STATE OF THE ART

Comments on how the task of reading research articles should be reported

Whenever the intern reads articles, the intern should report the following aspects:

1) What are the problems (research questions) that are addressed? (Objective(s))
2) How are these problems attacked? (Methodology)
3) What the obtained results? (Results)
4) How important are these results? (Discussion/Impact)
5) What are the novelties through this work? (Contribution)
6) What are your critiques? (Your opinion)
7) Can you propose something else? (Possible future works)

1st research paper: Detecting, Preventing, and Mitigating Online Firestorms in Brand Communities

1)

How can we detect/prevent/mitigate firestorms in Brand Communities? & How can we limit the impact of negative eWOM?

2)

The authors wanted to observe if a certain type of response is effective, so they suppose 6 hypothesis:

H1: The intensity of high-arousal emotion words in negative eWOM messages relates to greater virality in online brand communities compared with the intensity of low arousal emotions words.

H2: Stronger structural ties between the sender of negative eWOM and the receiving online brand community relate to greater virality

H3: Closer LSM between the sender of negative eWOM and the receiving online brand communities relates to greater virality

H4: More explanation, rather than more empathy, in firm responses is better suited to contain negative eWOM with more intensive high-arousal emotions.

H5: More empathy, rather than more explanation, in firm responses is better suited to co,tain negative eWOM with more intensive low-arousal emotions

H6a: Consecutive firm responses with varying rather than repeated empathic intensity are better suited to mitigating evolved online firestorms.

H6b: Consecutive firm responses with varying rather than repeated explanatory intensity are better suited to mitigating evolved online firestorms

Sampling Frame

They used Facebook's Application Programming Interface (API) to gather the US firms listed on the S&P 500 between 11/01/11 – 01/31/2016.

They choose this setting for 3 main reasons:

-Facebook is a very popular social media, and customers used it to interact with firms in their brand communities and to complain through it.

-Firms actively participate in Facebook conversations and responds to customer posts.

-The count of likes and comments indicate the degree to which other approves and share a message and provides an objective measure of virality.

Text Analysis Procedure

The focus is based on negative eWOM, so they analyzed text-based features to determine which posts were negative in 2 steps:

-Applied the R Quanteda package using Linguistic Inquiry and Word Count (LIWC) text-mining dictionaries to derive the intensity of positive and negative-emotions words in each post

-Applied the Standford Sentence and Grammatical dependency Parser (Standford Natural Language Processing Group 2014) to subdivide each post into sentences and identify dependencies between emotion words and negations

Negative positive emotions words were counted toward negativity and negated negative emotions words towards positivity. If a customer post is more negative than positive overall, they count it as a potential firestorm.

The final sample counted 472,995 negative customer posts in English across 89 online brand communities

Indeed, to sort the data they have excluded 48 420 posts that contained external content, 14O posts that contained fewer than 3 words because it is not understandable for the receiver and to finish, they excluded 128 681 posts with no customers reactions because they are interested in the inflation of the virality.

Measurement

SST: Strength of Structural Ties known as the frequency of communication

$$\begin{aligned} \mathrm{SST}_{\mathrm{ic}} = \sum_{\tau=0}^{t-1} & \text{Received Likes}_{\mathrm{ic}}^{\tau} + \text{Received Comments}_{\mathrm{ic}}^{\tau} \\ & + \text{Received Shares}_{\mathrm{ic}}^{\tau} + \sum_{\tau=0}^{t-1} \text{Likes Given}_{\mathrm{ic}}^{\tau} \\ & + \text{Comments Given}_{\mathrm{ic}}^{\tau} \end{aligned}$$

t-1: entire period prior to the post at time t

SST***ic***: sum of likes***c*** ,comments***c*** , and shares***c*** , that customer***i*** received from others in the brand community***c*** before the post at ***t*** , as well as sum of likes***i*** , and comments***i*** the customer gave the others in the brand community ***c*** prior to the post at ***t.***

LSM: Linguistical Style Match known as the degree of the communication style matching with the online brand community before the post.

They derived the degree of LSM between customer ***i*** posting negative eWOM at time t with the receiving brand communities ***c*** in 3 steps:

- First, they mined the use intensity of each of the nine function word categories ***j*** separately in focal customer **i**'s message and across all customer messages (negative and positive) in the brand community ***c*** posted in the previous three months in response to the focal negative eWOM post (moving community average)

-Second, the degree of similar use intensity LSM of each function word category (***FWj***) by customer ***i*** posting the negative eWOM into community ***c*** comes from the formula:

$$\mathrm{LSMj}_{\mathrm{ic}} = 1 - \left(\frac{|\mathrm{FWj}_{\mathrm{i}} - \overline{\mathrm{FWj}}_{\mathrm{ic}}|}{\mathrm{FWj}_{\mathrm{i}} + \overline{\mathrm{FWj}}_{\mathrm{ic}} + .0001} \right)$$

-Third, by aggregating all nine LSM scores with equal weights, they obtain an LSM score bound between 0 and 1, and scores closer to 1 reflect greater degree of communication style matching between customer ***i*** and the online brand community ***c***.

Modeling Approach

To determine whether a multilevel approach is warranted, they conducted a oneway analysis of variance with random effects to reveal any systematic between-group variance in the virality of negative eWOM. They find significant between-group variance (X^2 (88) = 818,729, $p < .01$). In addition, the design effect of 36.74 suggests that a multilevel structure is possible. The maximum variance inflation factor score across all models is 3, indicating no potential threat of multicollinearity

They specified a series of separate hierarchical models, with parameters at the post and firm/brand community level, using full information maximum likehood estimation and grand mean-centering.

Virality is the focal outcome measure (Gamma).

. Virality^{t-1} (Detect): Total number of likes and comments from other customers any time after posting at t.

$$\begin{aligned}\text{Virality}_{ic}^{t-1} = {} & \gamma_{00} + \gamma_{01-04}\text{Firm Controls}_c \\ & + \gamma_{05-10}\text{Brand Community Controls}_c \\ & + \gamma_{11-17}\text{Post Controls}_{ic} \\ & + \gamma_{18}\text{Dum No Firm Response}_{ic} \\ & + \gamma_{19-23}\text{Post Predictors}_{ic} \\ & + \gamma_{24-43}\text{Dum Timing}_{ic} + u_{0c} + r_{ic},\end{aligned}$$

Where t_1 is the time period after the time t of customer i's post in band communities c.

$\text{Virality}_{ic}^{t-1}$ = the combined sum of likes and comments post i receives from other customers in community c any time after it was posted (brand community-centered and log-transformed);

Firm Controls_c = community-specific controls using the Global Industry Classification Standard: GICS Consumer Discretionary_c, GICS Consumer Staples_c, Brand Familiarity_c, and Brand Reputation_c;

Brand Community Controls_c = Brand Community Size_c, Brand Community Attentiveness_c, Brand Community Expressiveness_c, Firm Engagement_c, Average Tie Strengths_c, and Variance in Linguistic Style_c;

Post Controls_{ic} = Competing Inputs_{ic}, Sentiment Previous Post_{ic}, Post Length_{ic}, Post Complexity_{ic}, Negation in Post_{ic}, and Previous Complains_{ic};

Dum No Firm Response_{ic} = 1 if there is no firm response at any time, and 0 otherwise;

Post Predictors_{ic} = Intensity of High Arousal_{ic}, Intensity of Low Arousal_{ic}, SST_{ic}, and LSM_{ic};

Dum Timing_{ic} = dummy variables for years (baseline is 2015), month (baseline is December), weekend day (baseline is week day), and time of the day (baseline is night time, EST);

u_{0c} = brand community–specific error term; and

r_{ic} = post-specific error term.

$\text{Virality}_{ic}^{t-2}$ (Prevent): Number of likes and comments from other customers any time after the first firm response.

$$\begin{aligned}\text{Virality}_{ic}^{t-2} = {} & \gamma_{00} + \gamma_{01-04}\text{Firm Controls}_c \\ & + \gamma_{05-10}\text{Brand Community Controls}_c \\ & + \gamma_{11-17}\text{Post Controls}_{ic} \\ & + \gamma_{18}\text{Firm Response Time}_{ic} \\ & + \gamma_{19-23}\text{Post Predictors}_{ic} \\ & + \gamma_{24-43}\text{Dum Ti ming}_{ic} \\ & + \gamma_{44-48}\text{First Firm Response}_{ic} \\ & + \gamma_{49-52}\text{Interactions}_{ic} + u_{0c} + r_{ic},\end{aligned}$$

where t_2 is the time period after the first firm response

$\text{Virality}_{ic}^{t-2}$ = the combined sum of likes and comments post i received from other customers in community c any time after the first firm response (brand community-centered and log-transformed);
Firm Response Time = time until the first firm response;
First Firm Response = Compensation$_{ic}$, Apology$_{ic}$, Channel Change$_{ic}$, Intensity of Empathy$_{ic}$, and Intensity of Explanation$_{ic}$; and
Interactions$_{ic}$ = Intensity of High Arousal$_{ic}$ × Intensity of Empathy$_{ic}$, Intensity of High Arousal$_{ic}$ × Intensity of Explanation$_{ic}$, Intensity of Low Arousal$_{ic}$ × Intensity of Empathy$_{ic}$, and Intensity of Low Arousal$_{ic}$ × Intensity of Empathy$_{ic}$.

Virality^{t_3} (Mitigate): The number of likes and comments from other customers any time after the last firm response

$$\begin{aligned}\text{Virality}_{ic}^{t-3} = {} & \gamma_{00} + \gamma_{01-04}\text{Firm Controls}_c \\ & + \gamma_{05-10}\text{Brand Community Controls}_c \\ & + \gamma_{11-17}\text{Post Controls}_{ic} \\ & + \gamma_{18}\text{Firm Response Time}_{ic} \\ & + \gamma_{19-23}\text{Post Predictors}_{ic} \\ & + \gamma_{24-43}\text{Dum Ti ming}_{ic} \\ & + \gamma_{44-48}\text{First Firm Response}_{ic} \\ & + \gamma_{49-51}\text{Subsequent Firm Responses}_{ci} \\ & + \gamma_{52-53}\text{Variance in Firm Responses}_{ci} + u_{0c} + r_{ic}\end{aligned}$$

where t_3, ..., T is the time period after the last firm response

$\text{Virality}_{ic}^{t-3}$ = the combined sum of likes and comments post i received from other customers in community c any time after the last firm response (brand community-centered and log-transformed);

$\text{Subsequent Firm Responses}_{ic}$ = include all firm responses after the first firm response, Compensation_{ic}, Apology_{ic}, $\text{Channel Change}_{ic}$, $\text{Intensity of Empathy}_{ic}$, and $\text{Intensity of Explanation}_{ic}$; and

$\text{Variance in Firm Responses}_{ci}$ = $\text{Variance in Empathy}_{ic}$ and $\text{Variance in Explanation}_{ic}$ (across all Firm Responses_{ic}).

3)

Number	Hypothesis	Gamma	Pvalue	H-Approuved
1	High arousal emotions words ↑ -> Virality in Brand communities ↑	Gha=0,186 >Gla=0,026	0,01	Yes
2	SST between the sender & brand community ↑-> Virality ↑	Gsst=1,432	0,01	Yes
3	LSM between the sender & brand community ↑ -> Virality ↑	Glsm=0,025	0,01	Yes
4	Explanation >> Empathy -> High arousal emotions ↑	Gemp=0,386>Gexp=0,180	0,01	Yes
5	Empathy >> Explanation -> Low arousal emotions ↑	Gemp=0,025>Gexp=0,016	0,1	No
6a	Var btwn empathy int of consecutives firms responses ↑ -> Online firestorms ↓	Gemp=-0,185	0,05	Yes
6b	Var btwn explanation int of consecutives firms responses ↑ -> Online firestorms ↓	Gemp=-0,185	0,01	Yes

Number: Number of hypotheses

Hypothesis: List of the hypothesis suggested by the authors

Gamma: Measure of the virality

Pvalue: Statistical measurement used to validate a hypothesis against observed data

H-Approuved: Hypothesis approuval

4)

As we know the gamma is the measurement of the virality and the reference value is the point 0. The more the gamma is positive (higher) the more there are virality and the same with the negative values (Lower virality).

The only problem here is with the 5th hypothesis indeed we have here the gamma of empathy & explanation that are very close so we cannot conclude that more empathy is better suited than more explanation for the people with intensive low-arousal emotions.

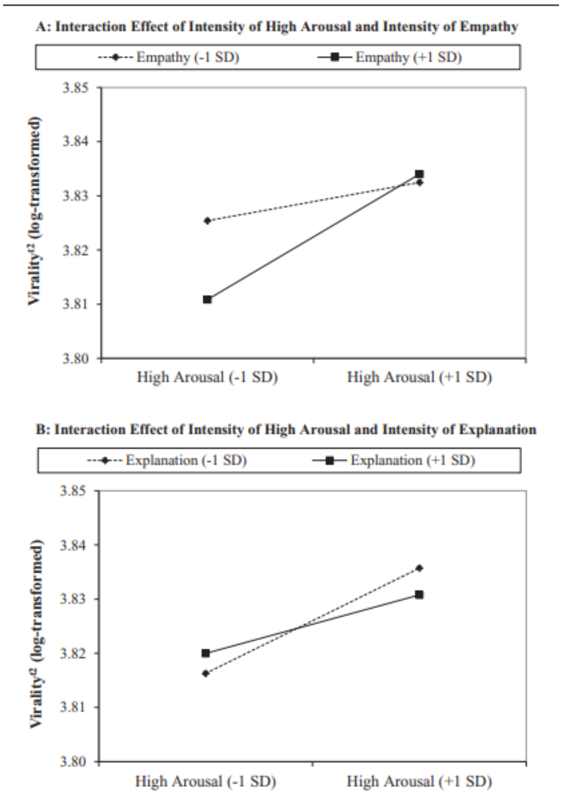

Figure 3: Firm responses strategies moderate the effect of high arousal emotions on virality

In the first graphic (at the top): The more we use empathy here the more the virality will increase for the people how have a high arousal emotions.

In the second graphic (at the bottom): We can see in this graphic that using explanation contains the online firestorms.

This graphic just confirms the hypothesis number 4.

5)

They emphasis few things:

-Negative WOM research to investigate how sender and relational aspects aid in the detection of potentials firestorms, then they specify how different levels of emotional arousal and the strength of the sender SST (Strength Structural Ties) and their similarity to the online brand community relate to the virality of negative eWOM.

- At an operational level, they established a reliable, computerized technique to determine the similarity of language use within online brand communities.

-Their findings provide insights into firms' ability to prevent online firestorms by issuing responses designed to engage with or disengage from customers online, (more explanatory responses are best for negative eWOM messages containing above-average negative high-arousal emotions; the effectiveness of disengaging approaches varies).

-They identify structured sequences of different engaging responses across multiple firm messages as a novel, actionable approach to mitigate the impact of evolved online firestorms.

6)

This paper works on how sentiment analysis plays a key role in firestorms in brand communities and how we can with sentiment analysis Detect Prevent and Mitigate with an appropriate answer.