“Social watching” a Civic Broadcast: Understanding the Effects of Positive Feedback and Other Users’ Opinions

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ABSTRACT

People increasingly turn to social media to augment their broadcast viewing experience with a parallel stream of information and opinion. Known as “social watching,” the practice of integrating broadcast media and social media has become routine for many citizens tracking live events and breaking news. In a controlled laboratory study, we examined how interactivity and exposure to social media opinions influence a sense of community, attitudes and discussion elaboration. The results suggest that receiving positive feedback to social media posts instills a psychological sense of community in the poster, and this feeling of connectedness is related to greater elaboration of the civic social media discussion. Secondly, the study found support for conformity effects. The third contribution of this work is a better understanding of how the valence of others’ social media posts and the user’s posting activity influences cognitive elaboration of social media discussions during social watching in civic contexts.

Author Keywords

Social media; television; social watching; second screening; interactivity; community; conformity; cognitive elaboration

ACM Classification Keywords

K.4.3 Organizational impacts; Computer-supported collaborative work

INTRODUCTION

Social media lets users find out about what others think, feel and say about a media event as it unfolds in real time. “Social watching”—or the activity of using social media such as Facebook or Twitter to simultaneously discuss or learn about video broadcasts—has become increasingly pervasive. A Nielsen global online survey of 30,000 respondents found that more than half, or 53 percent, say they keep up with television shows as a way to join conversations on social

media [43]. Many people intertwine social media and broadcast media simultaneously through “second screening” or “dual screening,” which is the use of a mobile device while watching television [43]. One platform that has been frequently used to track live broadcasts is the microblogging site Twitter, which allows people to post messages in 140 characters or less and “follow” any public account. People use Twitter to connect socially, get information, find entertainment, express their thoughts and get attention and recognition [5,28,40,52,68]. Twitter’s hashtag feature—topical metadata preceded by the “#” symbol—serves as an embedded vehicle for “ambient communion” [67]. It allows people to find information about breaking news [24], sports events [31] or natural disasters [32] as they unfold in real time.

The CHI and CSCW communities have explored the phenomenon of social watching during live broadcasts to better understand user motivations [17], information diffusion [16], behavioral patterns [3,35,62] and topic detection [9,42]. Only recently, experiments and surveys have explored how the activity relates to political deliberation [36] and political participation [17,62]. Experimental and quasi-experimental studies have found social watching influences attitudes toward candidates [22,36,37], memory [23], engagement [22,23] and conformity [4,36]. However, the effects of receiving feedback during social watching is little understood, a gap which this study is designed to address.

Through a controlled laboratory experiment, we examined whether posting or receiving Twitter-like “favorites” influenced the poster’s sense of community with others who are also posting about the same topic. The study also explores whether people conform to the majority opinion on social media during social watching. Finally, it examined the extent to which posting and receiving feedback or viewing different social media opinions influenced cognitive elaboration of discussions.

LITERATURE REVIEW

In this paper, we are interested in social watching and its relationship between: interactivity and community, conformity, and cognitive elaboration. As such, we draw on and present the literature across these three spaces, defining research accordingly.

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Interactivity and a Sense of Community

Recent research on social watching has explored the extent to which levels of engagement influence users' vote decisions [36] and political participation [17,62]. For instance, Vaccari, Chadwick and O'Loughlin [62] identified "bundles" of "lean forward" and "lean back" social watching practices. "Lean forward" practices such as commenting on Twitter significantly predicted political participation, while "lean back" activities such as passively reading messages in one's timeline did not. They suggested that social watching increased political participation when people actively contributed to the online discussion [62]. While promising, social watching research has yet to explore how the next step in the communication process—whether the poster receives feedback from his or her audience or not—influences the poster. The question extends beyond self-expression into interactivity and is the focus of this study.

Whereas there is no academic consensus on how to define interactivity [37,47,54], to frame this exploration we draw on McMillan's [39] conceptualization of interactivity which operationalizes interactivity as having three dimensions: user-to-user, user-to-system and user-to-document interaction. User-to-user interactivity refers to how people interact with each other through media; user-to-system interactivity refers to how humans interact with machines; and user-to-document interactivity refers to interaction with document creators (e.g., users writing to journalists) or interaction with documents (e.g., users reading or creating news content). This study focuses on the influence of simulated user-to-user interactivity—specifically, feedback in the form of a "favorite," a way of indicating agreement, support or positive affect toward user-generated content, as well as a way to bookmark a post.

Interactivity through positive feedback such as "favorites" or "likes" on social media are common, especially among young people, according to a study comparing behavior of teens and adults on Instagram [25]. These acts of positive validation beget more reciprocal acts on a social network site, as Surma [59] found in an analysis of nearly 400 undergraduates' Facebook data in Poland. People may even adjust their social media behavior because they expect feedback [19]. A study that analyzed the behavior of 2.4 million Facebook users found that users checked the site more often after posting—possibly because they were expecting a response [19].

In this study, we explore how receiving responses to posts influences users' connection with their audience, or their community. Scholars have defined online communities in terms of relationships, while others focus on the software and spaces for interaction such as email threads, bulletin boards and chat forums [51]. At least one definition of community by Benedict Anderson [2] emphasizes a sense of connectedness in the mind of the individual. Anderson [2] studied nationalism among citizens who are unlikely to interact but share a sense of unity and identity—using the

term "imagined community" to describe the way people living in modern civilizations imagine a connection to other citizens, despite the impossibility of interacting with everyone in their society. More recently, scholars have used the concept of imagined community as an analytical lens to study the microblogging site Twitter [20].

However, in this study we adopt the definition of community deployed by McMillan and Chavis [38], as they operationalize a sense of community in a way that is independent of interactions or proximity. Their model has four dimensions: group membership, the potential to sway other members and be influenced, needs fulfillment and emotional connection [38].

Group membership is defined as feeling like a rightful part of a group and has five components: group identification and belonging, emotional safety, personal investment, boundaries and a common symbol system [38]. *Influence* is defined as mutual sway between individuals and the group to which they belong, meaning members feel they can impact the group, and the group can also pressure individuals to conform [38]. *Needs fulfillment* refers to the idea that membership should be rewarding to members [38]. Rewards for membership could include prestige, success of the community or the competence of members [38]. In a strong community, members help each other achieve their goals while also satisfying their own needs. *Emotional connection* hinges on identifying with a shared history [38]. This can depend on the investment a person makes into the group, as well as the frequency and quality of interactions. Connection is also forged through closure, or resolution of tasks [38].

As people engage with others, the interactivity through positive feedback would be expected to instill a sense of community in the recipient. Literature on flattery—or praise that is delivered without regard for a person's actual performance—suggests that people who receive it tend to feel good, like people who flatter them and evaluate the flatterer more positively [15]. Based on this research, we question whether positive feedback—even flattery delivered indiscriminately—increases a sense of community in the recipient, which leads to our first research question:

RQ1. *During social watching, does receiving positive feedback increase a sense of community in the poster?*

Conformity During Social Watching

Studies on social watching suggest people who use social media to learn about or discuss a broadcast may conform to the majority opinion, even when they are viewing posts by people they do not know [4,36]. In a study by Cameron et al. [4], participants watched a pre-recorded *American Idol* performance or political speech while viewing a positive-leaning Twitter feed, a negative-leaning feed or no Twitter feed. The posts were pre-scripted, and participants did not post tweets themselves. Participants who viewed Twitter feeds while watching a broadcast conformed to the majority opinion [4]. In another study by Maruyama, Robertson,

Douglas, Semaan and Faucett [36], participants watched a televised political debate while using their own Twitter accounts on their own device from their own homes. The experimental manipulation in the field study was the level of Twitter participation: post on Twitter versus observe but do not post versus do not use Twitter [36]. Participants who posted on Twitter were more likely to switch their vote opinion, and most of the vote switchers conformed to the majority opinion on the hashtag feed [36].

The literature on conformity suggest there are two types: informational and normative [8]. The former is based on a desire to hold accurate views and behave appropriately according to a shared reality [21], while the latter happens because people want to gain social acceptance [7]. Both accuracy and social affiliation motivations can serve to protect a person's self-concept and self-esteem [7]. Based on prior studies on conformity during social watching, this study asks whether people who use social media to learn about or discuss a civic broadcast change their attitude to reflect the majority opinion on the social media feed or not, which leads to our second research question:

RQ2. *During social watching, does the majority opinion on the social media feed influence the viewer's attitudes?*

Discussion Elaboration

Cognitive elaboration is the process of "attempting to access relevant associations, images and experiences from memory" [49]. Generating these associations is considered a form of "higher-order thinking" [63:190]. In a journalistic context, elaboration has been described as "the use of news information to make cognitive connections to past experience and prior knowledge and to derive new implications from news content" [63:190]. The information discussed in the news, particularly in political stories, often influences citizens' lives directly or indirectly. However, these implications are not always clear to the news consumer [33]. Being able to understand how an issue relates to an individual and society extends beyond recollection of discrete facts. In other words, a person's ability to recall a candidates' name or policies is an important first step to becoming informed, but reformulation, elaboration and synthesis of information is necessary to make personal relevance clear and move a citizen to action. Moreover, connections between new content and previous knowledge [46] increases the overall relatedness of information in memory through a more redundant memory structure, which helps with retrieval and inferring information that is unavailable [46].

Robert Slavin [58] outlines four theoretical explanations for why discussion leads to greater elaboration. First, the cognitive elaboration perspective argues that anticipating conversation motivates the communicator to restructure and elaborate on his or her arguments. Research on explainer-listener and tutor-tutee pairs have found the speaker experiences better learning gains than the listener through the

cognitive reformulation [63]. Because the benefits occur while crafting speech acts in one's mind, the mere intent to share information improves learning, even if no information is shared [41]. The developmental perspective refers to the idea it is *only* through peer interaction that learners become acquainted with new perspectives, challenge their own beliefs and develop mastery of concepts [58]. When discussions expose disagreement between members, individuals resolve their own cognitive dissonance through higher reasoning [61]. The motivational perspective is based on the idea that cooperative incentive structures increase interdependence and motivation to learn together [58]. The social cohesion perspective suggests that people learn more in groups not only due to extrinsic rewards, but also because group members care about each other [27,58]. It is important to note that these perspectives are not mutually exclusive [58].

Communication researcher William Eveland [12] has also explored how discussion influences elaboration. He explored three different rationales: (1) exposure to a discussion partner's ideas about the news leads to learning, which is similar to the two-step flow of communication [30], (2) anticipating discussion motivates discussants to elaborate on ideas prior to conversation, and learning benefits accrue even if the discussion does not occur [11], and (3) the act of discussing leads to increased learning as discussants retrieve memories and reprocess them during verbalization [12]. The first and third explanations are most similar to Slavin's [58] developmental perspective because learning benefits only accrue during discussion, while the second explanation is most like his cognitive elaboration perspective [58]. In an analysis of telephone survey data collected prior to the 1996 election, Eveland [12] found support for his second and third explanations, suggesting that expecting discussion and actually discussing increases elaboration. Eveland and Thomson [13] designed a measure of discussion elaboration, or cognitive elaboration due to conversation, which was used in this study.

Based on these perspectives, it seems posting and receiving feedback may increase discussion elaboration. Yet, media multitasking studies have found that attending to a video while reading inhibits comprehension and counter-arguing [26,64]. Therefore, posting and receiving feedback may distract participants from the broadcast and inhibit elaboration of the content. Based on this conflicting research, the following question is posed:

RQ3. *During social watching, does posting or receiving positive feedback influence discussion elaboration?*

Not only might the level interactivity influence the way people think about the discussion, but the valence of the civic discussion on social media may also impact the extent to which people elaborate. Research suggests that news framed in a negative tone can seem more important [57] and that positive coverage can seem less consequential [55]. On the

other hand, research on social media and political deliberation suggests that users are averse to flaming due to political disagreements [10,56]. Studies found that people avoid conflict by creating positive spaces of civic discussion [56] and removing people with negative and heated opinions from their newsfeeds [10]. Because it's unclear how the valence of social media posts would influence discussion elaboration during social watching, we ask the following question:

RQ4. *During social watching, does viewing positive versus oppositional versus balanced opinions influence discussion elaboration?*

METHOD

To explore our research questions, we conducted a controlled laboratory study in which participants used a tool designed by the first author to view a pre-recorded televised broadcast and a microblogging feed. The experimenter told participants they were watching and participating in a live discussion with participants in their group and another group elsewhere on campus. In actuality, none of the participants interacted with each other. All of the posts and interactions were programmed in advance using a bot-like system, and there was no other group on campus. The story about a simultaneous group in another laboratory was intended to explain why participants saw posts on the feed when no one in the room was posting. When a participant did post, only the author could see it in his or her feed.

The simulation was designed to maintain high internal validity. If the participants interacted with each other, then participants may influence each other in a way that could confound results. For instance, a talkative participant's level of user-to-user interactivity might "spill over" into another participant's interactivity treatment level, violating the Stable Unit Treatment Value Assumption (SUTVA), which assumes each unit is unaffected by the assignment of another unit [54]. Moreover, the design controlled for confounding variables that emerge in live conversations, such as the number of posts, the pace of interaction and the identities of sources.

The design of the experimental laboratory study contrasted different levels of user-to-user interactivity on social media (Interactivity). It also contrasted exposure to varying levels of favorable and unfavorable opinions toward a civic issue in social media posts as another factor (Opinion). The Interactivity factor had three levels: posting on social media and receiving positive feedback, posting on social media and receiving no response, and observing the social media feed without posting. The Opinion factor also had three levels: social media material that supported a position toward a civic issue, social media material that opposed a position toward a civic issue and social media material that was balanced in support and opposition.

Therefore, the Interactivity factor was crossed with the Opinion factor in a 3 (Interactivity: post and receive

feedback vs. post without feedback vs. observe) x 3 (Opinion: support vs. oppose vs. balanced) factorial design, where one factor manipulated the user's level of interactivity, while the second factor varied the social media opinion they were exposed to. Participants were randomly assigned in groups to an Interactivity and Opinion condition. Table 1 shows the number of participants in each combination of the factors.

Interactivity	Opinion		
	Support	Oppose	Balanced
Post and Receive Feedback	15	12	15
Post without Feedback	12	13	13
Observe	13	17	12

Table 1. The number of participants in each combination of Interactivity and Opinion factors.

Sample

One hundred thirty-one undergraduate students from a large American university were recruited and received class points or extra credit for their participation. Nine participants were excluded from the analysis because either they had previously participated in a related pilot study, they did not follow the study directions or they disclosed in post-experiment interviews that they did not believe they were interacting with real users. This left 122 participants with usable data, including 77 women and 43 men (two non-responses).

Ninety-seven percent of the participants were younger than 30, and 72% were 20 years old or younger. The majority, 80% of participants, reported being "social watchers." They used social media while watching TV to learn about what they were viewing, and many reported doing so regularly. About 63% of participants reported posting on social media while watching TV to talk about what they are viewing, and a quarter did so a few times per week or more. When asked what media they use to social watch, the top online platform was Facebook, followed by YouTube and Instagram. The fourth platform was Twitter, with about 42% of participants using the microblogging platform to track what they watch on TV. Prior to the experiment, 70% of the participants (two non-responses) reported being "undecided" about the civic topic discussed during the study's social watching session.

Setting

During the experimental session, participants were exposed to a video and social media posts about recent development in a neighborhood called Kaka'ako, which is located in the City of Honolulu in the United States. Once a cradle of agriculture and a home to indigenous royalty during ancient times [66], the community developed into an immigrant camp, then later a gridded district of industrial low-rise buildings known for its automobile repair shops, wholesaling and warehouses. This once-quiet industrial neighborhood

has recently drawn developers' attention and rapidly transformed into one of the fastest growing communities on the island. Squeezed between upscale shopping near the state's largest shopping mall and towering skyscrapers of the city's downtown area, the 600-acre district¹ has been touted by developers and government leaders as a potentially vibrant core of luxury and affordable housing, retail, restaurants and new rail stops.

In 1976, legislation gave a state agency the dual missions of both incentivizing redevelopment and regulating it. Decisions made by the agency have drawn suspicion and citizen protest. Surfers and fishermen rallied against a proposal to build residential towers near the neighborhood's waterfront, which led state lawmakers to nix the project. More recently, an environmental nonprofit unsuccessfully backed legislation that would abolish the state agency that oversees development in the neighborhood².

Materials

Broadcast

All of the participants, regardless of their group assignment, watched the same broadcast: a televised panel discussion about development in the neighborhood. The episode aired on that state's Public Broadcasting Station on April 3, 2014. This broadcast was chosen because it provided more contextual and balanced information than other stories on the topic. In the show, a panel of four stakeholders discussed the question, "Is Kaka'ako moving in the right direction?" The panelists included the executive director of the state agency that oversees property development in the district, the director of the county planning and permitting department, a trustee representing a state agency that has rights to develop in the area, and a community activist that opposes the way the government is allowing the neighborhood to be developed.

Social Media Posts

Crafting the social media content displayed by the bot-like system was a detailed process. Existing social media posts were chosen and modified to appear to respond to the broadcast. Twitter posts—or tweets—from the night of the broadcast were collected by searching for the hashtag promoted by the show's moderator. Also in the corpus were tweets posted throughout the following year with the #Kakaako hashtag. We lightly edited tweets so they seemed to respond to the broadcast. We also wrote tweets that fell into broad categories that emerged from a study of Twitter posts about a television broadcast on poverty in the U.K. [3]: posts about how the topic was framed, posts about panelists' responses and posts that reflected on societal issues. These

tweets were designed to mimic posts that are typically posted during social watching [3].

To ensure that each tweet was plausible and understandable, four to five trained raters evaluated each post in the 318-tweet corpus for believability, comprehensibility, and valence toward the neighborhood's development. Raters included one undergraduate, two Ph.D. students, a post-doctoral researcher and a professor at the university where the experiment was conducted. Researchers have used similar methods to evaluate the suitability of experimental stimuli in persuasion studies [48]. The following questions were asked about each post: (1) "How believable is this tweet?" (where 1 = not at all believable and 5 = very believable); (2) "How comprehensible is this tweet?" (where 1 = not at all comprehensible and 5 = very comprehensible); and (3) "How much does this tweet support the way Kaka'ako is being developed right now?" (where 1 = oppose strongly and 5 = support strongly).

Posts whose believability, comprehensibility and valence received high rater agreement—as measured by standard deviations of .58 or less—were included as experimental stimuli. Posts with an average believability or comprehensibility score of 4.75 or greater were kept, meaning they were on average closer to "very believable" and "very comprehensible." The valence scores were used to identify posts as neutral, supportive or opposing development in the neighborhood. Neutral posts received a 3 rating ("neutral") from all raters. Supportive posts received an average rating of 4.75 or higher (closer to "support strongly" than "support somewhat"). Opposing posts got an average rating of 1.75 or less (closer to "oppose strongly" than "oppose somewhat"). Based on these requirements, 47 tweets were chosen, including 5 neutral posts, 21 supportive posts and 21 opposing posts.

Participants in each Opinion group viewed the same posts. Participants in the support group viewed posts that mostly supported development in the area (70 percent support, 15 percent oppose and 15 percent neutral). Participants in the oppose group mostly viewed posts that opposed construction in the neighborhood (70 percent oppose, 15 percent support and 15 percent neutral). Participants in the balanced group viewed posts evenly divided in opinion (42.5 percent support, 42.5 percent oppose and 15 percent neutral). The distribution of valence was modeled after another study on conformity during social watching [4].

Once tweets were selected, names for sources of the tweets were created using an online random name generator³. User handles remained constant across conditions to minimize any influence source names might have on interpretation of the

¹ <http://dbedt.hawaii.gov/hcda/discover-kakaako/>

² The full text of HB 18664 is available at http://capitol.hawaii.gov/Archives/measure_indiv_Archives.aspx?billtype=HB&billnumber=1864&year=2014

³ <http://www.behindthename.com/random/>

associated tweet. Aside from the generated names, no additional profile information or photos were displayed to the participants. Otherwise, the posts were designed to look like messages on the microblogging site Twitter.

Interface

Prior to using the interface, participants received a 5-minute tutorial on how to use the tool's features. Participants started by creating a username for the session on a log-in page. After logging in, the video started immediately. The interface was evenly split between the video and a microblogging feed similar to the popular platform Twitter. Participants pressed a refresh button to view social media posts that seemed to respond to the broadcast, but were actually programmed in advance—unbeknownst to the participants. The participants' username and a count of the number of favorites and retweets their posts received were displayed in the upper left corner. Users could favorite, retweet and reply to posts. If a post was retweeted or favorited, its retweet or favorite count under the post would increase when the feed refreshed. Figure 1 shows the interface of the mock Twitter tool.

Figure 1. The interface used by participants during the study.

The participants in the *post and receive feedback* condition received automated favorites to their posts. To increase realism, not every tweet posted by participants in the condition received a favorite. The first post received zero favorites. The second post received one favorite. The third and fourth posts received no favorites, then the fifth post received three favorites. The pattern then repeated. The participants in the *post without feedback* condition received no response, and participants in the *observe* condition refreshed their feed without posting—and, therefore, did not receive a favorite since there was no participant-generated post to favorite. A pilot study tested the interface with undergraduates at the same university ($n = 17$). Post-experiment focus group interviews during the pilot study revealed no usability problems with the tool. **Procedure** Participants attended study sessions in a campus laboratory in groups of up to seven at a time. Students were told they would be using a closed platform similar to Twitter, where their posts would only be seen by participants in their session, as well as participants in another session in another room on campus. In actuality, none of their posts could be

seen by other participants, and all of the social media content they viewed was programmed in advance.

Participants began with a pre-exposure online survey using SurveyMonkey. Then, an experimenter gave the participants a tutorial on the tool they would be using and delivered instructions based on their random assignment to an Interactivity group. The conditions that posted (Post and Receive Feedback and Post without Feedback) were asked to submit at least three original tweets. The Observe condition was asked to view the feed without posting. Besides these instructions, they were asked to use the tool as they would normally use social media.

The experimenter appeared to sync the broadcast with another classroom, then asked the participants to create an account and begin using the tool for 30 minutes. After the session, participants completed a post-exposure online survey. The session concluded with a brief group discussion about the experience of using the tool. Following the study, participants were debriefed about the intricacies of the study design and goals of the work.

Measures

Several dependent variables were measured during the survey, which are described below.

Brief Sense of Community Scale

The Brief Sense of Community scale measures a psychological connection to a group and operationalizes feelings of group membership, needs fulfillment, mutual influence and emotional connection [47], shortening the original scale by McMillan and Chavis [38]. The 8-item measure was modified to reflect the participants' experience in the session by substituting references of "this neighborhood" with "this social media feed" [47]. Participants indicated their agreement to the following 8 statements using a 7-point scale, where 1 = strongly disagree and 7 = strongly agree:

Item 1: I could get what I needed on this social media feed.

Item 2: This social media feed helped me fulfill my needs.

Item 3: I felt like a member of this group on the social media feed.

Item 4: I belonged in this social media feed.

Item 5: I had a say about what went on in this social media feed.

Item 6: People on this social media feed were good at influencing each other.

Item 7: I felt connected to this social media feed.

Item 8: I had a good bond with others on this social media feed.

Post-exposure Attitude Extremity

Attitude extremity refers to how favorable a person feels toward something [1]. While extremity has been measured

using multiple semantic differentials such as good–bad, wise–foolish, beneficial–harmful or favor–oppose [34], a single feeling thermometer scale has also been used [65]. Participants used a feeling thermometer to self-report their favorability toward a topic on a numeric scale, where the polar ends were labeled extremely unfavorable and extremely favorable [1]. A 7-point scale similar to the feeling thermometer asked, “How favorably or unfavorably do you feel toward the way Kaka’ako is being developed,” where 1 = extremely unfavorable and 7 = extremely favorable.

Discussion Elaboration

The discussion elaboration variable measures how people processed information related to the social media discussion. In a study on the effects of conversation on political knowledge, Eveland and Thomson [13] averaged six items related to cognitive elaboration due to discussion, including imagining and empathizing with others while anticipating discussion [18] and being exposed to new ideas during discussion. The items were changed from a 6-point scale to a 7-point scale to provide a mid-point category of “Neutral” to participants who were ambivalent, indifferent or uncertain. Participants who posted on social media expressed agreement, where 1 = I definitely disagree and 6 = I definitely agree, to the following statements:

Item 1: When I knew I was going to post on social media just now, I tried to think of things to say in advance.

Item 2: When I knew I was going to post on social media just now, I tried to think of good arguments ahead of time.

Item 3: When I posted on social media just now, it made me think more about my own opinions and beliefs.

Item 4: When I posted on social media just now, I thought about how other posts relate to my own personal experiences.

Item 5: After I posted on social media just now, I continued to think about what other people posted later.

Item 6: Posting on social media just now made me think about that topic after the posting was over.

Participants who were in the observe condition responded to statements modified to reflect their experience, such as: “When I knew I was going to view posts on social media just now, I tried to think of good arguments ahead of time.”

Covariate: Pre-exposure Attitude Extremity

A covariate of pre-exposure attitude extremity was taken to control for pre-existing attitudes. In the pre-exposure survey, participants rated their favorability toward the way the neighborhood is being developed by responding to the following item, where 1 = extremely unfavorable and 7 = extremely favorable: “How favorably or unfavorably do you feel toward the way Kaka’ako is being developed?”

Covariate: Attitudinal Dissimilarity

Attitudinal dissimilarity measured the difference between participants’ pre-exposure attitude extremity and their

perception of the popular opinion on the social media feed. It was calculated by subtracting the pre-exposure attitude extremity score from the item below.

In the post-exposure survey, participants rated how other social media users felt toward the way the neighborhood was being developed on a 7-point scale, where 1 = extremely unfavorable and 7 = extremely favorable. The item asked, “Overall, how favorable were the tweets you saw in today’s study toward the way Kaka’ako is being developed?”

For instance, if a participant rated their pre-exposure attitude extremity as extremely favorable (“7”) and their perception of others’ attitudes as extremely unfavorable (“1”), then their attitudinal dissimilarity measure would be “-6.” This would indicate that they believed that other users felt much more negatively about the issue than they did.

Covariate: Pre-exposure Interest

To measure pre-exposure interest, we asked participants to indicate how much they agreed with the following statement, where 1 = strongly disagree and 7 = strongly agree [45]: “I am interested in the way Kaka’ako is being developed” and “I would like to know more about the way Kaka’ako is being developed.”

Covariate: Pre-exposure Knowledge

To control for pre-exposure knowledge, we asked participants to indicate their level of knowledge about development in the neighborhood using the following 5-point item, where 1 = No knowledge and 5 = Very high knowledge: “Please indicate your general knowledge about development in Kaka’ako.”

RESULTS

Data Screening

Prior to conducting Analyses of Covariance, data were screened for missing values, internal consistency, normality and collinearity. For the 8-item measure of Brief Sense of Community, each item was missing no more than four data points. Most variables were only missing one or two cases. Absent data are a less critical concern if 5 percent or less of the data are missing, which was the case in this study, and methods of dealing with missing data will likely yield similar results when under this threshold [60]. Group mean substitution was used to replace missing data, which is an acceptable method of dealing with missing cases [60].

Group	<i>n</i>	Unadjusted Mean	<i>SD</i>	Adjusted Mean	Std. Error	Bonferroni Comparisons	
						Post and receive feedback	Post without feedback
Post and receive feedback	40	4.16	.99	4.20	.16		
Post without feedback	42	4.05	1.05	4.04	.16	1.00	
Observe	40	3.59	1.02	3.55	.16	.02	.08

Table 2: The Interactivity groups' unadjusted means for post-exposure sense of community and adjusted means, after controlling for pre-exposure knowledge, pre-exposure interest and attitude dissimilarity

Internal consistency was sufficient for the 8-item Brief Sense of Community measure ($M = 3.95$, $SD = 1.07$, $\alpha = .869$), pre-exposure interest ($M = 4.95$, $SD = .84$, $\alpha = .672$) and post-exposure interest ($M = 5.21$, $SD = .90$, $\alpha = .657$).

All other covariates and dependent variables were measured with a single item. Most of the dependent variables and covariates were normally distributed, with skewness and kurtosis between -1 to +1.5, with the exception of positive kurtosis for pre-exposure favorability and discussion elaboration. However, Tabachnick and Fidell [60] write that underestimates of variance related to positive kurtosis diminish with samples of 100 or more. This study sample included 122 participants. Collinearity was not a problem. Correlations among covariates of pre-exposure knowledge, pre-exposure interest and pre-exposure attitude extremity were explored using Pearson product-moment correlation coefficient. Correlations among covariates were either non-existent or small, with coefficients of .345 or less.

Brief Sense of Community (RQ1)

A one-way analysis of covariance was conducted to compare the effect of Interactivity (post and receive feedback vs. post without feedback vs. observe) on the dependent measure of brief sense of community. Pre-exposure measures of knowledge and interest were included as covariates, as well as attitude dissimilarity, which represents how different a person feels his or her attitude is compared to the attitudes of other users on the social media feed. Selection of covariates was based on theory. Cognitive elaboration would be expected to be influenced by ability to process the topic due to prior knowledge and interest in the topic, according to dual-processing theories such as the Elaboration Likelihood Model (ELM) [48]. Attitude dissimilarity was included because people are more likely to affiliate with like-minded others [38]. After adjusting for the covariates, there was a significant difference between Interactivity groups on sense of community scores, $F(2, 116) = 4.508$, $p = .013$, partial eta squared = .072. Post-hoc comparisons using Bonferroni correction, shown in Table 2, indicated the mean score for the group that posted and received a favorite was significantly greater than the mean score for the group that observed. Table 2 displays the unadjusted means for the Interactivity groups' (post and receive feedback vs. post without feedback vs. observe) sense of community scores

and adjusted mean after controlling for pre-exposure interest, pre-exposure knowledge and attitude dissimilarity.

A Pearson product-moment correlation coefficient was used to test the construct's relationship to anticipatory discussion elaboration and reflective discussion elaboration. Brief sense of community was also correlated to anticipatory discussion elaboration, $r = .18$, $n = 122$, $p < .05$, and reflective discussion elaboration, $r = .29$, $n = 122$, $p < .01$.

Conformity (RQ2)

A one-way analysis of covariance was conducted to compare the effect of Opinion (support vs. oppose vs. balanced) on the dependent measure of post-exposure attitude extremity. Covariates of pre-exposure interest, pre-exposure knowledge and pre-exposure attitude extremity were used. Covariate selection was theoretically informed. According to dual-processing theories, persuasion results from elaboration, which is influenced by interest and knowledge [48]. Pre-exposure attitude extremity was entered into the model to control for pre-existing differences between individuals that may not have been accounted for through random assignment. After adjusting for these scores, there was a significant difference between the three Opinion groups on post-exposure attitude extremity, $F(2, 115) = 10.39$, $p < .001$. The effect size, calculated using partial eta squared, was .15.

Post-hoc comparisons using Bonferroni correction indicated the mean score for the oppose group was significantly less than the balanced group and support group. The balanced and support groups did not differ significantly from each other. There was a moderate relationship between pre-exposure attitude extremity and post-exposure attitude extremity, as indicated by a partial eta squared value of .32.

Discussion Elaboration (RQ3 and RQ4)

Elaboration related to discussion was measured using a 6-item scale based on the Eveland and Thomson scale [13]. From the modified scale emerged two components with eigenvalues exceeding 1, explaining 41.1 percent and 24.5 percent of the variance, respectively. The scale [13] was subjected to principal components analysis after the suitability of data for factor analysis were assessed. Inspection of the correlation matrix revealed Items 1 and 2 measured anticipation of discussion and were significantly correlated to each other, and the remaining items were

significantly correlated to each other. Coefficients were .3 or more.

The Kaiser-Meyer-Olkin value was .62, exceeding the recommended value of .6 [29], and Bartlett's Test of Sphericity reached statistical significance, supporting the factorability of the correlation matrix. Both components showed strong loadings, and there was a weak correlation between the two factors ($r = .197$). Despite being used as one scale in Eveland and Thomson [13], this analysis suggests two separate constructs in this data: elaboration related to anticipation of discussion as measured by Items 1 and 2 ($M = 3.93$, $SD = 1.50$, $\alpha = .792$) and elaboration due to reflection on discussion as measured by Items 3, 4, 5 and 6 ($M = 5.33$, $SD = .83$, $\alpha = .741$). The resulting components—anticipatory discussion elaboration (Items 1-2) and reflective discussion elaboration (Items 3-6)—emerged from the analysis.

Anticipatory Discussion Elaboration

A 3 (Interactivity: post and receive feedback vs. post without feedback vs. observe) by 3 (Opinion: support vs. oppose vs. balanced) independent groups factorial analysis of covariance was used on the dependent measure of anticipatory discussion elaboration. Pre-exposure measures of interest and attitude extremity were included as covariates, based on dual-processing theories [48]. Knowledge was not included as a covariate because a review of homogeneity of regression slopes indicated a significant interaction ($p < .05$) between the Opinion factor and pre-exposure knowledge for anticipatory discussion elaboration. After adjusting for the covariate scores, there was a significant difference between the three Opinion groups on anticipatory discussion elaboration scores, $F(1, 117) = 3.91$, $p = .02$, partial eta squared = .06. Post-hoc comparisons using Bonferroni correction indicated the mean score for the support group was significantly greater than the oppose group. The balanced group did not differ significantly from either the oppose or support groups.

There was also a significant difference between the three Interactivity groups on anticipatory discussion elaboration scores, $F(1, 111) = 3.97$, $p = .02$, partial eta squared = .07. Post-hoc comparisons for the three Interactivity groups suggest the mean score for the group that observed was significantly higher than the mean score for the group that posted and received a favorite. The post and receive feedback group did not differ significantly from either the post without feedback and observe groups.

Reflective Discussion Elaboration

A 3 (Interactivity: post and receive feedback vs. post without feedback vs. observe) by 3 (Opinion: support vs. oppose vs. balanced) independent groups factorial analysis of covariance was used on the dependent measure of reflective discussion elaboration. Pre-exposure measures of knowledge, interest and attitude extremity were included as covariates for theoretical reasons [48]. After adjusting for these Opinion, there was a significant difference between the three Opinion groups on post-exposure reflective discussion

elaboration scores, $F(1, 116) = 3.55$, $p = .03$, partial eta squared = .06. Post-hoc comparisons using Bonferroni correction indicated the mean score for the support group was greater than the oppose and balanced groups.

DISCUSSION

Social watching is on the rise. People increasingly use platforms such as Facebook and Twitter to share their opinions and thoughts about video broadcasts. Novel applications such as Facebook Live and Twitter's Periscope enable any user with a mobile device and Internet connection to share live video to a potentially wide audience of followers, which has may increase the number of real-time interactions around live video. This study explored the effects of this interactivity on brief sense of community and discussion elaboration. The study also examined how other users' opinions on social media comments influenced attitudes and discussion elaboration.

Receiving a Favorite Increases Sense of Community

People who received a favorite felt a stronger sense of community on the social media feed compared to people who observed (RQ1). Despite having only interacted for 30 minutes, participants who received the feedback reported feeling stronger sense of group membership, needs fulfillment, mutual influence and emotional connection to other social media "users" on the feed [38]. The discovery that a fleeting phatic expression—nothing more than an unknown person clicking a star icon on your post—strengthened a sense of belonging on the feed seems to suggest that proximate strangers can develop a sense of connection in a short period of time.

When participants who received positive feedback were asked how they felt when their posts received a favorite through an open-ended question in the post-exposure survey, they responded by writing that they felt: "*Happy*;" "*Good, because people liked what I was saying. I think people look for approval when they tweet*;" "*i felt good and like someone was actually listening to me and hearing me out*;" "*I felt like I shared a common opinion that others either liked or agreed with*;" and "*Felt like my opinions mattered and that people related with me*."

Participants who did not realize they were favorited or had not been favorited responded with disappointment and ambivalence, writing, "*If my posts were favored, I would feel connected because at least I know that someone out there agrees with me*;" and "*Sad because no one faved any of my posts :(*" The data were not coded systematically, as this would be beyond the scope of this paper, but the anecdotes provide valuable insight into why the group that received a favorite may have felt a greater sense of community in the social media feed.

Interestingly, the brief sense of community measure was positively correlated to the discussion elaboration measures. In other words, people who felt a stronger connection to users on the social media feed reported higher levels of trying to

come up with good arguments (anticipatory discussion elaboration) and thinking about their own opinions on the topic, thinking about how others' posts relate to their own experiences and ruminating about the topic and what people posted after the session was over (reflective discussion elaboration). The correlation was significant both in the group that received a favorite and across all groups.

Robert Slavin's [58] theoretical perspective on the benefits of cooperative learning provide insight into the complex process through which different motivations may influence cognitive elaboration. He suggests group cohesion—incited by shared incentive structures—increases socio-emotional connections and can lead to enhanced learning [58]. This study also suggests that the elaboration may be occurring through a socio-emotional process. The work lays a foundation for theory development regarding the effects of praise and feedback for community bonding and learning. While the goal of study was not to make explicit recommendations for design, insights about cognitive and affective processes can also lead to further research on which sociotechnical affordances and types of content encourage people to feel commitment to online groups [53].

Literature on flattery suggests that people who receive praise tend to feel good, to like people who flatter them and to evaluate the flatterer more positively [15]. They also tend to believe that the flatterer is telling the truth [53]. Participants in the study believed they were interacting with other users; therefore, the study emulates human-to-human flattery. However, the results may have implications for computer-to-human flattery by Twitter bots, which are semi-automated programs that can post tweets in a human's absence [6]. The mock Twitter system was, in essence, a bot-like system. A study about flattery by computers [15] suggests that participants find praise from a machine to be just as effective as flattery from a human, even when they know it is automated. Participants in this earlier study felt just as good about themselves when they knew praise was unrelated to their actual performance as when they thought the feedback was sincere [15]. Future research may explore whether users would experience a similar boost in psychological connectedness to fellow Twitter users, even when knowing they are being indiscriminately favorited by a bot.

Conformity to the Majority Opinion on Social Media

Findings suggest a conformity effect occurs during social watching (RQ2). People tended to adopt the views expressed on the social media feed, after controlling for prior attitudes, prior knowledge and prior interest. The findings align with Maruyama et al.'s [36] observation of possible conformity on the social media feed. It also supports an experiment on conformity during social watching by Cameron and Geidner [4]. Researchers have long believed conformity occurs offline and online even among strangers, especially when anonymity de-emphasizes a person's individual identity and promotes identification with the group [14,50]. In this study,

even though participants did not know who was posting, their attitudes shifted to conform to the majority opinion.

Observing without Posting Increases Anticipatory Discussion Elaboration

People who observed without posting reported higher levels of trying to come up with good arguments when they knew they would be viewing social media posts (RQ3). Phrased in reverse, people who posted during the session reported significantly lower levels of thinking of what they would write on the feed. One possible explanation for the result is that posting led to cognitive overload. Another explanation is that people who do not post are more cognitively engaged than what one might assume. For instance, Nonnecke, Preece and Andrews [44] found that "lurkers" shied away from voicing themselves, but they were still silently asking questions. A third explanation is that people who posted were self-conscious about their posts and were, therefore, more hesitant to admit they put a lot of thought what they wrote. Because people who do not post are often invisible in data sets drawn from social media APIs, they are an understudied population. Future research should explore information processing among users who view social media without posting.

Viewing Positive Opinions on Social Media Increases Anticipatory and Reflective Discussion Elaboration

Participants who viewed posts that were favorable toward development in the neighborhood reported higher levels of anticipatory and reflective discussion elaboration. This "positivity bias" is supported by qualitative studies on social media use for political deliberation, which suggest that while people do seek out diverse opinions, many are averse to flaming during political conversations [10,56]. People use various strategies to avoid unproductive conflict, from constructing their own online spaces where they can control who can participate [56] to hiding friends with negatively charged opinions from their Facebook newsfeeds [10]. In this study, participants could not control where and with whom they were interacting, but they could control the extent to which they cognitively engaged with critical content. Those who viewed supportive posts reported thinking more deeply about what others said and how they would contribute to the conversation. The findings conflict with prior research that suggest news framed in a negative tone seems more significant [55, 57]. We suggest that more work on the effect of valence on perceived importance and cognitive elaboration should be conducted.

LIMITATIONS

We want to point out three limitations that should be considered when building on this work. Firstly, participants were young undergraduates from one university, and they were mostly undecided about the civic topic discussed in the study. People who are older, more opinionated or have varied levels of education may feel differently toward other users and be more or less likely to conform to and elaborate on social media opinions. Secondly, while we tried to maintain realism by vetting the posts' believability in advance, the

social media content may have been different in content and tone than what the young participants usually read on social media feeds. Moreover, participants were not interacting using their real account or with their actual network. Instead, posts were ascribed to pseudonyms for people they may or may not know, which emulated the weak tie or stranger interactions that can occur when searching a hashtag about a live event. Third, we focused on a particular topic—gentrification—in a local setting, and results may not apply to other civic topics or locales.

FUTURE WORK

The results suggest positive feedback increased a sense of community, and the more users felt connected, the more they elaborated on their social media discussion. The study also found that supportive opinions boosted elaboration about the online conversation and civic topic. However, more research on the nature of participants' elaboration should be conducted. This is especially true because the study suggested conformity effects. Our quantitative findings could be interpreted in multiple ways, and depending on which explanation for the results is proposed, the study could bode well or not so well for civic deliberation. Future research questions might include: Were users weighing the merits of the arguments on both sides of the issue or were they relying on superficial heuristics? Were they considering the common good or their own self-interest? Were they blindly accepting the legitimacy of others' claims or were they thinking independently and critically to arrive at their opinions? Our next study—a qualitative analysis of social watchers' thoughts reported retrospectively—will explore these questions in more depth, and perhaps shed more light on the value of the current study's findings to the CSCW and CHI community.

Like most experimental studies, the goal of the research was to maintain high internal validity, rather than maintain high external validity. Future research may increase realism by studying how posting and receiving positive feedback influences a sense of community in a more naturalistic setting. For instance, a content analysis of social media data could provide insight into whether receiving favorites increased the use of community- or social-related words in subsequent posts. A survey or diary study could assess users' feelings and cognitions before and after receiving feedback to better understand how the anticipation of feedback influences thoughts, emotions, judgments and behavior.

Another avenue for future research would be to study exactly what kind of feedback influences a sense of community or cognitive elaboration. Social media interactions can take many forms, from a typed reply to a packaged expression of affect such as a Facebook “like” or Twitter “favorite.” A study by Oeldorf-Hirsch and Sundar [45] suggests the perceived quality of the responses matters; participants who received valuable feedback felt more interested, more informed, and curious than when they perceived feedback as being less valuable. Emotional congruence in feedback also

may matter. News consumers may seek validation of their emotions. For instance, users who were experiencing anger may want affirmation of their heated feelings, while people experiencing hope may be searching for optimism, and those who were feeling fear may want reassurance or advice. A ripe area for future research would be to study how varying feedback in format and valence influences the recipient.

CONCLUSION

Our study makes several meaningful contributions to the literature on social watching in civic contexts. The first major contribution was an expanded understanding of how receiving feedback to social media posts instills a psychological sense of community. Despite receiving favorites from unknown sources during a 30-minute window, people who received the validation felt significantly stronger group membership, needs fulfillment, mutual influence and an emotional connection on the social media feed. This sense of community was positively related to anticipatory discussion elaboration and reflective discussion elaboration. In other words, the more people felt they belonged on the social media feed, the more they elaborated on the social media conversation. Based on the findings, if we can encourage users to post and perceive reciprocated responses as favorable, we may be able to boost connectedness to other users, commitment to online communities and cognitive elaboration around civic issues.

The second major contribution of the study was support for previous findings suggesting conformity during social watching. It adds to growing evidence suggesting that people who use social media to learn about or discuss broadcasts conform to the majority opinion, even if they are viewing posts by people they do not know.

The third major contribution is exploration of a positivity bias hypothesis, in which social media users elaborate more about supportive comments than negative comments. Because this hypothesis contradicts research that suggests negative news is perceived to be more important, more research should be conducted on the influence of valence on elaboration of social media discussions.

Social watching will continue to grow in importance as news becomes distributed across multiple platforms, as social tools are added to virtually all information outlets, and as exposure to news becomes more intertwined with other sociotechnical activities. Since this is likely to change the way people understand news content, it is critical to continue research in this area.

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