Understanding Feedback Expectations on Facebook

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ABSTRACT
When people share updates with their friends on Facebook they have varying expectations for the feedback they will receive. In this study, we quantitatively examine the factors contributing to feedback expectations and the potential outcomes of expectation fulfillment. We conducted two sets of surveys: one asking people about their feedback expectations immediately after posting on Facebook and the other asking how the amount of feedback received on a post matched the participant's expectations. Participants were more likely to expect feedback on content they evaluated as more important, and to a lesser extent more personal. Expectations also depended on participants' age, gender, and level of activity on Facebook. When asked about feedback expectations from specific friends, participants were more likely to expect feedback from closer friends, but expectations varied considerably based on recency of communication, geographical proximity, and the type of relationship (e.g. family, co-worker). Finally, receiving more feedback relative to expectations correlated with a greater feeling of connectedness to one's Facebook friends. The findings suggest implications for the theory and the design of social network sites.

Author Keywords
Feedback expectations; Computer-mediated communication; Social Media; Facebook; Information Sharing

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION
Posting and receiving feedback shapes the experience of people on social media. Feedback, whether it is expressed via lightweight one-click communication or more, carries social value that motivates people to post, provides social and emotional support, and shapes relationships over time [12,13,19]. While a considerable body of work has studied the role of feedback in social network sites [12, 15, 19, 26, 37, 46], little research examined the expectations for feedback people have when sharing content to their social network. In this paper we focus on the feedback expectations associated with posting content on Facebook, and the way that expectations vary from one person to another, are dependent on the properties of the post, and are impacted by the relationship to other individuals.

Expectations are an important measure that guides social behavior and attitude, which can inform the design of social network sites. Expectations motivate us to take action and help us choose among alternatives. For example, expectation of feedback is a key motivating factor for participation in online forums, contribution to Wikipedia, and posting on social media [17, 28, 31, 39, 41]. In a recent study, we showed that people visit Facebook more often after posting a status update, potentially in expectation of feedback, even when there was no evidence of actual feedback received [27].

Despite the importance of feedback expectations, previous research did not directly model people's expectations for feedback from their online social networks, nor did it examine the implications of expectation fulfillment. Existing theories of interpersonal communication such as Expectancy Violation Theory [5, 8] do not immediately translate to expectations from online social networks, where feedback is often aggregated and knowledge of viewership is lacking or incomplete. Previous studies on social media touched on several aspects related to expectations such as the "imagined audience", perceived audience size, feedback preferences, norms evolution and violation [3, 13, 32, 33, 35, 44], but did not directly model feedback expectations. Without a clear understanding of feedback expectations it is unclear how actual feedback is perceived and how that feedback (or lack thereof) affects people's experience on social media.

This paper examines people's expectations for receiving Likes and Comments on Facebook, and the relation between fulfillment of expectations to feeling connected to one's Facebook friends. We build on Expectancy Violation Theory (EVT) [5,8] as inspiration for the conceptual framework used in this work. We conduct a comprehensive, in-context examination of the factors associated with feedback expectations immediately after posting on social media. Our investigation borrows from EVT the key elements of the model that contribute to expectation: properties of the communicated content properties, characteristics of the individual who posted it, and individual's relationships to others on the platform. Not only do we look at factors that contribute to expectations, we also study the fulfillment of feedback expectations and its relation to feeling of connectedness to one's Facebook friends, an important outcome for individual well being [15, 29].

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To this end, we use two large-scale surveys to ask people about feedback expectations, fulfillment of expectations, and connectedness to friends. First, we surveyed people immediately after posting on Facebook and asked them about their feedback expectations on that particular post, both in terms of total feedback and from specific Facebook friends. We complemented survey responses with de-identified, aggregated log data to understand how the characteristics of the individuals, posts, and interpersonal relationships are associated with feedback expectations. Using this dataset, we built predictive models of feedback expectations. In addition, we conducted a separate survey, asking participants about an earlier post they made, and how the amount of feedback received compared to their expectations. We also asked participants in this lagged survey how connected they feel to their Facebook friends in order to establish a link between fulfillment of expectations and connectedness.

This study offers a general framework for thinking about feedback, behavior and attitude on social media in the context of expectations. We identify the significant factors associated with higher than usual feedback expectations on a post and the important properties of relationships linked with expectations from specific friends. In addition, we show an association between the congruency of feedback and expectations on a post to an important outcome – individuals' connectedness to their friends. Last, our predictive models can be used in practice to evaluate how well people's expectations are met, and to explore ways of potentially improving the experience of people when posting on social media platforms.

RELATED WORK

Previous work identified several benefits of posting on social media, among them are self-expression, relational development, social validation, and approval [1]. Social media use had been shown to impact both social capital and well being [14–16, 19, 20, 30]. Many of the benefits of social media use come through feedback mechanisms such as Likes and Comments on Facebook. Support and help via feedback are important for alleviating loneliness [15,29], getting emotional support after losing a job or when sharing emotional content [11,12], enabling information seeking [26,37], maintaining relationships [19,46,47], and more. While feedback is a necessary component for all of these benefits, as Bazarova et al. point out, it is one's subjective satisfaction from the feedback received that determines its value for the communicating individual [2].

Other work studied people's perceptions around audience and feedback in computer-mediated communications. People have an imagined audience in mind when posting to friends on social media [32,33], but as Bernstein et al. showed, people's mental model of audience underestimates the number of people who actually see their posts and overestimate the rate at which friends give Likes and Comments [3]. Wang et al. found that posters and outsiders evaluate Facebook updates differently, particularly around topics of self-presentation and relationships [51]. Perceptions about feedback are also highly subjective – different people may have different interpretations of social interactions online. A recent study by Scissors et al. examined the perceptions around lightweight communications on Facebook and found that most people do not consider receiving "enough" Likes as important and assigning importance to getting enough Likes is positively correlated with high levels of self-monitoring and negatively correlated with self-esteem [44]. Previous work did not directly tie the diverse perspectives people have about activities on social media to expectations, which offer a more general view of social behavior as we describe next.

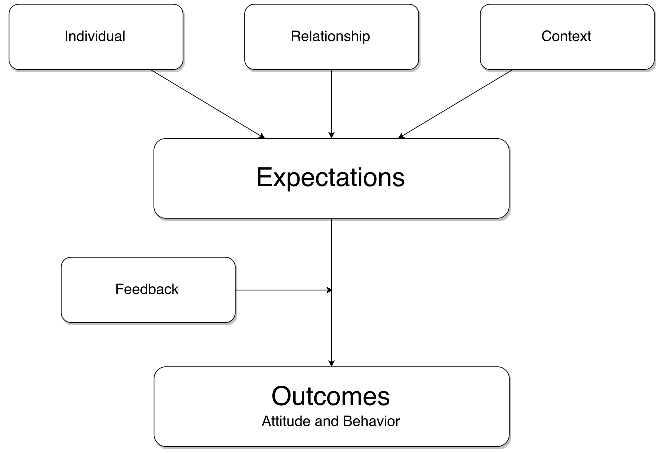

Figure 1. The conceptual framework used in this work, inspired by Expectancy Violation Theory by Burgoon [6].

The notion of expectations is central to many theories about human behavior as it proposes a general framework for understanding behavior and attitude. The conceptual framework used in the current work was inspired by Expectancy Violation Theory (EVT) in communication [5, 8]. EVT was originally developed based on studies of proxemic behavior in face-to-face communication and was later extended to a variety of behaviors [5, 7, 9, 10, 49]. Burgoon defines expectancies as "enduring pattern of anticipated behavior", which derive from three classes of factors: communicator (e.g. demographics, personality, appearance), relationship (e.g. familiarity, similarity, status difference), and context (e.g. private/public environment, the message communicated) [6]. According to EVT, expectancies "serve as framing devices that define and shape interpersonal interactions . . . [and] significantly influence how social information is processed". The congruency between enacted behavior and expectations determines how behavior is perceived, the impression people have of each other, and the outcomes of the interaction. Previous work applied EVT to study norm evolution and violation on Facebook [4,21,35], but focused more on incidents of norm violations by individual friends, well-aligned with the original theory. However, as EVT focuses on single individuals' behavior, it does not directly apply to studying aggregate expectations as we do here. Instead, we use the overall framework of EVT as inspiration for our research model.

Figure 1 shows the conceptual framework used in this work. At the top are three categories of factors that mirror the original EVT model [6], which we also expect to affect expectations of feedback: individual, relationship, and context properties. The characteristics of the individual can include demographics, personality traits, and more. Relationship properties may consist of tie strength between two individuals, differences in status, shared interests and other factors that affect interactions between people. Context includes the additional factors needed to describe a particular situation. In the current study, context primarily consists of properties of the posted content and past interactions on previous posts. The three categories of factors at the top of the figure jointly contribute to people's expectations, which are then compared against the actual feedback received. If, for example, the amount of feedback an individual received from friends exceeded their expectations, they may be more inclined to post in the future, and may feel more connected to their friends. In contrast, unsatisfying feedback experiences may be one of the mechanisms behind departure from online social platforms [55]. As proposed by EVT, and suggested here, the congruency between the observed feedback and expectations determines people's attitude and subsequent behavior.

Much like the early studies of proxemic behavior in face-to-face communication [5, 9], we seek to understand the important factors behind feedback expectations on social network sites (top of Figure 1). Our first two research questions focus on characteristics of the individual (left) and the posted status update, i.e. the context (right). It is important to distinguish expectations across people because individuals experience social media very differently: seeing different sets of stories and a variety of interactions with them (see [53] for an example). Similarly, distinguishing between expectations for different posts is important because posts vary in content and importance to the individual [38, 50]. Therefore, our first two research questions are:

RQ1*: What are the characteristics of individuals (e.g. age, gender, etc.) that affect feedback expectations?*

RQ2*: What are the properties of posts (e.g. length, topic, etc.) that affect feedback expectations?*

Next, we study the third category of factors in Figure 1 that affects feedback expectations – relationship properties. Previous studies showed that people have different preferences for feedback from strong and weak ties on Facebook [13, 35] and from different social groups (e.g. close friends, family, co-workers, etc.) [44]. However, prior work did not directly examine expectations from specific friends (rather than abstract social groups), on a specific post, for different forms of feedback (e.g Likes and Comments), and at the time of posting (rather than retroactively). The complexity of social relations calls for a joint examination of all the above aspects of relationships in order to gain a more comprehensive understanding of relationship expectations. Therefore, our third research question is:

RQ3*: What are the relationship properties (e.g. based on relationship type, tie strength, age difference, etc.) that affect feedback expectations?*

Finally, motivated by work on social capital and well being [14–16, 18–20, 30], we investigate one potential outcome of fulfilling feedback expectations. Self-Determination Theory describes a basic human need for relatedness – to belong and feel connected to the people, group or culture sharing the individual's goals [43]. In offline settings, greater relatedness was shown to contribute to daily well being [42]. Since getting feedback is one of the key motivating factors for participation online [17, 28, 31, 39, 41] it is likely that the actual feedback received would affect people's satisfaction with their relationships. In fact, two recent studies point in that direction, showing that when people share emotional content on Facebook, friends respond with more emotional and supportive Comments, which is associated with greater satisfaction with communication goals [2, 11]. Previous findings, however, did not extend beyond emotional content or tie received feedback to relationship satisfaction. The conceptual framework in Figure 1 borrows from EVT to suggest that both expectations and observed behavior (whether they are met) will affect outcomes. Specifically, our question is:

RQ4*: How does the fulfillment of feedback expectations relate to feeling connected to one's Facebook friends?*

With these questions in mind, we performed a quantitative mixed-methods study of feedback expectations on Facebook, as we describe next.

METHODS

In this section we describe the mixed-methods approach we used in order to address our research questions about feedback expectations. Following previous work, we use survey mechanisms to ask people about their subjective perceptions of social media activities [3, 44]. We then complement survey responses with observational log data to gain better understanding of the contextual factors that explain expectations.

Surveys

We conducted two online surveys by recruiting participants on Facebook's web interface (Facebook.com)[1]. The first survey asked participants about their expectations for feedback for a specific post. The survey was offered to people immediately after they posted a status update, as a pop-up dialog. We refer to it here as the *Immediate survey*. The second survey was offered to people 23-27 hours after they posted a status update, as a banner on their Facebook page. This *Lagged survey* asked participants about fulfillment of expectations for that day-old post. The surveys were limited to English speakers in the U.S. with 20 friends or more that did not participate in any survey conducted by Facebook in the six months prior to ours. Participation in both surveys was voluntary and did not involve compensation in any form. The surveys ran for 20 days, between July 27, 2015 to August 16, 2015. The samples for both surveys were drawn from the same sampling frame, but were non-overlapping (people were invited to participate in either one of the surveys, but not both[2]). The response rate varied between the two surveys, with a lower response rate of

[1] Due to the length and complexity of surveys we left the development of mobile versions to future work.

[2] we choose this design over repeated surveys of the same people for two reasons: 1) to eliminate the potential bias that answering questions in the Immediate survey influences answers to the Lagged survey, and 2) lower the burden on people of answering repeated surveys day after day.

Average difference from a random sample	Immediate survey	Lagged survey
# Log in days out of 28	**3.4***	**4.4***
# Log in days out of 7	**1.0***	**1.2***
Friend count	**151***	6
Gender (% Female)	0.0%	**5%***
Age	-0.7	**1.9***
N	2788	4032
Response rate	33%	78%

*p<0.001 using 2-sample t-test comparing each survey separately to the random sample.

Table 1. Usage and demographic statistics of survey participants relative to a random sample of English speakers in the US who logged-in to Facebook on the web at least once in the month prior to both surveys.

33% for the Immediate survey versus 78% for the Lagged survey. The difference was probably due to the Immediate survey's disruptive nature as a pop-up immediately after posting compared to the more organic banner of the Lagged survey[3]. In total, 2788 people completed the Immediate survey and 4032 completed the Lagged survey.

Table 1 summarizes key differences between demographic and usage characteristics of survey participants and other people on Facebook. We compare the participants in the surveys to a random sample of US, English speaking individuals who accessed Facebook's web interface at least once in the month prior to our surveys. As highlighted in Table 1, survey participants are more active Facebook users compared to the random sample, logging-in to Facebook about 4 additional days over the course of 28 days. Participants in the Immediate survey have more friends on average, while more females and older individuals participated in the Lagged survey. Overall, we conclude that the participants in the surveys are slightly more active on Facebook than a random sample, but no other major differences are evident.

Measures

We now turn to describe the measures included in our surveys about feedback expectations and their fulfillment. Certain common elements are likely to affect both the expectations on a particular post, measured in the Immediate survey, and fulfillment of expectations, measured in the Lagged survey. Therefore, we include in both surveys the following 5-point Likert scale questions:

- **Connectedness**: how connected do you feel to your Facebook friends? (1=very disconnected, 5=very connected).
- **Importance**: how important is this post to you compared to your average post? (1=much less than usual, 5=much more than usual).
- **Personal**: how personal is this post? (1=not at all, 5=very personal).

[3]A pop-up was necessary in the Immediate survey to capture responses before any other action is taken on the site. We opted for a banner in the second survey because a pop-up in this case would have been out-of-context and hence much more disruptive to the user experience.

Figure 2. The *Friends Grid* question that was populated with a stratified sample of the participant's friends (in random order). Participants were asked to specify for each friend whether they expect a Like and/or a Comment on their latest post, shortly after posting it. Profile pictures and names are blurred in this figure, drawn for demonstration from the first author's account, in order to preserve individuals' privacy.

In addition, the Immediate survey asked participants about feedback expectations for the post:

- **Post-level expectations**: how many Likes and Comments do you expect to get on your latest post? (1=far fewer than usual, 5=far more than usual).
- **Friend-level expectations**: we presented a personalized *Friends Grid*, a two column grid populated with a sample of up to 22 of the participant's friends (described below), asking participants to indicate whether they expect a Like and/or a Comment from each individual friend.

The Lagged survey, on the other hand, first showed participants their post along with its feedback (as it appears in News Feed). Then, it asked participants about:

- **Fulfillment of feedback expectations**: how did the Likes and Comments received so far match your expectations? (1=far fewer than expected, 5=far more than expected).

Figure 2 shows the layout of the Friends Grid used in the Immediate survey. In order to get a more balanced sample of friends with and without feedback expectations we included in the Friends Grid a stratified sample of the participant's friends. We chose a stratified sample of friends over a random sample because a random sample is mostly dominated by weak ties that may not be associated with any feedback expectations. Our stratification randomly picked friends of the participant from Facebook lists the person may maintain (close friends, acquaintances), friends with overlapping profile information (same workplace, college, high-school, home town or current city), self-reported family ties (parent, child, sibling, spouse), and most recent interactions (last Like or Comment, given or received). In addition to sampling a random friend from each of these groups we included the friend from each group that the person communicated with most frequently (without introducing duplication).

Checkboxes in the Friends Grid may remain unchecked because the participant had no feedback expectations from that friend or because it is the default option. To address this bias, we use an assumption that people scan items visually from top to bottom, and from left to right[4]. This linear scanning assumption has been studied extensively in the analysis of search results and was shown to improve results relevance [45]. In our case, a friend is associated with "no expectation" only if the participant made a selection in a lower position in the grid or to the right. After processing the raw responses, our dataset consisted of 568 participants who labeled 5,256 of their friends with expectations for only a Like (30.1%), only a Comment (3.8%), Like and a Comment (11.4%), or no feedback (54.7%).

Log data

We complemented the survey responses with Facebook's server logs in the 12 weeks prior to the survey in order to better understand the context of reported expectations. All log data were observational – no experiment was performed and no individual's experience on the site was altered. The log data includes the posts that participants were asked about, profile information such as education or work history, and friendship information. We took significant steps to ensure people's privacy: all data were de-identified and analyzed in aggregate such that no individual's text could be viewed by researchers.

POST-LEVEL EXPECTATIONS

This section addresses our first two research questions about feedback expectations of different people (RQ1) on different posts (RQ2), and then focuses on estimating how accurately these expectations can be predicted.

We address our first two research questions by fitting a logistic regression to the reported expectations on a post (from the Immediate survey) with covariates that describe the individual, the feedback received on the individual's previous posts, and the newly posted content. We include both individual and post-level covariates in the regression model in order to understand how each group of factors varies while the others are held constant. For example, in addressing RQ1 we examine the characteristics of individuals that associate with higher than usual expectations while holding the properties of the post constant at their mean value. Our dependent variable in the regression is positive whenever a person reported expecting more than usual feedback on her post (4 or 5 on the Likert scale, where 3 was labeled "about the same as usual") and negative otherwise. We focus in particular on cases with higher than usual expectations since these are most likely to result in an unsatisfying experience when unmet.

Individual differences: Different people are likely to have different expectations. Therefore, we include in the regression information about age, gender, tenure on Facebook (years since creating the Facebook account), friend count, and the number of days in the past week that the participant logged in to Facebook (L7). Age, tenure and L7 were centered; friend count was log-transformed (base 2) to account for skew prior to standardization and the rest were centered and scaled using two standard deviations[5].

Past feedback: Feedback on previous posts is also likely to affect expectations. Therefore, we compute the median and interquartile range (IQR)[6] for the following measures of feedback based on the individual's posts in the prior 12 weeks: number of Likes per post, Comments per post, Likes per view, and Comments per view. We also include the number of Likes and Comments on the most recent post of the individual since these might have greater impact on expectations. All variables were standardized as described earlier, except for the number of Likes/Comments per view which were log-transformed prior to standardization.

Content properties: Posts interest people to various degrees and therefore result in different expectations. Our dataset contained only few posts with photos and therefore we excluded those and focused only on textual posts. Our content properties include a variety of features: basic (word count, does the post contain a URL?), subjective assessments (how personal/important is this post?), topics, and emotional dimensions. The text was preprocessed and converted to lowercase, tokenized, and punctuation, stopwords and terms appearing in less than 5 posts were removed. All of the textual features were extracted using standard scripts over de-identified content such that no member of the research group examined any individual post.

We used Supervised Latent Dirichlet Allocation (sLDA) to model the topics that appear in posts [34]. The benefit of sLDA over "standard" unsupervised LDA is that topics are fit to better separate class labels. In our case, we used higher than usual feedback expectations as binary class labels. We experimented with different numbers of topics ranging from 10 to 60 (in increments of 10) and found no significant improvement in log-likelihood beyond using 20 topics. Using the trained sLDA model (using 10-fold cross validation) we get a single probability that represents the likelihood that a post is associated with higher than usual feedback expectations. We include the sLDA prediction in our final model.

Emotional dimensions were extracted using the 2007 version of Linguistic Inquiry and Word Count (LIWC) [40]. Most fine-grained LIWC categories (e.g. filler words) had no or very little support in our dataset and therefore we only included high-level categories such as function words, positive and negative emotions, social terms, achievement terms, and time orientation information (references to past, present or future). All of the LIWC features were included in the form of proportion of the total number of words in the post.

Without limiting the number of content properties in our regression, we run the risk of overfitting the data and finding spurious correlations as statistically significant. We address this concern in two different ways. First, we keep the number of covariates small relative to the number of survey responses

[4]The left to right assumption is reasonable since all of our participants are English speakers.

[5]Unless specified otherwise, all continuous covariates were centered and scaled by two standard deviation in order to put them on roughly the same scale as untransformed binary variables [23].

[6]a robust measure of dispersion, defined as the difference between the upper and lower quartiles.

Higher than usual feedback exp. ~	Coef.	SE
Intercept	-1.56^{***}	.15
Individual differences		
Age (years)	0.0098^{**}	.0037
Is male	0.13	.13
Tenure (years)	-0.14^{***}	.03
Log_2(Friend count)	0.93^{***}	.14
Connectedness	0.58^{***}	.13
L7	−0.041	.055
Posts per day	−0.002	.024
Past feedback:		
Likes(last post)	−0.26	.20
Comments(last post)	0.02	.16
IQR(Likes per post)	0.01	.21
$Median$(Likes per post)	0.19	.22
IQR(Comments per post)	0.48^{*}	.19
$Median$(Comments per post)	−0.38	.21
IQR(Likes per view)	0.00	.19
Log_2($Median$(Likes per view))	0.09	.15
IQR(Comments per view)	−0.19	.22
Log_2($Median$(Comments per view))	0.33^{*}	.16
Post:		
Importance	1.22^{***}	.15
Personal	0.36^{*}	.14
Has link	−0.22	.20
Log_2(Word count)	−0.08	.17
sLDA prediction	0.26^{*}	.13
LIWC:		
funct	0.18	.16
posemo	−0.27	.16
negemo	0.19	.12
social	0.04	.14
percept	0.22	.12
bio	−0.17	.13
achieve	0.32^{**}	.12
past	−0.19	.15
present	−0.14	.15
future	−0.10	.15
$P(Y\|X)$	20.47%	
Log Likelihood	-813.4	
Akaike Inf. Crit.	1886.8	

$N = 2,788$; *p<0.5; **p<0.01; ***p<0.001

Table 2. Coefficients of Bayesian logistic regression for having higher than usual feedback expectations on a post.

(2,788) by limiting the number of topics and emotional dimensions we include. Second, we use Bayesian logistic regression with a non-informative Cauchy prior (0 median and 2.5 scale) to pull regression coefficients slightly towards zero apriori, but allow for large coefficients when the data does support it [24]. The coefficients in a Bayesian logistic regression have the same interpretation as those of a "standard" logistic regression.

Findings

Table 2 shows the resulting coefficients of the Bayesian logistic regression with the binary dependent variable of having higher than usual feedback expectations on a post. All variance inflation factors (VIF) were less than two, indicating that multicollinearity is not an issue in our independent variables. The logistic regression assigns a probability of 20.47% for having high expectations to the average person (designated by $P(Y|X)$ in the table), closely matching the empirical proportion in the dataset with less than 0.01% in difference. Significant coefficients appear in all three categories of features, as we describe next.

In terms of individual differences (RQ1), four properties of the person posting the content are statistically significant: age, tenure on Facebook, number of friends and Connectedness. Each additional year of age is associated with a exp(0.0098) = 1.009 = +0.9% increase in the odds of having higher than usual expectations. More significantly, doubling the number of friends on Facebook and feeling more connected to friends increases the odds by 38.6% and 29.6%, respectively. In contrast, each additional year of having a Facebook profile is associated with a -13.3% decrease in the odds of having higher than usual expectations.

Past feedback also contributes to higher feedback expectations, but only through Comments. There is an increase of 11.4% in the odds of high expectations for every additional Comment in the individual's interquartile range, and 23.9% increase in odds when doubling the median rate of Comments per view. None of the measures based on past Likes or feedback on the last post were significant. These findings suggest that greater variability in past Comments (but not Likes) contributes to higher feedback expectations, and that people learn over time the rate at which their friends comment on their posts even without explicit knowledge about views.

Several aspects of the post's content affect feedback expectations (RQ2). First, increases in the Importance and Personal scales translate into higher expectations (78% and 16% increase in odds, respectively)[7]. The fact that personal and important posts are associated with considerably higher feedback expectations highlights the value in better understanding these subjective assessments by people, which is beyond the scope of the current work. Second, sLDA predictions based on broad topics found in the post increase the odds ratio modestly (+5.5%). The only emotional aspect that is significant is the occurrence of achievement terms. None of the other LIWC dimensions such as positive or negative emotions significantly affect expectations.

In summary, our findings show that individual differences, past feedback and posts' content are linked to higher than usual feedback expectations on a post. Age, number of friends and Connectedness are positively associated high expectations, while tenure on Facebook is negatively associated. Past Comments (and not Likes) affect expectations, and posts that are important, personal, and refer to achievements have higher expectations. Overall, we see that different people have different expectations for different posts, and that past behavior of friends (mostly in commenting) affects future expectations.

Next, we evaluate how well feedback expectations for a post can be predicted in order to assess the practicality of integrating feedback expectations into the design of social networks sites.

Predicting post-level expectations

In this part we examine how well different subsets of the features from Table 2 predict the feedback expectations that an author has for her Facebook post. We test the following three

[7] recall that all of surveyed content had the same privacy settings: posts shared by participants with all of their Facebook friends.

Higher than usual exp. ~	AUC	P@R5	P@R50	P@R95
baseline: last post percentile	49.0 53.0 57.0	22.6 29.5 36.5	19.6 21.3 22.9	19.3 20.6 22.0
individual differences Age + Gender + # Friends	60.2 62.6 65.0	33.8 55.9 78.0	25.0 29.5 34.0	18.8 21.4 24.0
+ past feedback	61.0 63.4 65.7	39.4 51.6 63.8	26.5 30.2 33.8	21.0 22.5 24.0
+ content:	67.4 **70.7** 73.9	57.9 **69.6** 81.3	38.7 **43.9** 49.1	21.9 **23.3** 24.7
+ self-reports: Connectedness + Post importance + Personal	75.4 **77.7** 80.0	68.6 **81.7** 94.7	46.6 **50.4** 54.2	23.0 **25.1** 27.2

Table 3. The predictive power of different feature sets obtained using either glmnet or gbm. P@R stands for precision at different recall levels of 5, 50 or 95 percent. Numbers above/below in each cell represent 95% confidence intervals.

predictive models as implemented in R: Elastic-Net Regularized Generalized Linear Models (glmnet [22]), Generalized Boosted Regression Modeling (gbm [54]), and Support Vector Machine (from the e1071 package [36]).

Table 3 summarizes the results of 10-fold cross-validation of the best-performing model for each feature-set. Our baseline, which uses a personalized percentile of feedback received on the last post relative to the individual's posts in the prior 12 weeks, only performs marginally better than random. The predictive performance improves significantly over the baseline when including user information (62.6% AUC), adding past feedback (63.4% AUC) and finally content features, reaching 70% AUC. Using log data alone, the model identifies posts with higher than usual feedback expectations with a precision of about 70% when retrieving only 5% of posts with high expectations. In other words, at the level of 5% recall, the model will return one out of 20 posts with high expectations and would correctly identify the expectations for seven out of every 10 posts returned. As shown in Table 3, precision naturally deteriorates when increasing the recall to 50% or 95%. Last, including participants' answers to survey questions improves performance even further, showing that subjective information is important and not fully captured by other variables. In particular, feeling connected to friends, knowing the post's importance and how personal it is, are all important predictors of high feedback expectations.

Next, we address our third research question about the characteristics of relationships that affect expectations for feedback from one friend and not another.

FRIEND-LEVEL EXPECTATIONS

In this section we use the responses from the *Friends Grid* in the Immediate survey to address RQ3: which properties of relationships affect expectations for feedback from different social ties? We examine how similarities and differences between two people as well as long-term and short-term communication patterns relate to expectations of feedback from that person. We fit two separate logistic regression models, one for Like expectations, the other for Comment expectations, on the same set of responses and relationship features.

Before we describe in greater detail the relationship properties used for addressing RQ3 we first specify the controls included in our models. We control for the order in which friends appeared in the Friends Grid, the characteristics of participants and the properties of posts. Despite the random order of friends in the Friends Grid, certain positions in the grid may receive more attention. Therefore, we include the position information in our model relative to the top (1-top to 11-bottom) and relative to the left (0-left, 1-right). In addition, as we saw in the previous section, individuals have different expectations for different posts. Since our focus here is on dyadic properties that affect expectations from a specific friend we control for non-dyadic features that were identified as significant in addressing RQ1 and RQ2. The complete list of control variables can be found in Table 4.

We describe below the three families of features we considered in our model for friend-level expectations: dyadic differences, topical similarity, and relationship properties.

Dyadic differences: the relative differences between participants and their friends may affect expectations. We include in our model demographic and activity information about the participant's friends in relative form, e.g. the difference between the friend's age and the participant's age. We also considered interactions between covariates, since different subpopulations may have different expectations. For example, age difference may be linked to higher expectations in general, but the gap can matter differently for younger and older adults.

Dyadic topics similarity: the perceived interest of a friend in a topic is likely to affect expectations for a response when the topic is discussed. Here, we develop a set of features aimed at capturing the overlap in topical interests of participants and their friends, and quantifying how a particular post fits into this overlap. For every individual, we aggregated the topics of all posts that they interacted with into a vector of high-level topical interests. Then, we computed interests similarity using cosine similarity between the participant (denoted as u) and their friend (denoted as f), and between the post (denoted as p) and the friend's interests. Due to the large amount of posts involved, we used a TagSpace model to extract the proportions of topics in posts [52], and reduced the topic space to 20 high-level most frequent topics (e.g. music, entertainment, education).

We also compute friend specificity to a topic in two different ways. First, we calculated the percent of the participant's friends that are highly interested in each of the post's topics[8] (denoted as $AUD(topic)$). As a second measure of specificity, we compute weighted friend share ($WFS(topic)$), based on the relative frequency the friend of interacts with a topic. We use tie strength (described below) as weights in WFS in or-

[8]We define "high interest" as exceeding a topic-specific threshold that is set to the upper quartile in the population. For example, a person who interacts with more than 8% of political posts would be considered as having high interest in politics.

der to give strong ties greater influence on the final measure of specificity than weaker ties. For both measures of topical specificity we took the maximal specificity score among the post's topics.

Dyadic relationship properties: this set of features focuses on social structure and communications between the participant and their friends. To represent social structure we create a set of indicator variables that designate whether the friend is a close family member (parent, child, sibling, spouse), member of a Facebook list that the participant maintains (close friends, acquaintances), or has overlapping profile information (same workplace, college, high-school, home town, or current city). In order to understand how expectations deviate for members of the same social structure, we also include a binary variable (designated by ^{best}) to indicate the strongest tie in that social circle.

Communication between people provides an additional dimension to social structure. We calculate a rough approximation of the tie strength between two people using the long-term frequency at which they communicate in any form (e.g. liking, commenting, tagging, direct messages) as recorded in our logs over 12 weeks. Gilbert and Karahalios showed that frequency of communication is one of strongest predictors of tie strength [25]. In order to evaluate the effect of recent communications, we include indicator variables for the most recent friend who gave a Like or a Comment to the participant or received one from her.

Findings

Table 4 and Figure 3 describe the separate logistic regression models we fitted (on the same feature set) to Like and Comment expectations from individual friends. Both models converged and produced comparable estimates ($P(Y|X)$) to the empirical percentages of expectations reported in the survey (41.68% for Likes, 15.2% for Comments). Significant coefficients appear in every category of features as we discuss next.

	Likes		**Comments**	
Friend expectation ~	*Coef.*	*SE*	*Coef.*	*SE*
Controls:				
Intercept	-0.82^{***}	.22	-2.95^{***}	.27
Position top	-0.02	.03	0.081^{*}	.036
Position right	0.130	.078	0.125	.099
Age	0.0071^{**}	.0024	0.0072^{*}	.0030
Is male	0.27^{**}	.10	0.48^{***}	.13
Q_1^{frnds}	-0.18	.11	0.40^{**}	.13
Q_3^{frnds}	0.039	.093	0.03	.12
Q_4^{frnds}	0.23^{*}	.10	0.06	.13
Tenure	-0.099^{***}	.020	-0.141^{***}	.025
L7	-0.137^{**}	.044	-0.009	.061
Connectedness	-0.070	.066	-0.291^{***}	.080
Importance	0.293^{***}	.073	0.43^{***}	.10
Personal	0.222^{**}	.073	0.22^{*}	.10
Individual diff.:				
ΔAge	0.0041	.0044	0.0048	.0057
$Age \times (\Delta Age)$	0.07	.15	0.17	.21
Is diff gender	0.146	.086	0.01	.11
Is male-female rel.	-0.28^{*}	.14	-0.32	.18
Δ Friends	-0.18	.22	-0.25	.30
$Q_1^{frnds} \times (\Delta$ Friends)	0.13	.30	-0.44	.40
$Q_3^{frnds} \times (\Delta$ Friends)	0.24	.26	0.05	.36
$Q_4^{frnds} \times (\Delta$ Friends)	0.22	.24	0.46	.32
$\Delta Tenure$	-0.023	.033	-0.133^{**}	.041
Tenure $\times (\Delta Tenure)$	-0.07	.14	0.33	.18
Δ L7	0.032	.067	0.114	.091
L7 $\times$ (ΔL7)	0.63^{*}	.28	-0.19	.37
Topical interests:				
$\cos(u, f)$	0.228^{***}	.068	0.25^{*}	.10
$\cos(p, f)$	-0.073	.069	0.08	.13
$max_{topic} AUD(topic)$	-0.071	.068	0.108	.079
$max_{topic} WFS(topic)$	0.152^{*}	.078	0.198^{**}	.071
Relationship:				
Relationship type	**(See Figure 3)**			
Tie strength (TS)	2.91^{***}	.19	1.79^{***}	.24
TS $\times$ Importance	-0.65^{*}	.30	-0.35	.40
TS $\times$ Personal	0.12	.30	-0.19	.39
$P(Y|X)$	41.27%		13.3%	
Log Likelihood	-2840.2		-1910.5	
Akaike Inf. Crit.	5796.3		3937.1	

$N = 5,256$; *p<0.5; **p<0.01; ***p<0.001

Table 4. Coefficients of Bayesian logistic regressions for expecting a Like and a Comment on a post from a particular friend.

Many of the findings for post-level expectations also hold for expectations from specific friends, but a more nuanced picture emerges. For example, participants with relatively fewer friends (in the lower quartile Q_1^{frnds} with $20 - 146$ friends) are more likely to expect a Comment from a friend while those with more friends (in the upper quartile Q_4^{frnds} with $632 - 5000$ friends) are more likely to expect a Like. This shift in expectations is in line with previous findings showing a preference for composed communications from strong ties and lightweight communications from weak ties [13]. In addition, we see that male participants expect more feedback than females, but as we will see next this effect is mitigated by the friend's gender.

Only some dyadic differences have a significant effect on feedback expectations from specific friends. The difference in activity levels between the listed friend and the participant ($\Delta L7$) is not significant on its own unless the participant herself is more active than average. Gender differences in general do not show a significant effect, but the interaction term ("Is male-female rel.") shows that males have lower expectations for Likes from their female friends. Gaps in the number of friends and age between participants and their friends are not significant.

Shared topical interests and specificity of close ties are associated with higher feedback expectations. The fact that our weighted measure (WFS) is statistically significant while the non-weighted measure ($AUD(topic)$) is not suggests that topical specificity matters more for close ties than weaker ties. These elevated levels of expectations can be explained by similarity to close ties or by the fact that one is more likely to know the topical interests of their close ties.

Other relationship properties are strongly correlated with feedback expectations. Doubling the frequency of communication with a friend increases the odds of a Like or a Comment expectation tremendously – by 5-17 times. The only exception to this general trend is for Likes on important posts, which can be seen in the negative coefficient of the interaction term of tie strength and the post's importance in the Likes

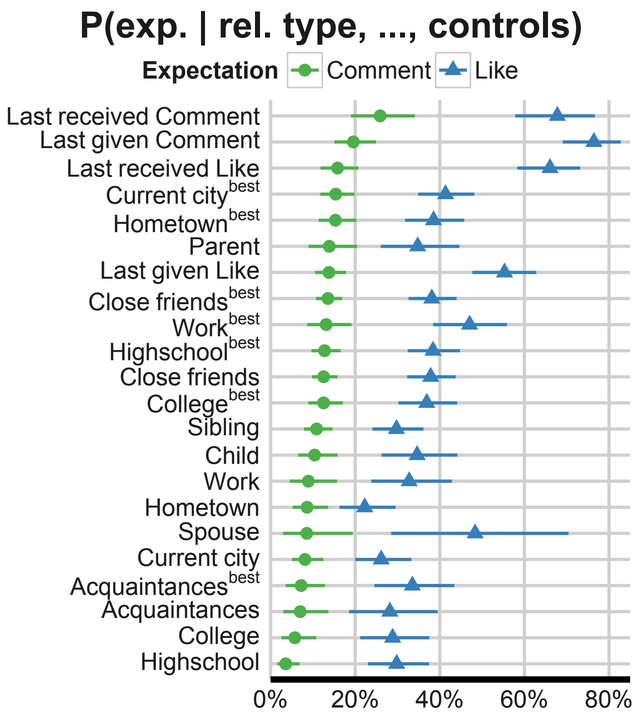

Figure 3. Probability of expecting a Like or a Comment from different social ties (95% CIs). X^{best} **indicates the friend in social circle** X **that the participant most frequently communicates with.**

model (TS × Importance). An important post is associated with slightly *lower* expectations from close ties, which shows that content moderates expectation differently for Likes and Comments, and from different social ties.

Figure 3 shows the impact of social structure on feedback expectations. The figure shows how the probability of expectations (x-axis) changes for different types of relationships (y-axis), when all other variables from Table 4 are held constant at their mean value. Comment expectations are presented with green points and Like expectations with blue triangles. For example, the second row of the figure shows that participants are about 80% likely to expect a Like from the last person whom they gave a Comment to.

The results in Figure 3 highlight four important aspects of social structures: recency, geographical proximity, family ties, and close friendships. The appearance of recently communicated friends at the top of the figure highlights the strong association between recency and feedback expectations, even after controlling for longer-term tie strength and a variety of other measures. In fact, the level of expectations for recently communicated friends is above and beyond close-family ties and most frequently communicated friends in every other social circle. We also see that the best friends from the current location (city or hometown) are associated with higher expectations than many other social ties. Parents and siblings are expected to comment more than friends with similar Likes expectations, while spouses are expected to like more than friends with similar Comments expectations[9]. It is possible

[9]The small number of spouses in our sample, 26, increases its confidence interval, but the gap between Likes and Comments' expectations is statistically significant with $p < 0.001$.

Friend exp. ∼	AUC	P@R5	P@R50	P@R95
Baseline: grid position	59.4 60.9 62.4	62.3 70.9 79.5	50.7 53.5 56.2	44.9 47.1 49.3
Demographics & activity info.:	62.9 64.0 65.0	59.6 66.2 72.8	55.1 57.1 59.1	47.5 49.0 50.6
+ Tie strength	74.0 75.8 77.6	88.4 92.3 96.3	71.4 73.7 76.0	49.6 51.3 53.1
+ Topical similarity and specificity	74.4 76.2 78.0	85.3 89.7 94.1	70.6 73.7 76.8	50.2 52.2 54.1
+ Social structure	79.7 **80.7** 81.8	92.3 **95.8** 99.4	77.7 **80.1** 82.5	51.3 **53.6** 56.0
+ self-reports: Connectedness + Post importance + Personal	79.8 **81.3** 82.7	91.4 **96.3** 100.0	78.0 **81.1** 84.2	51.9 **54.8** 57.7

Table 5. Predicting friend-level expectations for a Like or a Comment using different feature sets obtained using gbm. P@R stands for precision at different recall levels of 5, 50 or 95 percent. Numbers above/below in each cell represent 95% CIs.

that lower expectations for Comments from spouses reveal a preferences for face-to-face feedback over online communications in this case. Last, we note that the best friend indicator variables were found significant in every social group except Acquaintances, for whom people have lower expectations in general. The significance of best friend variables demonstrates that the closest-ties in most social circles have much higher feedback expectations, beyond what is expected based on the frequency of communication with them or any other factor in our models. Therefore, we conclude that recent communication, geographical proximity, family ties, and close friendships increase feedback expectations considerably, even after controlling for individual differences, posted content, and other relationship properties.

Predicting friend-level expectations

Models that identify friend-level feedback expectations can help social network sites evaluate how often people's expectations from their friends are met, identify possible reasons for unmet expectations, and ultimately guide the design of platforms to do better targeting and deliver more satisfying experiences to people. Therefore, our goal in this section is to assess how well a predictive model can identify friend-level expectations in practice.

We test different subsets of features from Table 4 in predicting the feedback expectations from a particular friend, without distinguishing between Likes and Comments for simplicity. Again, we use three different machine learning models for predicting expectations (glmnet, gbm and SVM), this time for feedback from a friend (Like or Comment) as reported in the Friends Grid. Table 5 summarizes the results of 10-fold cross-validation of the best-performing model for each feature-set.

The baseline model obtains 60% AUC using information about the friend's position in the grid alone. However, simple demographic and activity information about people's Facebook activity surpasses the baseline with 64% AUC. Then, including tie strength improves the predictive ability considerably, from 64% to 75.8% AUC. The topical features alone achieve 66% AUC (not in the table), but when added to the rest of the features improve the predictive accuracy only marginally. A second considerable increase in performance is obtained using information about the relationship type – the AUC increases from 76% to closer to 81%, demonstrating that social structure carries valuable information about expectations that is not captured by other variables. Last, subjective information about Connectedness and the post's importance and intimacy only adds little to the predictive ability of the model. Most likely, the self-reported variables encode information already captured by other variables.

Our predictive model outperforms the baseline and identifies friend-level expectations with good accuracy (80%) using log data alone (no self-reported measures). When the model is set to retrieve only half of the cases with expectations (recall of 50%) it will correctly identify feedback expectations of held out individuals for four out of five of their friends (80%). At this level of performance, social media platforms can begin to estimate how well people's expectations are met and explore designs that improve people's satisfaction from their online interactions.

FULFILLMENT OF EXPECTATIONS & CONNECTEDNESS

Finally, we analyze participants' responses from the Lagged survey to understand the relationship between fulfillment of expectations and feeling of Connectedness (RQ4). First, we examine the relationship between two of the measures from the Lagged survey: *Fulfillment of feedback expectation* and *Connectedness*. Then, we establish that feedback expectations carry valuable information about connectedness that is not captured by the raw amount of feedback received or other measures.

Figure 4 shows a positive correlation between Connectedness and fulfillment of expectations, as reported by participants in the Lagged survey. The measure of Connectedness (y-axis) is presented using numerical values (1=very disconnected, 3=neither connected nor disconnected, and 5=very connected) and the measure of Fulfillment of expectations is presented on the x-axis. For example, people who reported receiving about the same amount of feedback as they expected averaged 3.86 on the 1-5 Connectedness scale.

The results in Figure 4 highlight an important relation between fulfillment of feedback expectations and connectedness. The more feedback received relative to expectations the more connected people feel to their Facebook friends: each unit increase on the fulfillment of feedback expectations scale translates into an addition 0.26 of connectedness. Overall, people move from 3 (neither connected nor disconnected) when their expectations are far from being met closer to 5 (very connected) when their expectations are exceeded considerably.

We ran an additional control survey to rule out the possibility that the response on the Connectedness question, which appeared first, may affected the response on fulfillment of expectations question. In the control survey we omitted the Connectedness question, and found no significant difference in the distribution of responses to the fulfillment of expectations question ($\chi^2 = 5.56$, df = 4, p-value = 0.23). Therefore, we conclude that there is no evidence of a priming effect between the two measures.

Next, we establish that knowledge of feedback expectations provides valuable information that is not captured otherwise. In particular, we show that neither the feedback on the particular post nor the feedback on previous posts can better explain connectedness than knowledge about people's expectations. We do so by using both linear and non-linear regression models to predict the Connectedness people reported in the Lagged survey. Our goal is not to perfectly explain Connectedness, which is a complex social and psychological construct, but rather show that expectations carry important additional information that is not captured by past (or present) feedback.

We calculate three different measures of feedback and compare them to the single measure of Fulfillment of expectations from the Lagged survey. First, for simplicity, we combine the Likes and Comments into a single measure of Weighted Feed-

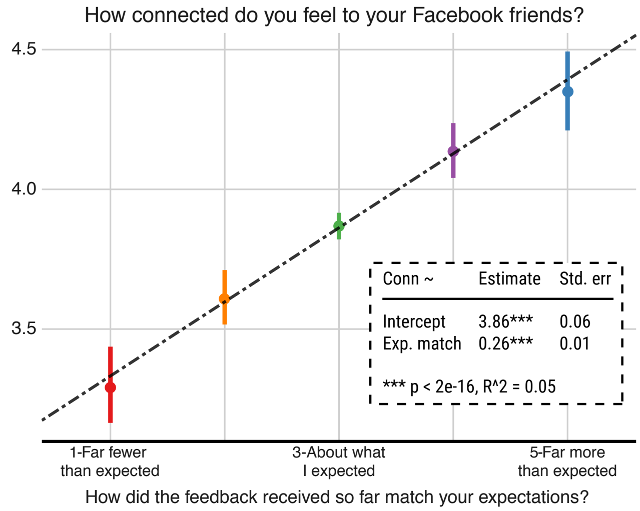

Figure 4. Responses from the 24h Lagged survey about fulfillment of expectations (x-axis) and feeling connected to Facebook friends (y-axis) with 95% CIs.

	AUC	
Connectedness ~	*Linear Regression*	*SVM*
Random answer	50.0%	50.0%
$log(1+WF) \times \log(\#Friends)$	55.0%	55.5%
$WF^{glbl} \times \log(\#Friends)$	55.0%	55.8%
$WF^{invd} \times \log(\#Friends)$	54.4%	55.3%
Fulfillment of expectations	**58.8%**	**58.8%**
All of the above	61.0%	**62.7%**

Table 6. The predictive power of feedback and expectation using linear regression and SVM. Fulfillment of expectations is the single strongest predictor for Connectedness with 58.8% AUC, only second to the model that uses feedback and expectations jointly.

back: $WF = Likes + 5 \times Comments$ that gives more weight to Comments since they are more rare[10]. WF is based on the Likes and Comments received on a single post in the 24 hours after posting, similar to timing of our Lagged survey. We then compute the percentile of WF relative to the distribution of all posts in our log data (denoted as WF^{glbl}) or the individual's previous posts (denoted as WF^{indv}). Since our measure of fulfillment of expectations implicitly incorporates knowledge of the friends network, we include the friend count of the individual both as a separate predictor and as an interaction term with the WF measures.

Table 6 shows separately the predictive power of our measures of received feedback, fulfillment of expectations, and the combination of actual feedback and expectations. For example, the model that uses received WF on the post and friend count to predict Connectedness achieves 55% area under the curve (AUC) using linear regression and 55.5% using SVM. The measure of fulfillment of feedback expectations is the single strongest predictor for Connectedness (with 58.8% AUC), outperforming models using the actual feedback (WF), feedback relative to the global distribution (WF^{glbl}), and a personalized measure of feedback (WF^{indv}). These results demonstrate that knowledge of expectations is valuable for important concepts like Connectedness, and cannot be simply substituted by feedback information.

DISCUSSION

In this study, we complemented survey responses with log data to better understand people's expectations for feedback on Facebook. We have shown that when feedback expectations are met people feel more connected to their friends on Facebook. We also presented a nuanced view of how those expectations are shaped. We showed that whether a participant expected a post to receive more feedback than usual depends on the importance, intimacy, and content of the post. This expectation also depended on the characteristics of the individuals themselves: their age and gender, as well as how long they had been active on Facebook. Furthermore, we demonstrated how the expectation for feedback from a particular friend varies depending on tie strength, recency of communication, geographical proximity, relationship type, and the relative strength of relationship within the social group it is embedded in.

In addressing our first two research questions we found supporting evidence that links some characteristics of individuals and posts to higher than usual feedback expectations. The subjective importance and intimacy of posts were the two strongest content properties associated with higher than usual feedback expectations. The result about intimacy of content is in line with self-disclosure literature [1, 48], which showed that people seek more social validation when broadcasting to many friends. Greater desire for social validation could also lead to increased feedback expectations. The fact that both the importance and intimacy were significant for post-level expectations highlights the need to better understand these important concepts. Future work could investigate what properties of the content (e.g. linguistic features, style, topics, etc.) makes a post subjectively more important for an individual. Similarly, future research can investigate the mechanisms behind some of the individual differences we found in feedback expectations on a post. For example, higher feedback expectations of older adults can be due to building stronger ties over time or because expectations are less calibrated.

As for expectations from specific friends (RQ3), we provided a nuanced view that integrates tie strength and social structure. Recent communicators are associated with the highest feedback expectations. Gilbert and Karahalios showed the importance of recent communications in the prediction of tie strength [25], but the considerable effect of recent communications on feedback expectation was not shown before. We also found a more nuanced preference for Comments over Likes that depends not only on tie strength but also on social structure. For example, spouses and best workplace friends have relatively low commenting expectations despite being strong ties, which perhaps reveals an expectation of face-to-face communications from these friends. These results add to the findings of Burke and Kraut about different communication preferences for strong and weak ties [13]. Finally, the best friends in each social group have higher expectations associated with them, even after controlling for their tie strength, social structure, and all other properties included in our models. Taken together, these results provide a glimpse into the complex and inter-connected nature of expectations from different social ties.

Our findings also suggest that the fulfillment of expectations on a single post has a sizable effect on how connected people feel to their friends (RQ4), and that this effect is not fully captured by information about feedback alone. This result shows that for one important outcome, people's sense of connectedness to their friends, the general framework of expectations does indeed help in understanding people's attitude better than any other measure in our models. Moreover, this result highlights one potential mechanism, fulfillment of expectations, through which social media use contributes to one's subjective well being (as found in other studies [15, 19]). We emphasize, however, that the correlation we found between fulfillment of expectation and Connectedness does not warrant a causal relation (despite our additional control survey). The experimental evidence in the literature (e.g. [42]) leads us to believe that fulfillment of expectations does indeed affect Connectedness, but further work is needed to establish a causal link.

Feedback expectations are not only important, but also predictable, which paves the way for studying how expectations can be incorporated in social systems. Our models identified feedback expectations for posts with good accuracy. The prediction of expectations for a representative sample of friends (rather than the stratified sample used in our study) is likely to attain even higher accuracy due to the higher proportion of weak ties that are likely to have no feedback expectations associated with them. However, it remains an open question whether systems should adapt to posters' expectations, and if

[10] other weighting of Comments did not significantly change the results.

so, to what extent. How can the prediction of feedback expectations be used to improve the experience for both the person creating the content and their friends? Is content associated with higher-than-usual feedback expectations more likely to be interesting to a wider range of a person's friends? How does the fulfillment of expectations on one post affect expectations on subsequent posts? And if having one's feedback expectations met correlates with a greater feeling of connectedness, would understanding one's audience [3] be helpful? We leave these and other questions for future work.

Limitations and future work

Despite our attempts to capture feedback expectations as accurately as possible, our study design has several limitations. People may have different interpretations for expectations, which may vary from the bare minimum of feedback that would be "enough" to desires and hopes. Moreover, directly asking people about expectations may elicit expectations that did not exist before taking the survey and may not always be well-calibrated. In addition, the length and complexity of surveys led us to rely on single-item measures, which are generally less reliable than multiple-item measures. As noted earlier, our findings are based on observational analysis that does not allow us to infer causality.

There are several remaining gaps that would be fruitful avenues for future research. First, our work identified many important factors for feedback expectations that are worthy of further investigation. For example, why does age contribute to feedback expectations? why do males have higher expectations from specific friends? does the impact of recent communications on expectations stem from memory mechanisms or reciprocity? Second, our surveys focused on a single post at a certain point in time. Therefore, it is not yet clear how expectations evolve over time, and whether people's expectations and feedback received on prior posts influence expectations on any subsequent post. In addition, our surveys merely asked people about the existence of Like and Comment expectations, which do not capture the full range of possible responses[11]. For example, people may expect supportive Comments from some friends, sarcastic replies from others, and more informative responses from acquaintances. Our work also identified potential value in developing language models that would better capture the subjective importance and intimacy of posts.

Our results may not accurately represent expectations in other populations, forms of media, and platforms. While the general framework of expectations was shown to be relatively universal [6], the concrete expectations people have may be specific to a certain culture, language, or community. Even within the population of people on Facebook, the stratified sample of friends we used may not accurately represent the entire friends network, especially in cases where people's profile information is incomplete. In addition, sharing other forms of media, such as photos, videos or mixed-media content may be associated with other factors that affect expectations. Finally, different social networks bring about different social dynamics and with it varied feedback expectations. For example, if people share more public content on Twitter then expectations for may perhaps shift towards Retweets rather than Likes. While some variables in our models are Facebook-specific, we believe that the categories we developed in this work and their relation to feedback expectations will generalize to other social network sites. That being said, the current work only looked at one social media site, at one point in time, and surveyed a tiny fraction of the people on Facebook. We look forward to other works that would utilize our survey design and conceptual framework to contrast our findings with those from other social media platforms.

[11] Our study was conducted before the introduction of Facebook Reactions, which are an extension of Likes.

Conclusion

This work demonstrated that feedback expectations vary considerably across people, posts, and interpersonal relationships. Higher than usual feedback expectations on a post are linked to the characteristics of the post (importance, intimacy, and content), individual (age, gender, activity on Facebook), and past Comments. Neither the length of posts nor the sentiment of posts were found significantly correlated with feedback expectations. People have higher expectations from closer ties in general, but these are moderated by recency of interactions, geographical proximity, relationship type, and close friendships. Moreover, we found that the fulfillment of expectations is associated with feeling more strongly connected to friends, thus potentially contributing to individuals' well being. Last, our predictive models can estimate people's expectations with good accuracy, which paves the way for future research into the benefits and limitations of integrating expectations in social systems.

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