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# An Empirical Study of Social Media Exchanges about a Controversial Topic: Confirmation Bias and Participant Characteristics

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There has been a significant amount of research into social media commentary influences on human behaviors, ranging from its role in affecting political elections to predicting corporate revenues; however, to this point, the factors and influences of social media have not been completely explained and it is not entirely clear whether social media influences or simply confirms preconceptions. Moreover, with sentiment analysis, much of the research has relied on human expert interpretation of the sentiments and semantics written in various social media. It has also tended to be interpretive rather than predictive in nature. In our study, we wanted to know if social media conversations were reflective or influencers of human behavior. Using a social media mining technology we were able to determine sentiments, sentiment intensity, and the characteristics of participants. We found strong evidence of confirmation bias, but that bias was influenced by personal characteristics, and in some cases, whether the sentiments were strongly positive or strongly negative.

*Keywords: confirmation bias, online sentiment, behavioral characteristics, natural language processing*

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Fom watching popular news media, one may get the impression that people have generally come to accept that social media influences people's thinking and their decisions. Furthermore, to this point, there has been a trove of marketing and behavioral literature that has focused on interpreting data after the fact regarding consumer decisions influenced by social media (c.f. Baird & Parasnis, 2011; Lee & Oh, 2017). While financials are often easily attained *ex post facto*, predicting future consumer behaviors has been challenging because not all of the semantic factors and human attributes have been determinable largely owing to a lack of theoretical grounding (Workman, Phelps, & Hare, 2013; Zafarani, Ali, & Liu, 2014). Moreover, those studies that have attempted to ascertain human attributes have tended to rely on selfreport or human expert raters, rather than algorithmically mined from the patterns in the extant data (c.f. Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011). Finally, the domain or topic of interest may also be a factor in terms of value; in other words, social media may be more influential with regard to making purchases from an online vendor compared to opinion shaping about religious or ethical beliefs (Forbes & Vespoli, 2013).

In spite of these challenges we wanted to know whether social media commentary changed people's minds, or whether social media commentary served to reinforce what people already believed (confirmation bias). Moreover, we were interested in if, and how, behavioral characteristics factored into this outcome. To help answer this question, for this study, we chose a finite and well-bounded controversial problem to study using a technologically advanced social media mining and semantic analysis application. The question is important to understand because enormous amounts of money (in the billions USD) is being spent yearly by industries to entice, collect, and sell information about people by companies such as Facebook, Twitter, YouTube, and Google, for the purposes of targeted marketing and other social engineering that has presumed additive if not exponential value to the acquisition third parties (Hanna, Rohm, & Crittenden, 2011). Many companies even provide free services and useful or fun mobile device applications to consumers just to collect their personal information for these reasons (Kaplan & Haenlien, 2010).

In this manuscript, we provide evidence that social media may be more reflective in terms of preconceptions and tends to reinforces already held beliefs, known as confirmation bias (Kahneman & Tversky, 1973), rather than acting in opinion shaping; but this depends on certain topics and the behavioral characteristics or attributes of the individual participants, combined with the intensity of their sentiments, regardless of whether the sentiments were positive, neutral, or negative. Furthermore, we build upon the extant social media research literature by, (1) articulating circumstances and characteristics that illuminate confirmation bias, (2) develop an explanation of attributes that modify this condition, which is not based on human raters or self-reports, and (3) we produce a theoretical framework for further testing in other contexts to help explain more widely human-social influence "online." We proceed as follows: (1) We situate the problem in a conceptual frame, (2) we introduce the theoretical components derived from the data excavation, (3) we conduct a multilevel analysis of the data to provide rich results, and (4) we present our findings and draw conclusions about if, why, and how people make determinations from conversations found in social media.

## THEORY FRAME AND HYPOTHESES

### Attitudes, Sentiment, and Social Influences

Attitudes have been defined as dispositional factors that lead to positive or negative evaluations about people, places and things as well as actions and behaviors –known as the target (Ajzen, 2001). These positive or negative evaluations reflect sentiment, which encapsulates the notions of positive, neutral, or negative feelings along with the property of intensity, or force (Argamon, Bloom, Esuli & Sebastiani, 2009).

According to social cognitive theory (Bandura, 1977), social influences contribute to positive or negative cognitive appraisals to varying degrees. As such, sentiments are conveyed through social processes (Suzuki, 1997), and supportive social influences lead to more positive attitudes about the target, while conversely, unsupportive social influences fosters more negative attitudes. As social influence increases, people are more inclined to yield to the normative pressure (Beck & Ajzen, 1991; Salanick & Pfeffer, 1978; Suzuki, 1997). If there is strong sentiment against an idea or a proposition, they are more likely to be dissuaded; whereas if there is strongly supporting sentiment, people are more likely to be persuaded (Terry & Hogg, 1996).

In online forums such as Youtube, Facebook, and blogs, people may express their sentiment in binary form such clicking on icons that represent thumbs up (for like) or thumbs down (for dislike), but more interestingly, it is discoverable through data excavation to determine what people like or dislike, as well as the force or intensity of those sentiments. Moreover, through advanced technologies, we may now mathematically infer clusters of human attributes, such as optimism versus pessimism (calculated on a normative scale).

There are a variety of technologies and techniques to accomplish this from online forums, such as Natural Language Processing (NLP) and Latent Semantic Analytics (LSA), which have been used to determine both what people are referring to in their sentiments and the relationships of the sentiments to specific terms, along with clusters of characteristics based on the prose (Baeza-Yates & Ribeiro-Neto, 1999; Danescu-Niculescu-Mizil, Gamon, & Dumais, 2011). These factors can be computed by number of stars selected on a scale, in addition to the use of adjectives, adverbs, and expletives used in context of the sentiment, among other linguistic terms. For example, adverbs used in a particular linguistic form describe how one perceives that something happens. Adjectives used in a particular linguistic form describe a particular quality, such as “disgusting” or “thoughtful” regarding the target or topic about which there is a particular negative or positive sentiment (Romero, Galub, Asur, & Huberman, 2011; Splunk Inc., 2017).

The entirety of these linguistic components in context enables semantic analysis software to infer intensity by means of the modifying terms, such as “This plan is absolutely wonderful” compared to “This plan is barely acceptable.” A semantic distance is computable between these two positive sentiments, which can be expressed in multiple ways such as geometrically or on a reproduced scale (Argamon, et al., 2009). A reproduced scale creates degrees of a form (a scale), where an absolute form is the lowest point on the scale, the middle point is known as the comparative form, and the highest point is called the superlative form (Pang & Lee, 2004).

Next, not all social media venues are alike in terms of how they allow ratings or in terms of what is rated. For instance, Amazon sells products online in which both the product and provider may be rated using 5 stars, plus comments. However, there has been vociferous criticism of most of these product promotion sites because they allow negative reviews to be removed by the providers, and because reputation companies frequently create artificial positive reviews to overwhelm legitimate negative ones (Chen, van der Lans & Phan, 2017; Workman, et. al., 2013).

Hence, for our research purposes, we determined that the best integrity of reviews would be to use a bounded discussion board that had no limit on commentary such that our analytics could richly mine the patterns in the prose, and without the worry of positive review contamination, and that focused on topical ideation rather than individual or personal dealings with a particular product or vendor.

**Confirmation Bias**

Among their many contributions to understanding of human conceptualizations and behavior, Kahneman and Tversky (1973) explained how biases affect intentions and decisions. In scope for our investigation was their notion of confirmation bias. To illustrate this concept, research using an implicit-association test (IAT) has shown that when people were asked to sort pictures of people of color and white people with positive and negative terms, participants were able to complete the sorting much faster when pictures of white people were paired with positive terms than when people of color were paired with positive terms, and vice versa (Greenwald, McGhee, & Schwartz, 1998). This indicates a latent bias that carries over into confirmation bias. Confirmation is form of cognitive bias, which is a systematic pattern that diverges from normative judgments. In other words, the bias leads to illogical perceptions and behaviors because these biases lead people to construct a social reality that matches their preconceptions and this may result in outcomes such as self-fulfilling prophesies (Darley & Gross, 1983).

Once sentiments are formed and become firmly held, they become calcified from systematic reinforcement, and thus they are not easily changeable (Swann, 1997). This differs from when someone is seeking new knowledge, prior to the formation of strongly held beliefs or opinions (Forbes & Vespoli, 2013). When sentiments have been formed, either positively or negatively about a target, certain ignitions such as when a topic is controversial may intensify these sentiments to the point where people become even more intransigent (Zadeh, 2015). Therefore, we hypothesize that:

**H1a0:** People will not change their sentiment based on social media discussions.

**H1b0:** People will not change their sentiment regardless of sentiment intensity based on social media discussions.

**Optimism and Pessimism**

Although there are different views regarding the source of optimistic and pessimistic outlooks, such as whether they are heritable or conditioned, optimism leads to more positive expectancies whereas pessimism leads to more negative expectancies (Bates, 2015). For example, in a study by Hollingsworth (2015), subjects in a company setting were given an inventory to assess their optimistic and pessimistic propensities. They were then called into a conference room where they were told that there would be a significant announcement the next day. After the meeting, they were asked whether they thought the announcement would be positive or negative. Those who were more optimistic maintained that the announcement would be positive, and conversely those who were more pessimistic expressed that they thought the announcement would be negative.

However, while people generally do not change their sentiments, this may depend on specific characteristics of the individual (Zadeh, 2015). For example, there is evidence that people who are more optimistic have been shown to be more open to the opinions of others and therefore may be more persuadable (Scheier, Carver, & Bridges, 2001). More specifically, people who are more optimistic tend to consider alternatives and weigh the pros and cons in greater proportion to those who are more pessimistic (Bayrami et al., 2012). Therefore,

**H2:** We hypothesize that people who are more optimistic will change their sentiments in greater proportion to those who are pessimistic based on social media discussions.

## Internal and External Focus

People have different ways of cognitively formulating concepts and processing information, referred to as cognitive styles (Sternberg, 1997). When considering a problem or an issue, some people are more self-reflective and self-reliant in terms of these cognitive processes, known as internal focused, compared to others who tend to rely on the formulation and ideation by means of group interaction, known as external-focused (Sternberg, 1980). The effects of this can be observed in the differences between people who need quiet solitude and concentration for ideational generation, and those who find group processes (such as group brainstorming) a means of cognitively priming ideas (Hayes & Allinson, 1998).

Since people who have internal cognitive styles tend to approach problem solving and information analysis in an introspective and deliberative fashion, they are less inclined to seek and take the advice of others. On the other hand, since people with external cognitive styles prefer group brainstorming, in which solutions to problems evolve through cooperative interaction, they are more inclined to seek advice and counsel of others (Workman, Kahnweiler, & Bommer, 2003). Thus:

> **H3:** Those who are more external focused will be more likely to change their sentiments based on social media commentary than those who are more internal focused.

**Social and Issue Focus**

When it comes to important topics, people have inclinations toward a social focus versus issue focus; meaning that some people may orient their sympathies to the social aspects of the topic as opposed to the more rational or logical implications of the issue itself, and vice versa (Calvin, 1996; Murphy, Ackermann, & Handgraaf, 2011; Stark, Baldwin, Hertel, & Rothman, 2017). One way of conceiving a social focus was defined by Ajzen (2001) in which he proposed the conception of subjective norm, which indicates one's degree of desire to comply with significant others' implicit and explicit views about a thing or a given behavior.

Subjective norm reflects both the extent of social influences as well as the depth of social identity (Bandura, 1977). Consequently, those who are highly sensitive to subjective norms seek approval and are dissuaded by disapproval from significant others; and they respond more readily to encouragement or discouragement by these important others (Terry, Hogg, & White, 1999). Thus, as social influences increase toward the extremes, people who are highly sensitive to subjective norms increasingly strive to conform to social cues and the normative pressures exerted by those they perceive as important, credible, or are of like mind (Terry & Hogg, 1996).

Alternatively, people who are more issue focused internalize the meanings of an issue and its consequences (Calvin, 1996). They aim to deduce cause-and-effect of the antecedent issue upon themselves and their immediate concerns (Reisberg, 1996). People who are issue focused are not easily convinced by brief expressions of alternative opinions, but rather demand strong justification for the premises and conclusions before they will even consider a proposition (Clore & Huntsinger, 2007; Evans, Over & Manktelow, 1993). Consequently we formally hypothesize that:

**H4:** Those who are more socially focused will be more likely change their sentiment compared to those who are more issue focused.

### Human Attributes and Interactions with Intensity

Do some people react differently when they feel passionately about the topic? Research has suggested that when people hold positions more deeply and passionately, they are less likely to change their positions on a topic depending on the topic in question (Larsen, Diener & Emmons, 1986). However, in some cases, if someone is intensely passionate about some issues such as social equality and justice, some may actually be more inclined to change their sentiments based on events that are shown to them to be inequitable (van den Bos, Maas, Waldring, & Waldring, 2003). Therefore, we acknowledge differences among human attributes we have posited in our previous hypotheses and the interactions with their sentiment affect intensity. Thus we formally hypothesize that:

**H5a:** People who are more intensely optimistic will be more likely to change their sentiments based on social media than those who are more intensely pessimistic.

**H5b:** People who were more intensely external focused will be more likely to change their sentiments based on social media commentary than those who were more intensely internal focused.

**H5c:** People who are more intensely socially focused will more likely change their sentiment compared to those who were more intensely issue focused.

## METHOD

### Environment

Studies (e.g. Forbes & Vespoli, 2013) have shown that social media influences may differ depending upon the forum, domain, and topic of interest, and therefore may differ in terms of value to a particular consumer. In particular, observations show that topics posted on social media often quickly devolve into trolling and random subject postings. The conversations often tend to atrophy and attenuate until the postings become entirely meaningless with regard to the original topic (Chen, et. al., 2017).

For example, we monitored for a period of months conversations on YouTube for a trailer of an animated movie (for another research project). Within four posts, the comments had devolved from the topic of the move into a political debate about the President of the United States, with many expletives and abundant derogatory commentary that were completely irrelevant to the movie. However, when we monitored on YouTube a topic such as "Giants of Philosophy" nearly all of the commentary for each philosopher (such as Kant and Spinoza) resulted in topical debates, such as whether or not there is freewill. Thus, we inductively determined that the topic and forum was essential to the value of the social media commentary, as well as in terms of the ability to influence opinions. Our observations were consistent with previous research into this question (Chen, et. al., 2017; Forbes & Vespoli, 2013). Consequently, we chose a controlled blog about a controversial subject, where participants were encouraged to post anonymously. We chose this method specifically to determine whether social media commentary would change minds or reinforce them, and whether there were differences in this outcome based on particular participant attributes.

**Participants**

A large global financial services corporation based on the east coast of the United States wanted to undertake a comprehensive pay and benefits restructuring including dropping merit raises and replacing it with a graduated bonus program. The main advantage of the merit raise included gradual salary increases over time, the main advantage of the bonus program was that one could receive significantly more money in single year compared to a merit increase, but it was not guaranteed year to year, and his/her base salary would remain constant. This subject was considered highly controversial, according to the human resources department.

The company brought in a third party human resources consulting group to determine employee sentiments about the changes and identify concerns. They created an opinion survey, a mandatory 25-30 minute online factual presentation explaining the proposed compensation program, which included a short quiz at the end to ensure that participants had viewed the presentation (if participants scored less than 80%, they were required to repeat the presentation), and finally, they produced a blog where participants would post anonymous (confidential) comments, which was advertised by the company as for the purposes of helping them to come to a decision. To maximize participation in the social media blog, people (associates) were regularly prompted to participate and were given "purchase points" for doing so, which could be applied to making purchases from affiliate merchants. They were also notified when someone viewed or commented on their post to get them to reengage. For example, bot generated prompts and cues were used to get participants to read the social media commentary, such as generating notifications that stated: "Hey, someone just viewed/commented on your posting."

From an academic perspective, we were interested in if, and how, the social media commentary changed people's sentiment about the program, and if so, did it do so in a positive or negative direction based on certain human attributes such as open or closed mindedness, which was determined by an advanced social media and semantic analysis application, the method largely explained by Sharma, Gupta, Agarwal & Bhattacharyya (2015), and Romero, Galuba, Asur, and Huberman, (2011).

Instrumentation and Approach

For our investigation, we developed a short questionnaire to inquire (on a 7 point scale, where 1 = strongly disapprove, 7 = strongly approve) of the changes. The questionnaire was presented to participants prior to their having viewed the presentation, immediately after they viewed the presentation, then again after 3 weeks of social media commentary.

Next, we ran an analysis of the discussions by commenter with a social media mining technology that utilizes natural language processing (NLP) and logistic regression for categorization of concepts, along with semantic clustering into attributes using a modified version of latent semantic analysis (Landauer, Foltz & Laham, 2009). This widely used commercial technology produced (among other things) a sentiment value, where -1 = negative, and 1 = neutral/informational, and 2 = positive. The technology employs a theorem derived from a formula published by Sharma, Gupta, Agarwal & Bhattacharyya (2015) to determine an additional measure: A scaled sentiment intensity ranging from 1 to 7 indicating mildly expressed to strongly expressed affect score.

These measures are mathematically formulated based on the use of clusters of adjectives, adverbs, and other semantic terms, including the use of profanity, and does not rely on human raters. Beyond these capabilities, the technology (an extended version of open source LingPipe and Lucine) has the ability to infer various attributes of posters geometrically from semantic terms in the prose. More specifically, the technology inferred certain attributes using a modified form a latent semantic analytics (LSA), augmented to cluster semantic concepts into the behavioral attributes: Optimism/Pessimism, Internal "I" focused/External "You" focused, and Social/Issue focused (c.f. Carpenter, 2004; Landauer, et. al., 2009).

**RESULTS**

After data screening and pretests, we were sufficiently confident in our analyses. The Muachly's test of sphericity was not significant ($\chi^2 = 3.54$, $p = .61$), which indicates that the correlation matrix was not significantly different from the identity matrix in which correlations between variables (Myers, Well & Lorch, 2010). This combined with a fairly large sample size, we were confident that the assumption of sphericity had not been violated. In support of continuing with the remaining analyses, the test for homogenity of variances was validated because the scatter was relatively equal (Myers, et. al., 2010). Moreover, Levene's test was not significant at the 0.05 level (Test 1: $F = 2.43$, $p = 0.07$, Test 2: $F = 5.72$, $p = 0.08$, and Test 3: $F = 2.70$, $p = 0.07$), which indicated that the assumption of homogeneity of the covariance matrices had been met (Myers, et. al., 2010). The descriptive statistics are shown in Table 1.

Table 1
Descriptive Statistics and Correlations

| Measure | μ | σ | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| Optimism/ Pessimism | 3.6 | 1.33 | -- | | | | | |
| Internal/External | 4.0 | 1.79 | -.14 | -- | | | | |
| Social/Issue | 3.4 | 1.57 | .17* | -.24** | -- | | | |
| Intensity | 4.3 | 1.89 | -.07 | -.17* | -.19** | -- | | |
| Pretest Sentiment | 3.0 | 1.43 | -.13* | .24** | -.16* | .13* | -- | |
| Posttest Sentiment | 3.4 | 1.91 | -.18* | .27** | -19* | .10* | .23** | -- |

N = 753. * p < .01, **p < .001

For the first stage of our analysis we conducted repeated measures ANOVA. Test 1: prior to viewing the informational video, Test 2: after viewing the informational video, Test 3: after social media commentary, based on the three survey inquiries. In H1a, we hypothesized that there would be no change in sentiment based on social media discussions, in other words the null hypothesis would be supported. We found that the informational video did significantly change participant sentiments ($F$ = 32.82, $p$ < 0.00), but that the social media conversations made no statistical difference ($F$ = 0.28, $p$ = 0.73). Similarly, for H1b, we argued that how intensely the sentiment was felt/expressed in social media would not change sentiments. Consistent with H1a, the analysis of H1b showed that the informational video did significantly change participant sentiments ($F$ = 12.49, $p$ < 0.00), but that the social media conversations made no statistical difference ($F$ = 2.91, $p$ = 0.06).

Given the results of our first stage analysis we tested our remaining hypotheses using multivariate analysis of covariance (MANCOVA). We wanted to determine whether there were significant differences among the cluster of attributes exhibited by participants, and since we wanted to isolate the effects upon sentiment without the transitive dependency, we used Test 2 (post-informational video) as the covariate to determine if there were significant changes in sentiment based on the social media commentary (Test 3). The overall MANCOVA model was significant ($F$ = 1.01, $p$ < .00, $r^2$adj = .72). Since we posited that there would be differences based on certain characteristics of the participants, in other words, beyond sentiment and intensity, we hypothesized that participant attributes would influence the outcomes; thus we proposed alternative hypotheses based on the following attributes that were mined and categorized by the technology: optimism/pessimism, internal "I" focused/external "You" focused and social/issue focused.

Since specific tests of hypotheses must be based on univariate results and not on the overall multivariate test, we conducted individual ANCOVA for the remaining hypotheses. In H2, we hypothesized that participants who were more optimistic ($\mu$ = 3.22, $\sigma$ = 0.47) would be more likely to change their sentiments based on social media than those who were more pessimistic ($\mu$ = 3.13, $\sigma$ = 0.20). This hypothesis was not supported ($F$ = 1.14, $p$ = 0.20, $\eta^2$ = 0.12). In H3, we suggested that those who were more external focused ($\mu$ = 3.08, $\sigma$ = 0.89) would be more likely to change their sentiments based on social media commentary than those who were more internal focused ($\mu$ = 4.36, $\sigma$ = 0.76). This hypothesis was supported ($F$ = 1.49, $p$ < 0.00, $\eta^2$ = 0.18). Finally, in H4, we hypothesized that those who were more socially focused ($\mu$ = 3.68, $\sigma$ = 0.73) would more likely change their sentiment compared to those who were more issue focused (μ= 3.32, σ = 0.55). This hypothesis was not supported ($F$= 1.27, $p$ = 0.61, $\eta^2$ = 0.14). See Tables 2-4.

Table 2
*ANCOVA for Optimism/ Pessimism; Dependent Variable: Post-Test*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Eta Squared |
|---|---|---|---|---|---|---|
| Corrected Model | 1905.131 | 81 | 23.520 | 18.581 | .000 | .692 |
| Intercept | 4.675 | 1 | 4.675 | 3.693 | .055 | .005 |
| Pretest | 1567.386 | 1 | 1567.386 | 1238.247 | .000 | .649 |
| Optimism | 115.251 | 80 | 1.441 | 1.138 | .203 | .119 |
| Error | 849.359 | 671 | 1.266 | | | |
| Total | 11904.479 | 753 | | | | |
| Corrected Total | 2754.489 | 752 | | | | |

R Squared = .692 (Adjusted R Squared = .654)

Table 3
*ANCOVA for Internal/External; Dependent Variable: Post-Test*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Eta Squared |
|---|---|---|---|---|---|---|
| Corrected Model | 1964.618 | 98 | 20.047 | 16.599 | .000 | .713 |
| Intercept | 1.471 | 1 | 1.471 | 1.218 | .270 | .002 |
| Pre-Test | 1513.089 | 1 | 1513.089 | 1252.812 | .000 | .657 |
| Internal | 174.738 | 97 | 1.801 | 1.492 | .003 | .181 |
| Error | 789.872 | 654 | 1.208 | | | |
| Total | 11904.479 | 753 | | | | |
| Corrected Total | 2754.489 | 752 | | | | |

R Squared = .713 (Adjusted R Squared = .670)

Table 4
ANCOVA for Social/Issue; Dependent Variable: Post-Test

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Eta Squared |
|---|---|---|---|---|---|---|
| Corrected Model | 1925.776 | 87 | 22.135 | 17.762 | .000 | .699 |
| Intercept | 1.855 | 1 | 1.855 | 1.489 | .223 | .002 |
| Pre-Test | 1503.589 | 1 | 1503.589 | 1206.553 | .000 | .645 |
| Social | 135.896 | 86 | 1.580 | 1.268 | .061 | .141 |
| Error | 828.714 | 665 | 1.246 | | | |
| Total | 11904.479 | 753 | | | | |
| Corrected Total | 2754.489 | 752 | | | | |

R Squared = .699 (Adjusted R Squared = .660)

In our final analysis, we proposed interactions. In H5a, we hypothesized that participants who were more intensely optimistic would be more likely to change their sentiments based on social media than those who were more intensely pessimistic. However, this hypothesis was not supported ($F = 1.20$, $p = 0.08$, $\eta^2 = 0.24$). H5b suggested that those who were more intensely external focused would be more likely to change their sentiments based on social media commentary than those who were more intensely internal focused. This hypothesis was supported ($F = 1.38$, $p < 0.00$, $\eta^2 = 0.32$). Finally, in H5c, we hypothesized that those who were more intensely socially focused would more likely change their sentiment compared to those who were more intensely issue focused. This hypothesis was also supported ($F = 1.41$, $p < 0.00$, $\eta^2 = 0.29$). See Tables 5-7.

Table 5
*ANCOVA for Optimism/Pessimism Intensity Interaction*
*Dependent Variable: Post-Test*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Eta Squared |
|---|---|---|---|---|---|---|
| Intercept | 6.916 | 1 | 6.916 | 4.152 | .049 | .101 |
| Error | 61.768 | 37.080 | 1.666 | | | |
| Pre-Test | 1255.327 | 1 | 1255.327 | 1066.657 | .000 | .669 |
| Error | 620.216 | 527 | 1.177 | | | |
| Optimism/ Pessimism | 114.745 | 80 | 1.434 | 1.120 | .240 | .168 |
| Error | 567.869 | 443.442 | 1.281 | | | |
| Intensity | 24.692 | 7 | 3.527 | 2.703 | .010 | .052 |
| Error | 448.809 | 343.870 | 1.305 | | | |
| Optimism * Intensity | 193.025 | 137 | 1.409 | 1.197 | .084 | .237 |
| Error | 620.216 | 527 | 1.177 | | | |

Table 6
*ANCOVA for Internal/External Intensity Interaction*
*Dependent Variable: Post-Test*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Eta Squared |
|---|---|---|---|---|---|---|
| Intercept | 2.141 | 1 | 2.141 | 1.471 | .232 | .036 |
| Error | 57.360 | 39.415 | 1.455 | | | |
| Pre-Test | 1200.358 | 1 | 1200.358 | 1151.571 | .000 | .704 |
| Error | 505.548 | 485 | 1.042 | | | |
| Internal/External | 187.440 | 97 | 1.932 | 1.521 | .003 | .300 |
| Error | 436.450 | 343.492 | 1.271 | | | |
| Intensity | 21.497 | 7 | 3.071 | 2.377 | .022 | .051 |
| Error | 396.174 | 306.694 | 1.292 | | | |
| Internal * Intensity | 232.328 | 162 | 1.434 | 1.376 | .005 | .315 |
| Error | 505.548 | 485 | 1.042 | | | |

Table 7
*ANCOVA for Social/Issue Intensity Interaction*
*Dependent Variable: Post-Test*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Eta Squared |
|---|---|---|---|---|---|---|
| Intercept | 1.821 | 1 | 1.821 | 1.115 | .298 | .031 |
| Error | 56.088 | 34.346 | 1.633 | | | |
| Pre-Test | 1239.151 | 1 | 1239.151 | 1125.223 | .000 | .687 |
| Error | 564.941 | 513 | 1.101 | | | |
| Social/Issue | 145.122 | 86 | 1.687 | 1.261 | .077 | .237 |
| Error | 465.983 | 348.300 | 1.338 | | | |
| Intensity | 26.639 | 7 | 3.806 | 2.760 | .009 | .064 |
| Error | 392.164 | 284.453 | 1.379 | | | |
| Social * Intensity | 224.704 | 145 | 1.550 | 1.407 | .004 | .285 |
| Error | 564.941 | 513 | 1.101 | | | |

## DISCUSSION

Topics posted on YouTube and many other social media may quickly devolve into trolling and random postings. For example, we monitored conversations on YouTube for a trailer of an animated movie. Within four posts, the conversation had quickly devolved from the topic of the movie to a political debate about the President of the United States, with many expletives and abundant derogatory commentary that had nothing to do with the original message. However, when we monitored a topic such as Giants of Philosophy on YouTube, nearly all of the commentary was a philosophical debate, such as whether or not there is freewill. The discussions were nearly all topical.

Thus, we determined that the issue or topic was critical to the value of the commentary found in social media. In the business world, issues pertinent to daily lives carry the most relevant social commentary in social media; thus, we selected an important and also controversial topic to study in that context. Overall, we were interested in whether or not social media commentary changed or confirmed previously held positions. We learned that there was strong support for confirmation bias, but there were also differences depending on intensity of the sentiment affect, and also attributes of people.

We concluded that generally speaking, people do not change their minds based on social media commentary. The research literature suggests that this is different from when people are searching for a product online and rely on other people's recommendations –although there have been many criticisms of this proposition as well since people are becoming more aware of reputation bots that inflate positive reviews. Nevertheless, the fact that we found that participants did tend to change their minds based on an informative presentation does tend to support the idea that there are differences between those who are seeking new information to form an opinion versus those who have already made up their minds.

Also, it is important to note that confirmation bias appears not to be universal and depends upon certain characteristics of those who are posting and reading online commentary regarding an important and controversial topic, such as changing how people are compensated at work. The sentiment mining technology we utilized produced patterns consisting of three attribute characteristics: optimism/pessimism, internal "I" focused/external "You" focused and social/issue focused, along with a dimensional scale reflecting intensity of sentiment. When we analyzed the data, we found that optimism versus pessimism and social focus versus issue focus made no difference in terms of influence from the social media conversation, but externals (as opposed to internals) were likely to change their sentiments.

Furthermore, we found that people who were more extremely external focused were more likely to change their sentiments based on social media commentary than those who were more extremely internal focused when sentiment affect intensity was taken into account, as well as people who were more extremely socially focused were more likely change their sentiment compared to those who were more extremely issue focused when sentiment affect intensity was taken into account.

With these findings we helped to elucidate some key nuances about online commentary in social media and their influences, as well as their value. Also, we produced a theoretical framework for further testing in other contexts to help explain more widely human-social influence "online" without relying on the judgment of human raters. We would like to see this work extended into various social media forums to determine if there are differences among those forums, as well as type of media expression, such as video versus prose.

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