a clear structure. Based on this structure, we set the cutoff for significant loadings to .3. This cutoff resulted in 14 components for the Day 33 and Day 66 data sets and 15 components for the Day 99 data set, as shown in Table 3. For each variable in each factor, we calculated the average of their factor means. This produced a single value for each of the factors for every participant. We used these values to fit the factors in a logistic regression with reversion as the dependent variable. These results are presented in Table 4.

Table 3. Factor analysis results across the three data sets. For factors with multiple high loadings, we manually assign a [Label].

Day 33 survey

Nurturing, warm [Comfort]	Entertaining, friendly, fun [Enjoyable]	Helpful, logical, supportive [Facilitating]
Inappropriate	Powerful	Manipulated
Orderly, organized [Work]	Annoying, insecure, irritable [Negative]	Monitored, watched [Surveillance]
Impulsive, rebellious [Disinhibited]	Careful, cautious [Worried]	Addicting, invasive [Perceived addiction]
Reliable	Self-conscious [Impression management]	

14 factors capturing 21.2% of variance

Day 66 survey

Careful, orderly, organized [Work]	Entertaining, helpful, supportive [Enjoyable]	Inhibited, insecure [Closed]
Reckless	Energetic	Rebellious
Inconsistent	Exhibitionistic	Uncertain
Nurturing, warm [Comfort]	Hasty, impulsive [Perceived addiction]	Friendly, joking [Amiable]
Suspicious, watched [Surveillance]	Cautious, on-stage, self-conscious [Impression management]	

14 factors capturing 24.4% of variance

Day 99 survey

Colorful, energetic [Lively]	Cautious, uncertain [Uncertainty]	Exhibitionistic, manipulated [Surveillance]
Nurturing, warm [Comfort]	Addicting, inappropriate [Perceived addiction]	On-stage [Impression management]
Unpredictable	Orderly	Joking
Logical	Judged	Showy
Dominant	Careful	Supportive

15 factors capturing 33.5% of variance

Table 4. Results of logistic regression showing which factors predict reversion for each data set.

Factor	Coefficient	Odds ratio
Day 33 survey		
Intercept	−1.193	.285 *
Surveillance	−.320	.319 **
Enjoyable	.488	1.869 *
Perceived addiction	.412	1.632 *
Impression management	.455	1.481 ***
Manipulated	−.676	.265 *
AIC = 1230, BIC = 1066		
Day 66 survey		
Intercept	−1.427	.404*
Impression management	.940	1.613 **
Surveillance	−.779	.410 *
Rebellious	−.197	.986 *
Closed	−.854	.697 *
AIC = 1499, BIC = 1549		
Day 99 survey		
Intercept	−1.470	.277 *
Impression management	.310	1.491 **
Surveillance	−.690	.470 **
Perceived addiction	.652	1.672 **
Judged	−.970	.072 *
AIC = 1974, BIC = 1853		

AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

Before discussing the results, it is important to consider what respondents' replies to this question mean. The first survey asked users to "Select the words that best describe your experiences, perceptions of, and attitudes about the 99 Days [pledge]," and subsequent surveys asked "How do you feel about [the pledge] since the last survey?," again, because Just expected the same respondents would complete all three surveys. Given responses, we suspect that respondents likely used these adjectives in part to describe their experiences of the pledge and in part to describe how taking the pledge altered their perceptions of Facebook.

For example, we see that adjectives associated with the Surveillance factor (e.g., watched, monitored, on-stage) predict decreased likelihood of reversion. This result is most readily interpretable as meaning not that the respondents felt surveilled during the 99 Days pledge but rather that their experiences during the pledge were associated with an increased feeling of being surveilled on Facebook. Experiences around impression management (e.g., on-stage, self-conscious), on the other hand, predicted increased likelihood of reversion. Again, we suggest this is most sensibly interpretable as meaning that the 99 Days of Freedom pledge led respondents to think more about Facebook in terms of impression management and, as a result, returned to Facebook to have better control over perceptions of their online identities. The importance of the Judged adjectives likely also pertains to social surveillance and boundary negotiation, though in a different way than impression management. Those who focus on managing their impressions on Facebook were more likely to revert, while those who felt judged were less likely. The factors for feeling Manipulated and, to a lesser extent, Rebellious may arise in part from 99 Days of Freedom coming as a reaction to the emotion contagion study. Respondents who felt manipulated by, and perhaps who were rebelling against, Facebook were less likely to revert. Lastly, adjectives associated with Perceived Addiction (e.g., impulsive, addicting, hasty) predict increased likelihood of reversion, but only during the Day 33 and Day 99 surveys. Full results are shown in Table 4. Two of these themes, *boundary negotiation* (i.e., surveillance and impression management) and *perceived addiction*, also occur in the third analysis.

Topic Modeling

Our third methodological approach analyzed the free-text responses, which provide rich snapshots of respondents' experiences. Traditionally, one might analyze these data using approaches such as grounded theory (Glaser & Strauss, 1967/2009), in which researchers iteratively develop codes, themes, and categories through repeated reading. Relatedly, one could develop a code book and then train human coders to annotate responses. Such approaches, however, scale poorly to the thousands of responses in our data.

As an alternative, recent work suggests that statistical topic models, such as latent Dirichlet allocation (LDA) (Blei et al., 2003), provide a robust, flexible approach to open-ended survey analysis (Roberts et al., 2014). Topic models represent each topic, that is, each theme, as a probability distribution or words that deal with that topic, and documents are represented as combinations of topics. Topic modeling algorithms attempt to infer these underlying topics from a set of unlabeled documents. Here, each response to each free-text question is treated as a single document. This approach does not capture syntactic relationships but is often surprisingly effective at modeling recognizable themes. In the context of survey analysis, we can think of automatically extracted topics as "codes" that have been assigned by an algorithm rather than by human coders. Topic models can be trained quickly and cheaply, running over tens of thousands of documents in a matter of minutes. This approach forfeits the linguistic and contextual knowledge of human coders, but in return, it provides a much more scalable approach for medium- to large-sized data sets.

For each survey, we trained a topic model on the individual responses to eight questions. We did not model responses to two questions that specifically involve reactions to *returning* to Facebook, since only respondents who returned answered those. Two more questions, one relating to plans for the next 30 days and one asking whether the respondent planned to quit any other habits, produced responses that shared no topics with other questions, so we omitted those as well. The topic proportions for each

respondent were then used as predictors in a binary logistic regression model, as in the two preceding subsections, "Demographics and Likert Responses," and "Exploratory Factor Analysis." This analysis allows us to determine whether describing certain types of experiences increased or decreased the likelihood that the respondent would return to Facebook. This subsection omits analysis of the Day 99 data as it included far fewer responses than the other two data sets. For full details, please see the Methodological Appendix.

Tables 5 and 6 contain results from the Day 33 and Day 66 surveys. Each topic is described using the top five words most likely to occur in responses about that topic. Collectively, these topics represent experiences of Facebook non-use commonly described by respondents. For instance, the Missed Content topic most frequently includes the words "friends, pictures, miss, photos, family," and the top responses for that topic describe experiences of missing out on photos and other updates posted by friends and family. The tables show how each topic predicts reversion in terms of logistic regression coefficients, odds ratios, and *p*. For those topics that predict a significant increase or decrease in likelihood of reversion, we also provide a manually assigned label. Given the exploratory nature of this approach, we do not report model diagnostics as in the Likert-style self-report and factor analysis sections above.

Table 5. At Day 33, respondents who described withdrawal-like experiences were more likely to return to Facebook. Those who described limited reactions from friends, who said they missed photos or updates from friends and family, or who reported that nothing bad or noteworthy happened were less likely to return. Table includes logistic regression coefficients and odds ratios for each topic, as well as manually assigned label for topics that significantly predict increased or decreased likelihood of reversion.

Day 33 survey

Label	Topic	Coeff.	Odds ratio
	Intercept	−1.049	.350 ***
Friends' reactions limited	About, know, one, don't, really	−.217	.804 *
	Break, wanted, take, experiment, needed	−.133	.875
	Events, missed, out, friends, missing	−.001	.998
	Feel, felt, like, more, free	.064	1.066
Withdrawal	First, felt, days, day, check	.321	1.378 ***
Missed content	Friends, pictures, miss, photos, family	−.165	.847 *
	Her, she, friend, with, his	−.036	.964
	I'm, nervous, will, back, nothing	−.153	.857
	Life, more, about, people, others	−.064	.937
	News, information, about, some, miss	.024	1.024
Nothing happened	Nothing, thing, happened, bad, really	−.161	.850 +
	Some, most, thought, why, said	−.091	.912
	Time, more, things, with, other	−.108	.897
	Time, social, much, too, media	−.006	.993
	What, about, know, friends, don't	−.108	.897
	With, friends, family, touch, keeping	.045	1.046
	With, friends, people, contact, some	−.110	.895
	With, people, tired, posts, their	−.089	.914
	You, don't, people, like, know	−.042	.958

Table 6. At Day 66, those respondents who said they missed out on photos, events, birthdays, or other content were less likely to return to Facebook. Those who described increased use of other social media were more likely to return. Table includes logistic regression coefficients and odds ratios for each topic, as well as manually assigned label for topics that significantly predict increased or decreased likelihood of reversion.

Day 66 survey

Label	Topic	Coefficient	Odds ratio
	Intercept	−1.040	.353 +
	About i'm nervous nothing all	.199	1.220
	Back will i'm use want	−.022	.977
	Feel more less feeling being	.206	1.229
	More people friends with phone	−.077	.925
	More time with spend things	−.119	.887
	New job getting work got	−.100	.904
	Nothing think really bad happened	−.119	.887
Missed content	Out events friends missed some	−.377	.685 *
	People don t about what know	.029	1.029
	Reading more books read watching	−.031	.968
Other social media	Social media other use network	.370	1.447 *
	With friend got went her	.166	1.180
	With friends family contact some	−.087	.916

Overall, we find that the topics respondents use to describe their experiences effectively serve as significant predictors for reversion, several of which resonate with themes from the previous two analyses. For example, at Day 33, those who described feelings of *perceived addiction*, seen in the Withdrawal topic, were 37.8% more likely to end up returning to the site. We also see a near-significant effect where those who said that "nothing bad happened" were 15% less likely to revert. At Day 66, those who talked about using *other social media* showed a 44.7% increase in likelihood of reversion. Interestingly, those who talked about missing out on events were 31.5% *less* likely to revert.

These results provide some insights about how different experiences of non-use change the likelihood of reversion. Many topics appear readily interpretable in terms of the most common words in the topic, but not all: for example, it is not obvious at first glance what the topic "about, know, one, don't, really" means.

To aid interpretation, we select representative examples of responses for each topic by finding the top 50 responses with the highest proportion of the topic. Reading through these responses in an iterative, inductive fashion (cf. Glaser & Strauss, 1967/2009) combines the computational power of topic modeling with some of the linguistic and contextual knowledge provided by human qualitative analysis. For each data set, we provide a close qualitative reading of responses for each of the topics that significantly predicts reversion.

Day 33 Topics
In the Day 33 responses, four topics significantly predicted reversion.

Withdrawal: first, felt, days, day, check
Responses for this topic often described one initial set of experiences, generally negative, sometimes followed by a different set of experiences, often positive. Many of these responses discuss habit, perceived addiction, withdrawal, and so on:

> In the first week I got the urge to check Facebook but after a week I did not have that urge anymore. I feel fine about it. (P#33.1031)

Like I was going through withdrawal from an addiction! I had to resist the urge to check it every few minutes. (P#33.1753)

In the first 10 days, I thought about Facebook a lot. Whenever I opened up a browser, my fingers would automatically go to 'f'. On day 9, I had a dream about accidentally logging in to Facebook—which showed that I was consciously thinking about it. (P#33.3517)

I was experiencing withdrawal and felt socially disconnected. The impulse to check FB was very strong, especially when I was feeling low. I caved in after about a week, and began checking FB a few times a day for about a week. But then I decided to quit FB again, which again only last 2-3 days. For the past 4 days I have been checking FB once-twice a day, spending around 5 min per day in total. (P#33.1381)

Respondents who described such initial withdrawal-like experiences, even if eventually overcome, had increased likelihood of returning to Facebook.

Friends' reactions limited: about, know, one, don't, really

Responses with high proportions of this topic come largely from the question about how the respondents' friends reacted. The responses describe a minimal reaction from friends, in some cases that friends did not even notice:

Not many really cared or commented. I don't think anyone shared in my revolt. (P#33.2766)

They didn't even notice that I wasn't there. No one called or emailed to ask what was up. (P#33.351)

Nobody is bothered. Nobody outside fb asked me why I did I do it. On fb if anybody asked I don't know. (P#33.2989)

Interestingly, many of these responses also note the fact that, since the respondent had not logged in, s/he had not seen the reaction from Facebook friends. Such statements carry a "doesn't know, don't care" connotation about friends' reactions on Facebook.

Missed content: friends, pictures, miss, photos, family

Representative responses for this topic come mostly from the question about what people miss about Facebook. Respondents describe missing not only the photos themselves but also what those photos connote: inside jokes, familial bonds, personal identity, and so on:

I missed my smart friends and their posts, I missed my inspiring friends and their uplifting words and photos. (P#33.2541)

Missing photo / status updates to share news from family overseas. (P#33.3331)

I miss seeing some of the family pictures posted, especially those that others post of my Grandson. (P#33.3585)

Not being able to share photos of my son. Not able to see other photos shared. (P#33.1420)

I miss seeing photos that friends and family are posting. My brother rarely shares photos of my infant niece in places other than FB. (P#33.1219)

Given these responses, it is perhaps surprising that this topic was associated with *decreased* likelihood of reversion. We suggest two possibilities. First, family members may be viewing photos via other routes, for example, the respondent may see the photos via another family member who has a Facebook account, a phenomenon known as displacement ([Satchell & Dourish, 2009](#)). Second, these may be friends with whom the respondent has regular offline contact, as well, and thus leaving Facebook simply means the loss of a single medium rather than a loss of the social tie entirely.

Missed content: out, events, friends, missed, some

Representative responses for this topic come from a mix of questions, including the worst thing since last survey, what the respondent was most nervous about during the next 33 days, and whether the respondent's relationship with her or his family had changed. The content of these responses deals not only with missing out on events but also other types of occurrences:

> Missing some of the pictures of the grandchildren. And missing some invitations to gatherings. (P#66.768)

> I missed a birthday because of not seeing the FB invite. (P#66.485)

> Missing out of messages from people and them thinking that I am ignoring them. Missing out on updates for group events. (P#66.2)

> I've missed notices and pictures that they expected me to see. (P#66.1261)

We can see that birthdays, messages, and photos, in addition to events, are a felt absence for respondents. However, as mentioned above, this topic somewhat surprisingly predicts *decreased* likelihood of reversion. The implication may be that, if missing a few birthdays and other events is the worst thing that has happened since leaving Facebook, that is not bad enough to precipitate a return before the planned 99 days have passed. In other words, while missing out on the *content* of social media emerged as a consistent theme, it is the people who describe compulsive *behaviors* who ultimately struggle with maintaining non-use.

Other social media: social, media, other, use, network

Responses for this topic evidence mixed experiences. Some of the responses describe filling the time previously spent on Facebook by instead using other social media:

> I just use other social media outlets more (instagram, pinterest, etc.). (P#66.163)

> Sadly, on other sites! (P#66.421)

> My family and I reside in different places, and Facebook is our primary code of contact. I have utilized other social media outlets for connection, and of course, email. (P#66.878)

However, responses for this topic also include more reflective considerations about the role of social media as well as both individual and collective engagement with and through it:

> [W]e have to be responsible for our actions on social media. It has great uses, but most people are using it for dramatic response. (P#66.529)

> I hate trends (social networks trends). Being out of them makes me feel different, wiser. I create my owm self-esteem, free and independent of "likeses" [sic]. (P#66.1369)

Freedom from social media and the obligation to keep checking and responding on useless information. (P#66.1226)

consider people for who they are and noy [not] for the mask that they weAr on social network [sic]. (P#66.455)

Better use of social media, detox and a bit more happy:) (P#66.374)

Such responses may explain, in part, why this topic predicts increased likelihood of reversion. These respondents are not likely rejecting Facebook on ideological grounds (cf. Portwood-Stacer, 2013) but rather trying to negotiate an acceptable level and style of use, both for themselves and for their social connections (cf. Harmon & Mazmanian, 2013). Reversion in this case may represent a successful accomplishment of such renegotiation.

Discussion

While each analysis above provides valuable insights, synthesizing across them enables us to triangulate on social media reversion from different perspectives. Doing so, we identify four themes—perceived addiction, boundary negotiation, mood, and other social media use—that recur in various ways, as well as show how this article builds upon prior work.

Experiences consistent with *perceived addiction* appear in the factor analysis and in the topic modeling. In both analyses, addiction-associated feelings (withdrawal, sudden urges, limited self-control, etc.) predicted increased likelihood of reversion. Whether or not these individuals would be medically or clinically diagnosed as addicted would require at least use of standardized measures (Andreassen, Torsheim, Brunborg, & Pallesen, 2012; Stieger, Burger, Bohn, & Voracek, 2013), if not consultation with medical and psychiatric experts. These self-report measures indicate only that respondents perceived their subjective experiences as consistent with addiction (Douglas et al., 2008). Nonetheless, this result helps confirm that our different methods triangulate to reinforce each others' results. This finding also confirms prior accounts of non-use as an attempt to break perceived addiction to or habitual use of social media (Baumer et al., 2013; Schoenebeck, 2014; Stieger et al., 2013). Furthermore, issues around (lack of) self-control call into question the role of volitionality in non-use (Wyatt, 2003), suggesting the possibility of non-volitional users.

Concerns around *boundary negotiation*, specifically surveillance and impression management, occur in the factor analysis for all three data sets. Those respondents who describe their experiences with adjectives connoting surveillance (e.g., watched, monitored, suspicious) were less likely to revert, while those who described it in terms of impression management (e.g., on-stage, self-conscious) were more likely to revert. Many of these adjectives align with the social surveillance mechanisms of watching, listening, and interaction (Marwick, 2012). Although surveillance does not occur prevalently in the topic modeling, some aspects of impression management can be seen. The topic around not knowing (and implicitly not caring) how people on Facebook reacted to the respondent's absence essentially deals with instances where impression management on Facebook is *not* particularly important to the respondent. Accordingly, this topic predicts decreased likelihood of reversion. In the demographic and Likert analysis, though, the question about how often others asked about the respondent about not being on Facebook was not a significant factor in our model. These findings extend prior work showing that concerns over surveillance lead users to avoid certain features of social networking platforms

([Guha & Birnholtz, 2013](#)). The results here show that such concerns can influence (non-)use of an entire site. Future work should examine more closely relationships between concerns over institutional surveillance (the government or Facebook watching users) and over social surveillance (users watching each other) (cf. [Baumer et al., 2013](#)).

In results from two of the three surveys, those reporting positive *moods* were less likely to revert, and those reporting negative were more likely to revert. This result can be seen directly in the demographic and Likert analysis, where mood emerges as a significant predictor in both the 33 and 99 days' results. A moderate resonance can be seen in the topic modeling results, specifically, in the "nothing bad happened" topic. Although this topic occurs fairly consistently across the data sets, it only significantly predicts (decreased) reversion in the Day 33 data. A similar resonance can also be seen in the factor analysis: the "enjoyable" factor predicted decreased likelihood of reversion in the Day 33 data. While perhaps obvious, only a few examples of prior work have directly considered the potential influence of mood on non-use. In comparing users and non-users of social networking sites, [Tufekci (2008)](#) finds that non-users perceive such sites as less appealing or enjoyable. In qualitative studies, participants often cite negative experiences as a motivation for ceasing use of a social technology ([Brubaker et al., 2014](#); [Portwood-Stacer, 2013](#); [Schoenebeck, 2014](#)). [Satchell and Dourish's (2009)](#) categories of "disenchantment" and "disinterest" both connote negative experiences as catalysts for non-use. While such prior work describes how mood might influence non-use, this article extends those findings by examining how mood influences the likelihood of returning from non-use back to use.

Finally, the use of *other social media* plays an important, though complex, role. Users will sometimes announce their departure from Facebook on other social media, for example, Twitter ([Portwood-Stacer, 2013](#)). The analysis here explores subsequent impacts of continued use of other social media. Initially, findings from the demographics and Likert responses seem to conflict with those from the topic modeling. In the former, use of other social media predicts *decreased* likelihood of reversion, while in the latter, the topic describing other social media use was associated with *increased* likelihood of reversion. As described above, though, this topic included not only descriptions of increased social media use but also reflections on the role of social media in personal relationships. Thus, simply increasing other social media use may decrease the likelihood of reversion, but incorporating personal reflection, renegotiation, and achievement of a more "authentic" self (cf. [Harmon & Mazmanian, 2013](#)) increases the likelihood of reversion.

This discussion demonstrates how our different methods complement one another to provide a rich picture of social media reversion. Furthermore, it describes how these findings build upon prior work to make contributions in our understanding of social media use and non-use.

Limitations and Future Work

Some of the findings above likely generalize broadly to all situations of technology non-use, while others may not. For instance, feelings associated with perceived addiction may be experienced when dis-using many types of technologies. However, questions around boundary negotiation, that is, impression management and social surveillance ([Marwick, 2012](#); [Palen & Dourish, 2003](#)), likely arise from the "social" aspects of "social media." Thus, factors similar to those we identified would likely arise with many computational technologies designed and/or used to support social interaction. The complex

question of where exactly we analytically demarcate between "social" media and other types of technologies or media, though, far exceeds the scope of this article (see, e.g., Papacharissi, 2015).

The data analyzed here come from a unique, real-world setting and include thousands of respondents. However, since over 40,000 people signed up for 99 Days of Freedom, the response rate is around 10%. Very few respondents completed more than one of the three surveys, and people who returned to Facebook may have been significantly less likely to complete the surveys, giving a skewed sample. Furthermore, since 99 Days of Freedom responded directly to the emotional contagion study (Kramer et al., 2014), those who took the pledge likely represent a particular subset of Facebook non-users. For instance, they may be more attuned to data privacy issues, which may explain in part the salience of concerns over surveillance. They also do not constitute a representative sample of Facebook rejecters (Wyatt, 2003). As noted above, though, these data are not the result of a purposeful, designed social scientific study but a convenience sample that happens to be uniquely suited to address questions around social media reversion (cf. Brubaker et al., 2014). Participants in the 99 Days pledge self-selected and had a vested interest in not using Facebook but still returned to the site before they had intended. That said, the above findings may not be representative of attempted non-use more broadly. Future work should examine other instances of attempted non-use followed by reversion. Furthermore, it could be valuable to explore how reversion evolves over time using, for example, experience sampling or other methods to generate more fine-grained temporal data.

With respect to methods, we suggest a wealth of work could be done expanding and codifying our approach to identifying relationships between topic modeling results and other types of data. The results above show how the exploratory techniques used here can provide unique and informative insights that both reinforce and build upon other analyses. However, the approximate nature of topic modeling means that exact results are not perfectly replicable. Although some recent work has explored selecting among different solutions in large document collections (Roberts et al., 2014), more work needs to be done in comparing topic modeling solutions, identifying consistent patterns across multiple solutions, and determining relationships between topics and other variables of interest, particularly for small- to medium-sized data sets.

Finally, this article provides a primarily empirical exploration of social media reversion. However, we see this area as ripe for theorization, especially by work that synthesizes across this and other related studies (e.g., Baumer et al., 2013; Brubaker et al., 2014; Rainie et al., 2013; Schoenebeck, 2014). In particular, we suggest individual (sense of) agency as a potentially focal concept. Much prior work deals with how and why individuals use or do not use particular technologies (e.g., Hargittai, 2008; Jurgenson, 2013; Lampe et al., 2013; Portwood-Stacer, 2013; Wyatt, 2003). However, many of our results, such as those pertaining to experiences consistent with perceived addiction and to social boundary negotiation, suggest a distributed locus of influence in technology (non-)use. Questions around how much agency an individual actually has, especially in comparison with how much s/he believes s/he has, in their own technology use should figure prominently in future research, both empirical and theoretical.

Conclusion

This article provides valuable contributions to analyzing and understanding experiences around social media. First, it explores the phenomenon of social media reversion, that is, becoming a technology non-

user and then subsequently resuming use of that technology. While hinted at in prior work ([Baumer et al., 2013](#); [Brubaker et al., 2014](#); [Schoenebeck, 2014](#)), this article provides the first indepth exploration of the phenomenon.

Second, this article analyzes a unique real-world data set using a novel combination of mixed methods. The analysis fuses multiple quantitative and computational techniques, including logistic regression modeling, factor analysis, and topic modeling. We complement these analyses with a close qualitative reading of a subset of responses. This synthesis highlights four recurrent influences on the likelihood of returning to Facebook. Experiences consistent with *perceived addiction* (e.g., withdrawal, compulsive urges) increased the likelihood of reversion. In terms of *boundary negotiation*, respondents who attended to surveillance on Facebook were less likely to return, but those who focused on impression management were more likely to return. Positive *moods* decreased the likelihood of reversion, while negative moods increased likelihood of reversion. Finally, respondents who replaced Facebook with other social media were less likely to revert unless they also reflected on and renegotiated their engagement with and through the site. This synthesis enables us to identify and to understand in depth how both individual traits and subjective experiences of non-use may play a role in affecting the likelihood of reversion.

Finally, this article suggests important directions for future work. Methodologically, it opens up intriguing possibilities for combining computational text analysis, such as topic modeling, with survey responses to enable novel, informative approaches to mixed-format data. Conceptually, it provides the first indepth study to focus specifically on social media reversion, demonstrating this as a fruitful area of inquiry and advancing our understanding of experiences around negotiating between use and non-use of social technologies.

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Notes

1. http://99daysoffreedom.com/

2. The full survey instrument is available upon request from the authors.

3. A full list of predictors is available from the authors upon request.

4. In all results, *p* are denoted by + < .1, * < .05, ** < .01, and *** < .001.

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