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IT'S WHAT YOU WRITE and HOW YOU WRITE ABOUT IT: THE POLICING FACEBOOK EXPERIENCE

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Abstract

This study focuses on social media use by law enforcement agencies. Based on media richness theory, we examined how the responses to Facebook messages posted by five police departments vary by type of cue, image vs. text, and across different content categories. Our findings suggest that although messages with richer information, namely more visual and verbal cues, receive more likes, topics such as Accident, Traffic and Announcement receive significantly fewer likes. Moreover, the presence of pictures in announcement messages reduces the number of likes. In addition, although people comment on messages about Property/Pets, they are much less inclined to comment on other topics. Our study contributes to media richness theory by demonstrating the importance of considering the nature and context of a communication, as represented by the content category, and to law enforcement agencies' practice by offering recommendations for how to measure public engagement and design strategies that will better leverage social media.

Keywords: Media Richness Theory, Social Media Use, Policing, Visual Cues, e-Government strategies.

1 INTRODUCTION

Social media and networking technologies (e.g., Twitter, Facebook, and YouTube) have become increasingly important in people's lives. Compared to individuals and companies, government agencies have been slow to adopt this new type of information and communication technology (ICT). Notably, despite widespread recognition of social media's growing importance in community policing and a desire to engage in social media, law enforcement agencies lack training, and have few personnel (and little if any budgetary means) to support social media initiatives, routine activities or interventions (Williams et al. 2015). The significant role played by social media in recent crises such as the terrorist attacks in San Bernardino, California, in Paris and in Brussels further highlight the importance of understanding how police departments and the public use and respond to these communications.

Indeed, social media could serve as an effective communication channel through which law enforcement agencies post information about public safety related events (e.g., traffic conditions and inclement weather warnings), call for assistance for policing activities (e.g., crime investigations), and offer self-defence and property protection tips. The use of social media by police departments potentially can increase public engagement and help build trusting relationships with the community. However, it remains unknown how community members respond to police-posted social media messages and whether such responses vary with different types of messages.

Dawes (2002) defines e-Government as "the use of information technology to support government operations, engage citizens, and provide government services." Her definition incorporates four dimensions reflecting the functions of government itself: e-Services, e-Democracy, e-Commerce, and e-Management.[1] As illustrated above, policing entails all of these. e-Government information technology is enabled by Wide Area Networks, the Internet, and mobile computing, among others (The World Bank[2]). Social media represent a new online platform hosted by any of those technologies. iCrossing[3] identifies five key elements of social media: participation, openness, conversation, community, connectedness. Boyd and Ellison (2008) expand on this, noting that what makes social network sites unique is not that they allow individuals to meet strangers, but rather that they enable users to articulate and make visible their social networks. In large social networks, participants are not so much looking to meet new people, as to communicate with those who are already in their extended social network. These are functions we seek to explore and delineate in this study.

Our research applies media richness theory to investigate how the public responds to visual cues and other types of information contained in messages posted on social media platforms by police departments. Since it was proposed, media richness theory has been used to explain and examine many types of behaviors related to media choice and communication channel selection in a wide

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[1] **E-services** is the electronic delivery of government information, programs, and services often (but not exclusively) over the Internet; **E-democracy** is the use of electronic communications to increase citizen participation in the public decision-making process; **E-commerce** is the electronic exchange of money for goods and services such as citizens paying taxes and utility bills, renewing vehicle registrations, and paying for recreation programs, or government buying supplies and auctioning surplus equipment; **E-managemen**t is the use of information technology to improve the management of government, from streamlining business processes to maintaining electronic records, to improving the flow and integration of information.

[2] http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTINFORMATIONANDCOMMUNICATIONANDTECHNOLOGIES/EXTEGOVERNMENT/0,,contentMDK:20507153~menuPK:702592~pagePK:148956~piPK:216618~theSitePK:702586,00.html

[3] http://www.icrossing.com/uk/ideas/fileadmin/uploads/ebooks/what_is_social_media_icrossing_ebook.pdf

variety of domains, including management, marketing, virtual teams and telecommunication, and education (Barnard 1991; Dennis & Kinney 1998; Fernandez et al. 2013; Ledford 2012; Turel & Zhang 2011). However, most of these studies focus on more traditional communication media (e.g., face-to-face communication, email, and instant messaging) (Koo et al. 2011; Ogara et al. 2014; Palvia et al. 2011); little research has been done to examine the information richness of social media whose wide adoption is more recent. Studies of social media use by law enforcement agencies, which differ from other types of government agencies, non-profit organizations, and commercial entities, are even more difficult to find. Moreover, most existing media richness research often relies on survey data, which have several limitations compared with direct observational data (Krosnick 1999).

This research will focus on one of the most popular social media platforms, Facebook, and its use by police departments. We intend to find out whether readers of messages prefer posts with richer information and cues (e.g., images) over text-only posts and whether their responses differ for different types of events. We also examine whether longer messages receive more responses than shorter ones. Instead of relying on surveys, we collect and analyze posts directly extracted from Facebook to study the relationships between our explanatory variables and outcome variables.

The remainder of this paper is organized as follows. The next section will review the status of social media use by law enforcement agencies and the challenges facing police departments regarding its use. We then turn to the literature on media richness theory and its application. Next, we describe the method and data used in our study, followed by a presentation of our results and their interpretation. Finally, we will discuss the implications of our research for theory and practice, acknowledge limitations in our study, lay out future research plans, and conclude the paper.

2 LITERATURE REVIEW

2.1 Social Media Use by Law Enforcement Agencies

Although its use is not well understood, police use of social media has increased dramatically in recent years. A nationwide survey of social media use by 500 U.S. law enforcement agencies in 2015 finds that 94 percent use Facebook, followed by Twitter (71.2%) and YouTube (40.0%) (IACP 2015). Among the stated purposes of social media communication, criminal investigation is the most common (88.7%), followed by notification of crimes (84.3%) and community outreach or citizen engagement (83.4%). Many police departments are still developing organizational policies concerning social media use (11.7% in process; 10.5% lacking) and training is lacking. The public generally is supportive of law enforcement agencies, but their responses to police departments' social media presentation are limited. An Accenture survey of 1,300 citizens in six countries (U.S., Canada, U.K. the Netherlands, Germany and Spain) finds 90 percent are willing to support social media use by their police force and believe it has an important role to play in helping deter crime (Shore 2012). Although Facebook (81%) and Twitter (35%) are selected as the preferred social media platforms, the number and frequency of posts, comments or likes by the public on police posted social media messages are generally low (Neiger et al. 2012). Citizens prefer anonymity and do not currently feel sufficiently well informed to help in crime prevention.

Turning to academic research, recent studies have sought to explain variations in social media activity by law enforcement agencies. Social media *adoption* may be influenced by both external factors (constituency demand characteristics such as urbanization (Neiger et al. 2012) or population (Guzman & Jones 2012; Yavuz & Welch 2014)), and internal capacities (e.g., bureaucratization (Yavuz & Welch 2014)), by organization size and by resource constraints including budget and staff (Kavanaugh et al. 2012), superiors' resistance, lack of managerial support and inadequate training (Briones et al. 2011). Regarding implementation, interview and survey data show that many police departments are only minimally aware of best practice guidelines, often lack articulated goals, objectives or strategic plans, and rarely identify or assess the value added of social media use (Williams et al. 2015). Most departments are oriented for the near-term rather than the longer term. They view social media as a stand-alone tool that is not typically integrated into police functions or organizational practices and processes.

In the law enforcement setting, police social media *use* is often reactive rather than pro-active with respect to constituent demand, and less likely to be used for routine functions (Yavuz & Welch 2014). Government agencies and/or police departments primarily disseminate information about their organizations and their activities, but rarely offer opportunities for engagement (Brainard & Edlins 2015; Crump 2011; Lovejoy & Saxton 2012; Waters et al. 2009). That is, communication is one-way and asymmetrical (Waters & Jensen, 2011). Because of a heavy reliance on auto feeds, agencies' content often does not match the interests and needs of their audiences (Neiger et al. 2012) even though Waters and Williams (2011) suggest that a one-way asymmetrical model is the most useful and appropriate in situations such as emergencies.

In terms of social media *impact*, some studies have found that the social media use by police departments increases public confidence (trust) and satisfaction (effectiveness and perceived legitimacy) (Meijer 2014; Ruddell & Jones 2013). Meijer (2014) also finds that social media use generates additional engagement for a limited group of people relative to face-to-face contact in routine police patrol work, but not in time-critical situations. In a singular comparative study of social media use by different kinds of organizations, Bird et al. (2012) find that users perceived government agency communications to be more accurate than those of community organizations, but the opposite held for perceived timeliness and utility.

Finally, studies of social media *engagement* find that the public's response extent and frequency vary by age and education (Ruddell & Jones 2013) as well as citizen interests (selective attention, cf. Harvey et al. 2011) and features of the communication (Petrovic et al. 2011). It is the latter aspect that motivates this research. For example, Mainka et al. (2015) find that city governments that posted many photos generated more followers and likes than those that posted mainly text and links. Lev-On and Steinfeld (2015) also report that photos generated the highest engagement levels relative to text, and notably, relative to videos as well, which they attribute to the time the latter take to view. Practitioner studies mirror these findings (Redsicker 2014). In another study, Lee et al. (2015) find that a longer reaction time impedes diffusion, and somewhat counter intuitively, so too does the use of hashtags. Finally, in crises, situational and geo-location updates are retweeted more than other on-topic tweets (Vieweg et al. 2010). These findings demonstrate how characteristics of the media itself can affect the impact of the message on its readership.

2.2 Media Richness Theory

Media richness theory extends social information processing theory (Galbraith 1973) by articulating a general framework for studying how different types of media may affect the outcomes of communication (Daft and Lengel 1986). Media vary in terms of their ability to reduce uncertainty and equivocality in information processing and to enhance shared understanding and interpretation of information during interpersonal communication. The extent to which a medium is rich is determined based on four factors (Daft et al. 1987): feedback capacity (i.e., the speed of transmission of feedback by the information receiver), number of cues (e.g., verbal and nonverbal cues, body gestures, etc.), language variety (e.g., numerical or natural language), and source (personal or impersonal). Based on these criteria, communication media are ranked along a continuum where face-to-face is the richest type of medium, followed by video conferencing, telephone, email, and web-based tools; bulletins and memos are the leanest media (Oke & Idiagbon-Oke 2010).

Considerable research has applied this theory to examine the impact of the richness of media on interpersonal relationships and satisfaction (Ogara et al. 2014; Suh 1999). For instance, a survey of 3,421 individuals regarding their relationship satisfaction with their close and extended family and close and distant friends reveals that richer communication methods are positively associated with relationship satisfaction, while leaner methods are negatively associated with relationship satisfaction

(Goodman-Deane et al. 2016). Jacob et al. (2010) find that when more audio cues are presented, participants are more satisfied with information presented on a tourist-oriented website.

Organizational studies using media richness theory often relate media types to outcome variables such as task performance (Koo et al. 2011), knowledge sharing (Klitmøller et al. 2013), and learning (Fernandez 2013). Wheeler et al. (2009) report that differences in information presentation modes (e.g., text-only or film-only) can affect individuals' cognitive decision-making and their task performance. However, another study found that email is not less efficient than face-to-face and video conferencing communication in facilitating knowledge exchange between buyers and suppliers in new product development process (Thomas 2013).

The decision concerning the selection of an appropriate media type may be affected by a number of factors such as culture and language (Klitmoller et al. 2013) and task characteristics and requirements. Lan and Sie (2010) compare SMS, email, and RSS in mobile learning and the results show that media types, which differ in terms of timeliness, richness, accuracy, and adaptability, lead to different performance for different types of tasks. For example, due to better timeliness, SMS may be more appropriate for immediate delivery of information; while email may be more useful for carrying a large amount of information because of its content richness. In addition, task characteristics such as analyzability, urgency, and complexity can influence an organization's selection of communication methods and media (Koo et al. 2011). Ledford (2012) proposes a typology of communication channels for marketers to select when designing promotional campaigns.

Although it is fairly clear from past research that media types reflect differing levels of familiarity (Koo et al. 2016), cost (Ledford 2012), timeliness, integrity and confidentiality (Palvia et al. 2011), the same media type may also present varying degrees of richness in different contexts. In particular, social media posts can range from the shortest of text response (e.g., "k" to signal agreement) to a lengthy soliloquy accompanied by photographs, emojis and pedigreed authorship. Our intent is to delve into typical social media communication alternatives more deeply to delimit further the richness characteristics these permit and the responses they elicit. In doing so, we would add to media richness research on content and context and to our understanding of the strengths and limitations of these communication options.

Our study first will investigate the impact of visual cues (e.g., text only vs. text + image) on response patterns (e.g., likes, comments) of message readers. In the context of police department's social media use, based on our understanding of visual cues as a property of media richness theory, we propose that:

> ***H1:*** *Messages with both text and images will receive more responses than text-only messages.*
> ***H1a:*** *Messages with both text and images will receive more likes than text-only messages.*
> ***H1b:*** *Messages with both text and images will receive more comments than text-only messages.*

In addition, succinctness of content also may affect richness variability. Thus, we include the second hypothesis that provides a control based on the length of the message. We recognize that longer texts may carry a larger amount of information and are more likely to attract attention and responses. As a result, this hypothesis offers a very high level approximation of the impact of message size on the responses a message elicits.

> ***H2:*** *Longer messages will receive more responses than short messages.*
> ***H2a:*** *Longer messages will receive more likes than short messages.*
> ***H2b:*** *Longer messages will receive more comments than short messages.*

Moreover, because messages differ based on characteristics of their topic (e.g., crimes, accidents, traffic, weather, etc.), their patterns of response also may be different. As a result, we expect that a category-based analysis will show which types of information are most successful when they include the added richness of photographs. We recognize that certain events or topics are inherently more popular or commonplace than others, so we do not attempt to make any predictions about the quantity of reaction types, only about their relative richness quotient. Thus this hypothesis explores differences in categories of messages to obtain an initial, high level understanding of how content type characteristics may impact the reaction of message recipients.

> ***H3:*** *Messages containing images in different content categories experience different response levels.*
> ***H3a:*** *On average, messages containing images in different content categories receive different numbers of likes.*
> ***H3b:*** *On average, messages containing images in different content categories receive different numbers of comments.*

3 DATA and METHOD

3.1 Data

Using the public APIs provided by Facebook, we extracted a dataset containing three months of social media activity (May 1st through July 31st, 2014) for five Massachusetts (U.S.) police departments: Billerica, Burlington, Peabody, Waltham, and Wellesley. These police departments are located within a 30-mile radius of each other and all are small communities in the suburbs of Boston. Our resulting sample contained 1,224 posts made via the five official police department accounts. We also extracted the number of “likes” and number of comments for each post. Table 1 reports the basic sample frequencies. For Billerica, all messages on Facebook were reposts from tweets. For Burlington, 223 posts originated as tweets while the remaining posts were created directly on Facebook. For the remaining three police departments, none of the posts originated from Twitter. Some police departments allowed followers and friends to post on the account wall while others did not. However, because of how Facebook handles security, we were unable to get the wall posts of the individual friends.

In this and the following sections, we use the terms “post” and “message” interchangeably. In a similar manner, photos, images, and pictures also all refer to the visual cues contained in messages.

3.2 Method

Using an open coding approach, we identified 10 categories by manually coding the content of the messages posted by the five police departments:

- **Accident**: Information about a specific incident such as a vehicle accident or a personal injury that might need medical attention.
- **Announcement**: Posts containing general information, news, etc.
- **Crime**: Posts related to a specific criminal incident, seeking public assistance in solving a crime, or reporting updates or arrests related to a crime.
- **Event**: Information about a future activity often with a specific date and time, aiming to generate participation in the event.
- **Interaction**: Posts aimed at a specific individual or individuals rather than information to the general public, or responses to posts from others.
- **Promotion**: Posts intended to influence the police department’s image or policing in general.
- **Property/Pets**: Posts informing the public about lost and found items or pets, and pet care (e.g., hot car warnings).
- **Safety**: Warnings to the public about safety concerns such as fraud schemes, ways to protect home or children, and general safety tips.
- **Traffic**: Posts notifying the public either to avoid an area or that a prior traffic incident has cleared.
- **Weather**: Posts providing the public information about a weather event and needed preparations.

Each post was assigned to a specific category code. Because these categories were not necessarily mutually exclusive, it was possible that the content of a message was related to more than one category. In this case, we assigned the message to the category that captured its most prominent content. Two coders independently categorized the messages and the inter-coder reliability was 0.86. Inconsistent category assignments were resolved by in-depth discussion between the coders.

3.3 Variables

The outcome variable, reader response to a post, is measured by the *Number of Likes* and the *Number of Comments* the post receives. Independent variables include a dummy variable, *Image* (if the message contains a picture), *Message Length* (the number of characters in the message[4]), and *Category*. The control variables include the *Police Department* indicator and the *Number of Friends*[5] (in logarithm) of the police department's Facebook account. Because different police departments post messages on Facebook in different frequencies (e.g., Billerica posted on average 55 messages per week over the three-month period and Peabody just a little more than 4 messages per week), we also calculate *Weekly Post Frequency* (the moving average of posts per week), hoping to capture part of the variation in these police departments' posting behaviors. In addition, given that older posts may have had a longer time to accumulate responses, the *Number of Days since Posted* (the time interval between the posting date of a message and the last day of the data collection period) is also used as one of the control variables.

4 ANALYSIS and RESULTS

On average, each post receives 5.38 likes (S.D. = 7.59, Max = 25) and 1.09 comments (S.D. = 3.43, Max = 25). The average message length is 115.8 characters (S.D. = 173.1, Max = 2,751). Tables 1 and 2 report the basic descriptive statics of the sample broken down by the five police departments and by the 10 content categories, respectively. The numbers in the parentheses in the *Number of Messages* row (or column) represent the percentages of posts with images over all posts by the particular police department (or category). The numbers in parentheses in other rows (or columns) are standard deviations.

	Billerica	**Burlington**	**Peabody**	**Waltham**	**Wellesley**
# Messages	769 (23%)	231 (54.5%)	62 (80.6%)	57 (84.2%)	105 (78.1%)
Average # Likes	3.72 (5.86)	2.25 (3.58)	11.76 (9.49)	20.61 (6.44)	12.12 (8.70)
Average # Comments	1.02 (3.51)	0.30 (0.9)	1.76 (3.63)	5.74 (6.22)	1.06 (1.9)
Average Message Length	79.5 (68.4)	139.8 (267.8)	230.0 (233.0)	260.2 (365.7)	182.7 (143.1)
# Friends	609	1,469	977	390	208

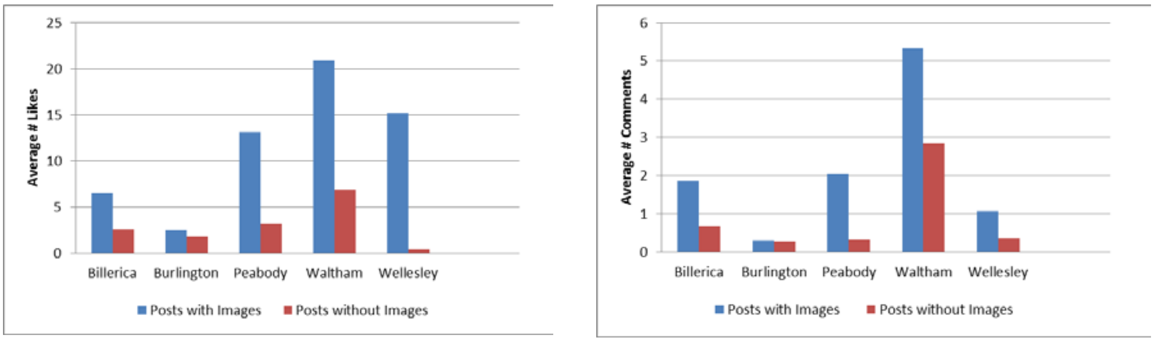
Table 1. Basic statistics of the sample broken down by the police departments.

[4] We chose not to use the number of words to measure *Message Length* because 68 percent of these Facebook messages were direct reposts from Twitter, which has a limitation on the maximum number of characters in a message. We believe that the number of characters is a more appropriate measure for *Message Length* for this analysis.
[5] Due to multicollinearity, we did not include the population of the town as a control variable.

Category	# Messages	Avg # Likes	Avg # Comments	Avg Message Length
Accident	249 (3.6%)	1.64 (2.86)	0.45 (1.99)	64.0 (59.72)
Announcements	201 (52.1%)	4.48 (6.32)	0.74 (2.93)	103.3 (46.59)
Crime	122 (29.5%)	8.25 (8.43)	2.57 (5.50)	126.3 (153.59)
Events	17 (55.6%)	5.81 (6.31)	1.65 (4.85)	410.3 (641.59)
Interaction	66 (69.7%)	7.56 (9.25)	0.76 (1.91)	104.2 (75.4)
Promotional	186 (86.6%)	12.24 (9.67)	1.43 (3.17)	197.8 (226.28)
Property/pets	17 (52.9%)	13.35 (11.31)	6.29 (8.56)	116.2 (51.57)
Safety	44 (54.5%)	6.70 (8.02)	1.80 (4.50)	177.0 (317.58)
Traffic	309 (5.2%)	2.45 (3.99)	0.67 (2.83)	88.1 (156.38)
Weather	12 (25%)	8.67 (9.44)	1.75 (2.80)	157.3 (147.33)

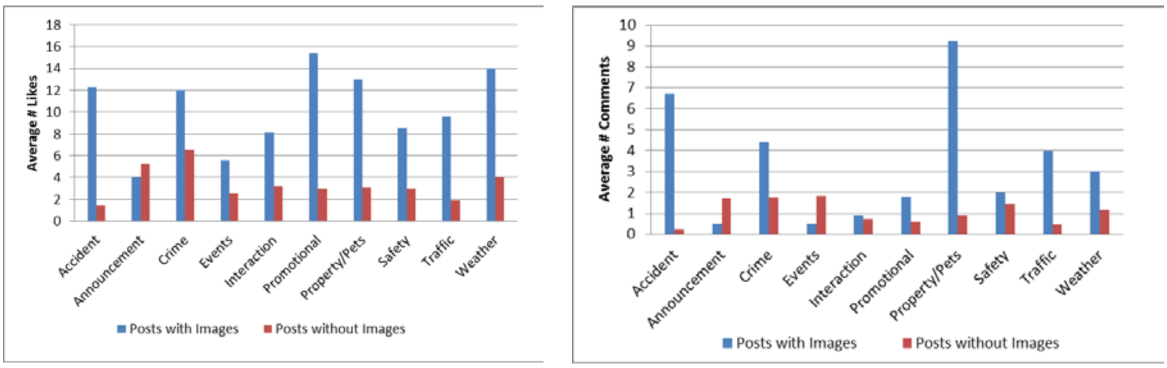
Table 2. Basic statistics broken down by content categories.

To first explore if visual cues contained in a message make a difference in the readers' responses, we compared the average number of likes (and comments) between posts with images and messages without images. Figure 1 presents the charts for average number of likes (Figure 1a) and comments (Figure 1b) received by messages containing images and messages with only texts across the five police departments. Figure 2 presents similar charts across the message content categories (Figure 2a for the number of likes and Figure 2b for the number of comments, respectively).



(a) (b)

Figure 1. Average number of likes (a) and comments (b) received by messages with images and by messages without images across police departments.



(a) (b)

Figure 2. Average number of likes (a) and comments (b) received by messages with images and by messages without images across content categories.

It is clear from these charts that message readers prefer posts with images over those without pictures. In general, they tend to perceive image posts more positively (with more likes) and are more willing to make comments on these posts. This pattern is consistent across the five police departments and across the content categories. An exception is the Announcement category, for which people prefer text-only messages over posts with embedded images. Similarly, although people like event messages to contain images they tend to leave comments on text-only event messages more often than on those with pictures.

To test our first hypothesis, we compared the means of the *Number of Likes* for posts with images and text-only messages using a one-tailed *t*-test. It is shown that posts with images receive significantly more likes than text-only posts ($t = 13.31$, $p < 0.001$). A similar *t*-test on the *Number of Comments* also finds a significantly strong difference ($t = 4.61$, $p < 0.001$). As a result, **both H1a and H1b are supported**. This result is consistent with the exploratory findings presented in Figures 1 and 2, and replicates Lev-On and Steinfeld (2015).

Regarding the relationship between *Message Length* and reader response, we calculated the Pearson correlation coefficients between *Message Length* and the *Number of Likes* ($r = 0.29$) and between *Message Length* and the *Number of Comments* ($r = 0.28$). The *t*-tests on the two dependent variables show that both of the positive correlations are significant at 0.1% level. Therefore, our hypotheses **H2a and H2b are also supported**, although the relationship is not strong. This implies that longer posts are more likely to receive positive feedback (likes) and reader comments.

	#Likes		**#Comments**	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Image	2.45^{**}	3.53^{**}	1.16^{**}	0.69^{**}
Message Length	0.01^{**}	0.01^{**}	0.01^{**}	0.01^{**}
Log(#Friends)	-9.62^{**}	-8.54^{**}	1.86	-0.47
Weekly Post Frequency	0.10	0.09	-0.001	-0.002
# Days since Posted	-0.04^{**}	-0.04^{**}	-0.01^{**}	-0.01^{**}
Police Department[6]				
Billerica				1.10^{**}
Burlington	-0.71	-1.43	-1.93^{*}	
Peabody	5.25^{**}	4.60^{**}	-0.73	0.82
Waltham	10.76^{**}	10.20^{**}	3.47^{**}	4.21^{**}
Category				
Accident	-5.63^{**}	-5.15^{**}		
Announcement	-4.22^{*}	-0.50		
Traffic	-5.19^{**}	-4.62^{**}		
Property/Pets			3.63^{**}	1.26
Accident X Image		1.23		
Announcement X Image		-4.80^{**}		
Traffic X Image		0.48		
Property/Pets X Image				6.47^{**}
R^2	0.52	0.52	0.23	0.22

** $p < 0.01$; * $p < 0.05$

Table 3. Regression analysis on Number of Likes and Number of Comments.[7]

[6] Because 81 percent of the messages were posted by the Billerica (62.8%) and Burlington (18.9%) police departments, it caused a high correlation between the dummy variables representing the two police departments (0.63). One of the two dummies thus was automatically dropped from the regression by the statistic software (IBM SPSS).
[7] Coefficients in the regression models in Table 3 are not standardized.

We conducted a series of regression analyses to further examine the relationships between the independent variables and dependent variables. Table 3 presents the results from regressing the *Number of Likes* (Models 1 and 2) and *Number of Comments* (Models 3 and 4) on different groups of independent variables. The R^2 of Models 1 and 2 is greater than 0.50, while the R^2 of the two models on *Number of Comments* are only slighter higher than 0.2.

In all these models, *Image* and *Message Length* exert positive influence on *Number of Likes* and *Number of Comments*, further supporting H1 and H2. Specifically, posts with pictures receive, on average, 2.45-3.53 more likes and 0.69-1.16 more comments than text-only posts; and a post gets 0.01 more likes and 0.01 more comments for each additional character in the message body.

In Model 1, *Category* of message content was used as an independent variable. However, only three categories (Accident, Announcement, and Traffic) have a significant effect on the number of likes; and the association is negative (Weather is used as the reference category). This is reasonable because if a message is a report of an accident or traffic problem, it would not make much sense for people to "like" the incident. Concerning announcement messages, which often are for notification purposes, message readers also may not feel that they have to respond. In Model 3, among all content categories, only Property/Pets has a significant positive association with the number of comments. Although not all categories are significant, Models 1 and 3 demonstrate that message content and the purpose it serves matters to a certain extent.

To test H3a, the variables representing the interactions between the three significant categories in Model 1 and the *Image* indicator were added to Model 2. The result shows that with the interactions, Accident and Traffic categories still maintain their main effects but do not interact with images. In contrast, the effect of Announcement is reflected by its interaction with images. That is, for messages announcing an event or activity, people prefer plain text over images. This pattern can also be seen in Figure 2a. In Model 4, which was used to test H3b, the interaction between Property/Pets and *Image* is also significant while this category's main effect becomes non-significant. That is, people tend to make comments on messages containing pictures of lost-and-found items and pets. These results may echo the finding of Havey, et al. (2011) that interest in the topic, or sender involvement, is positively related to message propagation across social media. Based on the results of the four models, we conclude that **H3 is mostly supported**.[8]

The control variables vary in their influence on the dependent variables. Interestingly, the *Number of Friends* a police department has on Facebook is negatively associated with the number of likes and number of comments its messages receive (with an exception in Model 3). In other words, the more friends a police department has, the less likely people will click on the "like" button on the messages or make a comment. This could be due to the social loafing effect, in which people expect others to respond to the posts when there are a large number of friends subscribed to an account.

Table 3 also shows that the number of likes and number of comments are not affected by the *Weekly Post Frequency*, although these five police departments have drastically different posting behaviors. The variation in posting behavior was partially captured by the *Police Department* indicator. Peabody and Waltham police departments performed significantly better than Wellesley Police Department (the reference dummy variable) in terms of getting likes for their posts (see Models 1 and 2), although these two departments posted significantly fewer messages over the three-month period (62 and 57 posts, respectively). Similarly, Billerica and Waltham police departments got more comments per post than the other three police departments (see Models 3 and 4). It is worth noting that among the five police departments, the Billerica Police Department was the most active and posted many messages on Facebook (769 in total). However, it did not necessarily receive more likes and comments on average (with the exception in Model 4). Because all Facebook messages created by the Billerica Police

[8] We also tested the effects of the interactions between *Category* and *Message Length*. None of these interaction variables has a significant impact on the dependent variables.

Department were direct reposts from Twitter, which has a restriction on the number of characters in a message, the information presented in each individual message, at the micro level, may have been perceived less rich and useful by people. In fact, the “flood” of messages even might have reduced its chance of getting positive feedback from its audience (see the negative sign of *Weekly Post Frequency* in Models 3 and 4). The sheer number of messages and frequent updates may have caused an “information overload” problem at the macro level, which diluted the audience’s attention to the content of individual messages and its propensity to make responses.

In addition, although older posts have a longer time to accumulate responses, the *Number of Days since Posted* exhibits a negative effect on the number of likes. It is likely that as time progresses, older messages become less relevant and people do not flip back to previous Facebook pages to read old posts. This would be consistent with the reaction time finding of Lee, et al. (2015).

In summary, H1 and H2 are fully supported by our data and H3 is mostly supported. Although different types of information (content, purpose) may exhibit varying impact on reader response, the overall pattern is quite clear. That is, message readers and audience are generally more engaged in social media posts with a higher level of information richness (e.g., more visual cues, longer texts). They perceive information rich messages more positively and are more likely to make comments on certain types of posts (e.g., Property/Pets).

5 DISCUSSION and FUTURE WORK

Our findings offer several insights into media richness theory in the context of social media and its application to policing. First, consistent with media richness theory, the number of cues contained in a message does have an impact on the communication outcome concerning audience engagement. That is, both pictures (visual cue) and message length (verbal cue) significantly increase the number of both likes and comments. The presence of more cues in a message increases the amount of information conveyed and reduces the *uncertainty* of the communication (Daft & Lengel 1986). Furthermore, as the theory predicts, communication with richer information can help clarify ambiguous issues, facilitate understanding in a timely manner, and reduce communication *equivocality* (Daft & Lengel 1986). We find that, in general, the audience prefers posts with pictures over text-only messages.

This finding validates the old saying: a picture is worth 1000 words. However, when we dig deeper into the context of the communication and take the communication purpose into consideration, we find that this does not hold for all topics. People do not “like” accidents, traffic or announcements even with plenty of cues. They especially do not “like” announcement messages that include pictures, which seem to be a distraction. In addition, they comment more frequently on property/pets than on all other categories. These findings imply that in the police domain, the public may not invariably prefer richer communication with more visual cues on social media.

Second, liking and commenting are distinct kinds of engagement: the former engages affect while the latter engages cognition at least in the sense that it takes longer and more time to compose an appropriate response. Given the functions of police, it is not surprising that several disliked activities are significant while none significantly promotes liking. On the other hand, because many people own pets, they relate to them and respond in numbers to those posts, all the more so when pictures accompany the posts.

Our research also has several important implications for practice. Our findings suggest that, to increase public engagement, police departments need to decide not only what they write about on the social media but also how they write about it. If time and resources permit, posting longer messages accompanied with images is an effective way of attracting more attention and responses from the public. The audience especially welcomes pictures in posts related to certain topics (e.g., lost-and-found and pets). However, for messages related to accidents and announcements, images may not help and even cause distractions.

Our findings regarding our control variables offer additional insights into the social media use by police departments. When evaluating the impact of their social media outreach initiatives and practices, police departments often face challenges finding appropriate measures. As one of the goals of using social media is to build and maintain relationships with the community, the size of the friend circle would seem to be a ready criterion. However, our findings suggest that having a large number of friends may impede engagement: the number of likes and comments diminish. This could signify that many of a police department's friends consist of casual observers rather than an actively engaged public: either smaller networks promote engagement or attract a greater number of self-selected activists. If the number of friends is the only performance measure police departments track, they could misjudge the impact of their social media outreach activities. A similar caution arises from our finding that frequency of posting is not significantly correlated with likes or comments. Greater frequency does not lead to greater engagement. This should be good news to departments that are strapped for staff and time to support their social media outreach.

Finally, our results indicate that police departments vary significantly in the degree to which they generate likes and comments, other factors being equal. The reasons will be important to investigate in future research. Given that Billerica's Facebook posts and tweets are redundant, do their audiences overlap such that Twitter is the preferred platform where readers register their responses? Otherwise, the positive (Peabody, Waltham) and negative (Billerica, Burlington) coefficients for the respective departments look more to be a case of "less is more." The findings for these attributes of the police *department's engagement* (*Number of Friends* and *Post Frequency*) stand in contrast to those depicting the media richness of the *messages themselves* (*Images* and *Message Length*), where more is more.

Taken together, our findings and the limitations of this study raise several questions that require further investigation. Our data set encompasses the police social media activity across one platform, Facebook, for five relatively small communities in a single state over a period of just three summer months. More and larger samples are needed to generalize from our findings to the population of law enforcement agencies and to other kinds of government agencies that would allow comparison with the private sector media richness research.

Our engagement measures are limited to likes and comments; it will be useful to extend these to "shares" or, in the case of Twitter, retweets. Unfortunately, as the count of shares was not as directly accessible from the Facebook's API as the number of likes (and comments) at the time of data collection, we could not test the impact of information richness on this specific aspect of enagement.

Just as likes and comments are influenced by the content category, police evaluation of the success of their social media posts and outreach more generally may depend on the purpose. Does a message seek to prevent or solve a crime, to better protect people and property, to encourage support or event attendance? Comments are more relevant to the first two, likes to the next and shares to the last. Attempting to directly tie social media activity to a policing outcome such as crime resolution is a very complex challenge that falls well beyond the scope of this type of analysis.

Our future reseach will be carried out in several directions. Because we find that message context matters, further content analysis of the messages themselves could be fruitful. Other dimensions of message content may also affect communication outcomes. For example, messages with different sentiments (e.g., happy vs. sad) and in different styles (e.g., humorous vs. monotoic) may very likely lead to drastically different reactions. Similarly, it will be interesting to study the patterns of responses. Are readers' posts merely affective (sentiment) or substantive, in the sense of providing new and or useful information?

As timeliness is one of the dimensions of information richness, how time sensitive (i.e., urgent or rountine) a message is also matters. This issue is particularly more relevant in the law enforcement context than in other contexts such as business and individuals. It will be worth discovering whether urgent messages (e.g., a call for immediate assistance with a crime investigation) and routine messages (e.g., personal safety tips) would incur different patterns of responses.

Our media richness indicators, pictures and message length, could be extended to include links and video. For social media, is the relationship between message length and engagement curvilinear rather than linear? If it is too short, the message is media “poor.” Messages that are too long could create information overload, leading to reader fatigue as suggested by our finding of a negative relationship with posting frequency. We also need to determine whether the social media platform matters and if media richness has different meaning in this environment compared to the traditional media context in which the theory developed. Additionally, as Facebook extended the Like feature with more expressive reaction options (e.g., Love, Sad, Angry) recently, a comparitive study using a more recent sample would be able to generate finer results on how people’s responses vary with comunication contents and contexts.

6 CONCLUSION

This study focuses on social media use by law enforcement agencies. Based on media richness theory, we examined how the responses to Facebook messages posted by five police departments vary by type of cue, image vs. text, and across different content categories. Our findings suggest that although messages with richer information, namely more visual and verbal cues, receive more likes, topics such as Accident, Traffic and Announcement receive significantly fewer likes. Moreover, the presence of pictures in announcement messages reduces the number of likes. In addition, although people comment on messages about Property/Pets, they are much less inclined to comment on other topics. Our study contributes to media richness theory by demonstrating the importance of considering the nature and context of a communication, as represented by the content category, and to law enforcement agencies' practice by offering recommendations for how to measure public engagement and design strategies that will better leverage social media.

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References

Barnard, J. (1991). The information environment of new managers. Journal of Business Communication, 28, 312-324.

Bird, D., Ling, M. and Haynes, K. (2012). Flooding Facebook – The use of social media during the Queensland and Victorian floods. The Australian Journal of Emergency Management 27(1), 27-33.

Boyd, D. and Ellison, N. (2008). Social network sites: Definition, history, and scholarship. Journal of Computer Mediated Communication, 13(1), 210-230.

Brainard, L. and Edlins, M. (2015). Top 10 U.S. municipal police departments and their social media usage. The American Review of Public Administration, 45(6), 728-745.

Briones, R.L., Kuch, B., Fisher Liu, B. and Jin, Y. (2011). Keeping up with the digital age: How the American Red Cross uses social media to build relationships. Public Relations Review 37(1), 37-43.

Crump, J. (2011). What are the police doing on Twitter? Social media, the police and the public. Policy & Internet 3(4): 1-27.

Daft, R.L. and Lengel, R.H. (1986). Organizational information requirements: Media richness and structural design. Management Science, 32(5), 554-571.

Daft, R.L., Lengel, R.H. and Trevino, L.K. (1987). Message equivocality, media selection, and manager performance: Implications for information systems. MIS Quarterly, 11(3), 355-366.

Dawes, S. (2002). The future of e-government. Testimony presented to the New York City Council Select Committee on Information Technology in Government’s hearing, “An Examination of New

York City's E-Government Initiatives." June 24. https://www.ctg.albany.edu/publications/reports/future_of_egov/future_of_egov.pdf.
Dennis, A.R. and Kinney, S. T. (1998). Testing media richness theory in the new media: The effects of cues, feedback, and task equivocality. Information Systems Research, 9(3), 256-274.
Fernandez, V., Simo, P., Sallan, J.M. and Enache, M. (2013). Evolution of online discussion forum richness according to channel expansion theory: A longitudinal panel data analysis. Computers & Education 62, 32-40.
Galbraith, J. (1973). Strategies of Organization Design. Addison-Wesley, Reading.
Goodman-Deane, J., Mieczakowski, A., Johnson, D. and Goldhaber, T. (2016). The impact of communication technologies on life and relationship satisfaction. Computers in Human Behavior 57, 219-229.
Harvey, C.G., Stewart, D.B. and Ewing, M.T. (2011).Forward or delete: What drives peer-to-peer message propagation across social networks? Journal of Consumer Behaviour, 10(6), 365-372.
IACP, International Association of Chiefs of Police (2015). 2015 Social Media Survey Results. http://www.iacpsocialmedia.org/Portals/1/documents/FULL 2015 Social Media Survey Results.pdf.
Jacob, C., Guéguen, N. and Petr, C. (2010). Media richness and internet exploration. International Journal of Tourism Research, 12(3), 303-305.
Guzman, M.C. and Jones, M.A. (2012). E-Policing: Environmental and organizational correlates of website features and characteristics among large police departments in the united states of america. International Journal of Electronic Government Research, 8(1), 64-82.
Kavanaugh, A.L., Fox, E.A., Sheetz, S.D., Yang, S., Li, L.T., Shoemaker, D.J., Natsev, A., Xie, L. (2012). Social media use by government: From the routine to the critical. Government Information Quarterly, 29(4), 480-491.
Klitmøller, A. and Lauring, J. (2013). When global virtual teams share knowledge: Media richness, cultural difference and language commonality. Journal of World Business, 48(3), 398-406.
Koo, C., Yulia W. and Jung, J.J. (2011). Examination of how social aspects moderate the relationship between task characteristics and usage of social communication technologies (SCTs) in organizations. International Journal of Information Management, 31(5), 445-459.
Krosnick, J. A. (1999). Survey research. Annual Review of Psychology, 50, 537-567.
Lan, Y. and Yang-Siang S. (2010). Using RSS to support mobile learning based on media richness theory. Computers & Education 55(2), 723-732.
Ledford, C.J.W. (2012). Changing channels: A theory-based guide to selecting traditional, new, and social media in strategic social marketing. Social Marketing Quarterly 18(3), 175-186.
Lee, J., Agrawal, M. and Rao, H.R. (2015). Message diffusion through social network service: The case of rumor and non-rumor related tweets during Boston bombing 2013. Information Systems Frontiers, 17, 997-1005.
Lev-On, A. and Steinfeld, N. (2015). Local engagement online: Municipal Facebook pages as hubs of interaction. Government Information Quarterly, 32, 299-307.
Lovejoy, K. and Saxton, G. D. (2012). Information, community, and action: How nonprofit organizations use social media. Journal of Computer-Mediated Communication, 17(3), 337-353.
Mainka, A., Hartmann, S., Stock, W.G. and Peters, I. (2015). Looking for friends and followers: A global investigation of governmental social media use. Transforming Government: People, Process and Policy, 9(2), 237 – 254.
Meijer, A. J. (2014). New media and the coproduction of safety: An empirical analysis of dutch practices. The American Review of Public Administration, 44(1), 17-34.
Neiger, B., Smith, A., Thackeray, R., Van Wagenen, S. (2012). Adoption and use of social media among public health departments. BMC Public Health, 12(1), 242.
Ogara, S.O., Chang E.K., and Prybutok, V. R. (2014). Investigating factors affecting social presence and user satisfaction with mobile instant messaging. Computers in Human Behavior, 36, 453-459.
Oke, A. and Idiagbon-Oke, M. (2010). Communication and channels, innovation tasks and NPD project outcomes in innovation-driven horizontal networks. Journal of Operations Management, 28(5), 442-453.

Palvia, P., Punjani, P., Cannoy, S. and Jacks. T. (2011). Contextual constraints in media choice: Beyond information richness. Decision Support Systems, 51(3), 657-670.
Petrovic, S., Osborne, M. and Lavrenko, V. (2011). RT to win! Predicting message propagation in Twitter. In Proceedings of the 5th International AAAI Conference on Weblogs and Social Media, 586-589.
Redsicker, P. (2014). Social photos generate more engagement: New research, http://www.socialmediaexaminer.com/photos-generate-engagement-research, accessed on May 13, 2014.
Ruddell, R. and Jones, N. (2013). Social media and policing: Matching the message to the audience. Safer Communities, 12(2), 64-70.
Shore, J. (2012). Accenture Survey. http://mashable.com/2012/10/09/police-social-media/
Suh, K. S. (1999). Impact of communication medium on task performance and satisfaction: An examination of media-richness theory. Information & Management, 35(5), 295-312.
Thomas, E. (2013). Supplier integration in new product development: Computer mediated communication, knowledge exchange and buyer performance. Industrial Marketing Management, 42(6), 890-899.
Turel, O. and Zhang, Y. J. (2011). Should I e-collaborate with this group? A multilevel model of usage intentions. Information & Management, 48(1), 62-68.
Vieweg, S., Hughes, A.L., Starbird, K., and Palen, L. (2010). Microblogging during two natural hazards events: What Twitter may contribute to situational awareness. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 1079-1088.
Waters, R. D., Burnett, E., Lamm, A. and Lucas, J. (2009). Engaging stakeholders through social networking: How nonprofit organizations are using Facebook. Public Relations Review, 35(2), 102-106.
Waters, R. D. and Williams, J.M. (2011). Squawking, tweeting, cooing, and hooting: Analyzing the communication patterns of government agencies on Twitter. Journal of Public Affairs, 11(4), 353-363.
Wheeler, P. and Arunachalam, V. (2009). The effects of multimedia on cognitive aspects of decision-making. International Journal of Accounting Information Systems, 10(2), 97-116.
Williams, C.B., Fedorowicz, J., Kavanaugh, A., Thatcher, J. and Haughton, D. (2015). Leveraging social media: The community policing case. In Proceedings of the 15th American Political Science Association (APSA) Annual Meeting, San Francisco, September 3-6.
Yavuz, N. and Welch, E. W. (2014). Factors affecting openness of local government websites: Examining the differences across planning, finance and police departments. Government Information Quarterly, 31(4), 574-583.