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NOTICES

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14. ABSTRACT

Passive social media consumption can result in the formation of an individual's opinion. If an individual trusts the veracity of the social media information, such newly formed opinion becomes a belief, and it has been argued that the purpose of belief is to guide action. Therefore, it is important to understand how social media information contributes toward the opinion formation of individuals because it may shape their future actions. The present study aims to identify thresholds estimated or perceived by an individual for the amount of social media data needed to form an individual's opinion. The goals of the current study are to accomplish the following: 1) identify perceived opinion formation thresholds for three distinct social media data-types (i.e., Images, Videos, and Messages), 2) understand the influence of different contexts (i.e., Low controversy, Medium controversy, High controversy, and None) over opinion formation thresholds, and 3) determine how opinion formation thresholds change with the source of social media information (i.e., Unknown or unspecified, Like-minded or similar perspectives, and Different-minded or diverse perspectives). An experiment on Amazon Mechanical Turk (MTurk) was performed and the results of 945 participants were analyzed. The results yield several findings: 1) opinion formation thresholds represented as population averages are identified across the three distinct data-types, 2) context has marginal influence over opinion formation thresholds, and 3) influence from sources depends on the data-type. These results provide an empirically derived set of opinion formation thresholds that correspond to different dimensions of social media information.

15. SUBJECT TERMS

social media; MTurk; human dynamics; experimental; opinion formation threshold; opinion spread

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1. Introduction

Passive social media consumers were estimated to make up the large majority of online communities (Nonnecke and Preece 1999). Passive social media consumption has been recently studied in disaster perception (Neubaum et al. 2014) to estimate population emotional reactions, brand marketing (Ashley and Tuten 2015) to approximate the efficacy of different marketing strategies, and information seeking (Khan 2017) to evaluate why individuals interact with online content. These studies point to the importance of passive social media consumption and provide insightful estimates of population perceptions. The present study aims to provide quantitative thresholds of opinion formation based on the perceived passive consumption of social media information by individuals.

Theoretical motivation for investigating estimated opinion formation thresholds as opposed to actual thresholds is to avoid three problems associated with physical content (real or fake): 1) content bias (Xiong and Liu 2014), 2) social influence (Cialdini and Goldstein 2004), and 3) different interpretations of facts associated with the same context (Gaines et al. 2007). Accordingly, the current study 1) minimizes content bias with the complete absence of physical content, 2) addresses social influence with general categories associated with distinct social media sources (e.g., like-minded vs. different-minded posting sources), and 3) provides ambiguous but discernable context categories that minimize differences of interpretations. Although these abstractions might ameliorate the problems described here, there is a sacrifice of result relevance and applicability that comes with the abstraction of details. Therefore, this work is geared towards providing a "low-resolution" estimate for ratios of, or relative population averaged, opinion formation thresholds, not explicitly a threshold model. However, the results from this work can be used to provide relative predictions or ratios for the amount of content that might be needed to effectively promote an idea or concept, for example, using select data-types. Furthermore, the results are intended to provide relative influence of the measured experimental dimensions instead of thresholds taken literally.

1.1 Social Media as a Platform for Information

Social media has become a powerful resource used primarily to link individuals with one another for communication purposes (Evans 2010). The introduction of social media into society comes with both positive and negative consequences in terms of cognitive, emotional, and social development (Immordino-Yang et al. 2012; Immordino-Yang 2015). In addition, social media is often used by individuals as their main information source (Westerman et al. 2014). However, a major problem with social media dependency arises from the frequently encountered absence of information verification. Currently, there is little opportunity to clearly establish the credibility for a large portion of information being exchanged between users. Additionally, research has shown that an individual's opinions can easily be influenced by the beliefs of their peers (Simpson et al. 2012). Thus, social media offers a dangerous opportunity for spreading misleading or persuasive information to a large population, influencing their beliefs, and potentially leading to behaviors based on those beliefs. Therefore, it is imperative to understand the factors that contribute to the formation of individuals' opinions from social media information.

1.2 Social Media Information and Opinion Formation

The interaction between people and information displayed through social media platforms provides a substantial opportunity to influence opinions, shape decision making, and otherwise effectively engage users in desired behaviors (Ahmad et al. 2016). Marketing techniques employ many strategies to shift a target's opinion about a product or idea (Loken 2006). These techniques are particularly powerful when incorporating some level of social influence or peer pressure within the message (Cialdini et al. 1976; Mani et al. 2013). Thus, it can be reasoned that an individual possesses considerable power to mold the opinions of others through social media, which introduces a system capable of manipulating, persuading, and exploiting human behavior.

Given the influence social media information can have over an individual's opinion, it is important to find how effective different social media data-types are for opinion formation. In the present study, opinion formation is defined as the change from a neutral (naïve) state of mind to a concrete belief or perspective, based on the accumulation of evidence (i.e., pieces of data or an amount of a distinct single-media data-type), resulting in a perceived veracity of the material. Thus, this work improves our understanding of how a population-averaged threshold for adopting a perspective depends on different single-media data-types (i.e., Images, Videos, or Messages) of the consumed social media information.

1.3 The Present Study

Throughout this article the term *opinion formation threshold* is used to describe the quantitative estimate provided by the participants for the amount of discrete pieces of information they believe they would need to view before adopting a perspective (i.e., opinion formation). In other words, an opinion formation threshold is the participant's self-reported estimate for the number of a distinct data-type (i.e., Images, Videos, or Messages) they would need to view, in order for them to form an opinion given a context and source.

Thus, the goals of the current research were to 1) identify opinion formation thresholds for different data-types (i.e., Images, Videos, and Messages), 2) understand the influence context has over the opinion formation thresholds, and 3) determine how distinct sources modify opinion formation thresholds.

We first provide the protocol for acquiring participants, an adequate description of the experimental design, and the data analysis technique in Section 2. Next, in Section 3 we demonstrate the findings derived from the data through analyses and present the relationship between our results and goals of the study. Lastly, the implications of this work and the directions for future research are discussed in Section 4.

2. Methods

Recent evidence showing the reliability of Amazon Mechanical Turk (MTurk) data (Holden et al. 2013; Rouse 2015) is the reason the platform was utilized to collect data from 945 participants in the present study. A simple computerized task required participants to enter a number that represented their estimate for the amount of a distinct social media data-type (i.e., Images, Videos, or Messages) along with a context (i.e., Low, Medium, High, or None) that they expected to view in a static time frame (one day) before formulating an opinion. The 945 participants were randomly assigned to 1 of 12 conditions (see Fig. 1). A condition consisted of one data-type (Images, Videos, or Messages) within one context (Low, Medium, High, or None) under three different source references (Unknown: no source was indicated; Like: data posted by like-minded individuals; Different: data posted by individuals with diverse perspectives).

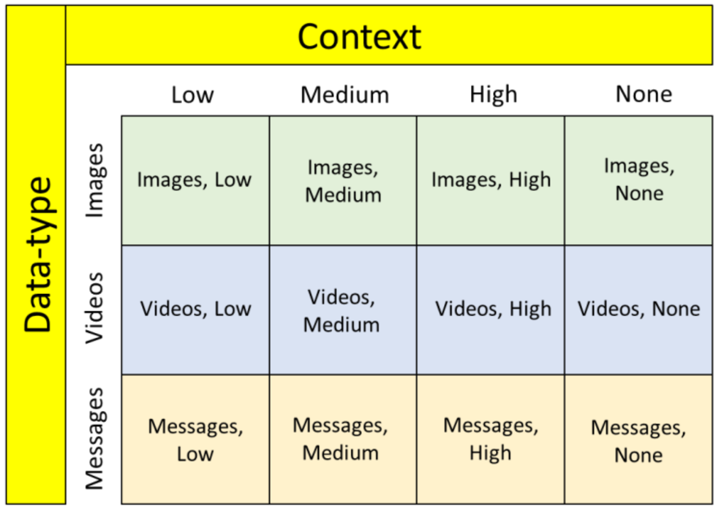

Fig. 1 Visualization of 12 conditions to which participants were randomly assigned. Each square represents a different condition, with the columns indicating the four contexts and the rows representing the three distinct data-types.

2.1 Experimental Population

Upon electing to participate in the study for a quarter ($0.25), participants were notified that it would require approximately 3 min to complete, and no personally identifiable information would be collected. Primary exclusionary criteria were determined from the participants' general use of social media. If a participant indicated that they did not use social media (see Appendix), they were thanked for their interest in the study, and their participation was ended without collecting any data. In the study, data were collected from 945 participants.

User bias was minimized by allowing each participant to complete the study only once and each participant was assigned only a single condition. The MTurk account name was used solely to determine if an account owner had participated in the study previously, in which case the owner was not allowed to participate.

First, participants completed a question about their usage of social media, which was the primary exclusionary criteria for the study, in addition to being at least 18 years of age and located in the United States. Participants that used social media were asked to complete a short demographic survey (see Appendix) prior to providing their estimates for opinion formation based on data-type, context, and source. At the conclusion of the experiment, participants were thanked for their participation and paid for completing the study.

2.2 Distinct Single-Media Data-Types

Participants were asked to estimate their opinion formation thresholds for one of three distinct data-types: 1) Images, 2) Videos, and 3) Messages. These data-types were selected for their easily identifiable differences. Participants were shown the following descriptions corresponding to the data-types:

- Images: data-type includes still pictures, images, and drawings.
- Videos: data-type includes any moving pictures, animations, and videos.
- Messages: data-type includes text, a tweet, or a post on Facebook.

2.3 Contexts

For the purposes of this report, the level of controversy was a means of capturing the effects of context and these two terms are used interchangeably. Participants were assigned one of four levels of controversy (i.e., Low, Medium, High, and None). To summarize, the four contexts were:

- Low: minimal controversy (some people would form an opinion).
- Medium: controversial (many people would form an opinion).
- High: highly controversial (most or all people would form an opinion).
- None: no reference to controversy.

With an exception for the “None” case, the different levels of controversy were introduced to the participants with a color-coded word and an example (see Fig. 2). These levels were selected to investigate the influence or impact context has on the estimate of a threshold for forming an opinion.

LOW → an example of a LOW level of controversy is:

A car company introduces a new standard car color in hot pink.

MEDIUM → an example of a MEDIUM level of controversy is:

A typically conservative state (e.g., Texas) approves a liberal law (e.g., recreational marijuana).

HIGH → an example of a HIGH level of controversy is:

A dictator-run country (e.g., North Korea) fires a chemical weapon into a U.S. allied country (e.g., France).

NONE → no context referenced

Fig. 2 Four different controversy levels were utilized (Low, Medium, High, and None) to capture the effects of context. Participants were provided with the example shown to introduce context into the experiment.

To distinguish the differences between the levels of controversy for this experiment, an example of the assigned level of controversy was given to the participant (see Fig. 2). This was done with the intention of yielding (or offering) clarity to the participant and not an attempt to shape their perspective or presume what should be important to the individual. It was assumed that participants might find the examples for controversy level helpful, given the absence of physical content.

2.4 Social Media Sources

Each MTurk participant was randomly assigned one condition (data-type and context) and asked to provide an estimate for each of the three different source types (i.e., Unknown source, Like-minded source, or Different-minded source) to investigate the influence of source on threshold for opinion formation.

The three different sources were provided to participants in the order below:

- Unknown: Before you FORM an OPINION how many data types listed below would you expect to view in a day?
- Like: Before you FORM an OPINION how many data types listed below would you expect to view in a day, given that the data types were posted by people who think like you?

- Different: Before you FORM an OPINION how many data types listed below would you expect to view in a day, given that the data type(s) were posted by people with different viewpoints?

The first question did not specify a source for the piece of information found on social media, and it was used as a control or baseline case (i.e., Unknown). Not specifying a source of the information means that the participant is unaware if the source has similar or different perspectives, which may have an effect on how they form an opinion. The second question emphasized that the information was posted by people with similar, like-minded perspectives (i.e., Like), aiming to measure the influence that in-group posts have on a participant's estimate of their opinion formation threshold. The third question emphasized that the information was posted by people with diverse, different-minded perspectives (i.e., Different), capturing the effects of out-of-group influence. Together, the three questions allowed us to measure influence from various sources over opinion formation threshold.

For our study, we wanted to determine whether source had a significant role in the formation of an opinion by comparing the opinion formation thresholds of Unknown sources versus Like-minded and Different-minded sources, and the opinion formation thresholds for Like-minded versus Different-minded sources. Due to the questions being presented in the same order for all participants (no random ordering), we cannot draw concrete conclusions from the opinion formation thresholds about source influence. However, relative conclusions can be made and verified using random ordering in future experiments.

2.5 Outlier Removal and Data Cleaning

In the estimation of social media opinion formation thresholds from subjective self-perceived ratings, it is important to establish sufficient criteria for identifying and removing outliers. The outlier removal technique was necessary to exclude data that introduced extraneous variance in the samples, and unreasonably (large or small) responses. In a pilot version of this work, an outlier technique was not used, and the results were difficult to interpret (Asher et al. 2017). In this article, a modified version of the median absolute deviation (MAD) technique was utilized (Leys et al. 2013). It is important to note that the outlier responses in this study do not represent a typical statistical outlier (e.g., errors or mistakes made by participants). Instead, these outlier responses are interpreted as participants indicating that they would not form an opinion from social media information by either entering a response too large to take seriously (e.g., 3000 images) or zero. In both cases, we interpret these responses as outliers because participants are indicating that social media information is not how they form opinions, and therefore do not provide any information towards the estimated opinion formation threshold of the population. A rendition of the MAD technique used in this article was based on participants' demographic responses to the Frequency and Duration of social media usage questions. These questions were utilized to determine outlier response boundaries per participant per sample. The two social media usage questions were recoded into categorical variables based on increasing quantity:

Frequency:	**Duration:**
"**Once in a while**" = 1	"**0-30 mins**" = 1
"**Once daily**" = 2	"**31–59 mins**" = 2
"**Multiple times daily**" = 3	"**1–2 hours**" = 3
	"**2+ hours**" = 4

Frequency is a measure of how often a participant uses social media ("How often do you use Social Media?") and Duration is a measure for the amount of time a participant spends on social media daily ("How much time do you spend on Social Media daily?"). The two usage variables (Frequency and Duration) were multiplied together to provide each participant with their usage score (with a maximum value of 12). The usage scores were multiplied by the median of the sample responses (i.e., for a given data-type, context, and source), to provide each participant with their own outlier boundary (outlier boundary = usage score * sample median) per sample. It should be noted that the samples were not the same as conditions; each participant provided a response for three sources per condition (see Fig. 1), resulting in three samples per participant per condition. If a participant's response was greater than their outlier boundary (i.e., their usage score multiplied by the median of the sample), the data point was considered an outlier. It should be noted that typical outlier boundaries were quite conservative (usually greater than 100). In addition, participants "0" (zero) responses were excluded from analysis as well. These values were grouped with outliers because in this experimental paradigm it is illogical for participants to form opinions without consuming a minimum of one piece of information. Likewise, a participant likely would not be interested in viewing hundreds of pieces of information before forming an opinion. The number of data points collected for each condition across the three sources, the number of outliers, and the percentage of data removed is shown in Table 1.

As an example of the outlier removal method, let's say that the median of a sample for a given condition (data-type – Images; context – Low) has a value of 10. A subject within the condition has a Frequency score of three ("Multiple times daily") and a Duration score of four ("2+ hours"), thus making their usage score 12. By multiplying the subject's usage score and the median of the sample for the given condition, 120 would be their outlier boundary. If a subject gave a response of seven images needed to form an opinion, the response would not be considered an outlier, because it is less than the outlier boundary (7 < 120). However, if the subject gave a response of 121 images needed before forming an opinion, the response would be removed, as it would be considered an outlier for exceeding their outlier boundary (121 > 120).

Before outliers were removed, it can be seen that the number of data points per condition were identical across the three sources (see Table 1: Original Data). This is due to the fact that all participants answered the three source questions per condition. The final samples shown in Table 1 are represented with color-coded rows that separate the table into the three different media types. The major column headers in gray show the number of participants initially collected per condition (Original Data), the outliers identified (Outliers), the number of participants per condition after the outliers were removed (Data without Outliers), and the percentage of data removed per condition and source (Percentage of Data Removed). The minor column headers in white indicate the data-types (Images, Videos, and Messages), contexts (Low, Medium, High, and None), and sources (Unknown, Like, and Different).

Table 1 Outliers removed for final samples

		Original Data			Outliers			Data without Outliers			Percentage of Data Removed		
Data-type	Context	Unknown	Like	Different	Unknown	Like	Different	Unknown	Like	Different	Unknown	Like	Different
Images	Low	86	86	86	16	7	11	70	79	75	19%	8%	13%
	Medium	83	83	83	18	11	13	65	72	70	22%	13%	16%
	High	76	76	76	16	9	10	60	67	66	21%	12%	13%
	None	85	85	85	17	8	13	68	77	72	20%	9%	15%
Totals		**330**	**330**	**330**	**67**	**35**	**47**	**263**	**295**	**283**	**20%**	**11%**	**14%**
Videos	Low	71	71	71	1	2	4	70	69	67	1%	3%	6%
	Medium	84	84	84	7	13	17	77	71	67	8%	15%	20%
	High	78	78	78	4	3	6	74	75	72	5%	4%	8%
	None	74	74	74	6	5	13	68	69	61	8%	7%	18%
Totals		**307**	**307**	**307**	**18**	**23**	**40**	**289**	**284**	**267**	**6%**	**7%**	**13%**
Messages	Low	80	80	80	10	4	8	70	76	72	13%	5%	10%
	Medium	78	78	78	7	9	6	71	69	72	9%	12%	8%
	High	75	75	75	7	10	4	68	65	71	9%	13%	5%
	None	75	75	75	10	13	8	65	62	67	13%	17%	11%
Totals		**308**	**308**	**308**	**34**	**36**	**26**	**274**	**272**	**282**	**11%**	**12%**	**8%**

It is notable that approximately 20% of the data were deemed outliers from all conditions related to Images for the Unknown source (see Table 1). Given that this is roughly 10% more outliers than both of the other source types (i.e., Like-minded and Different-minded), it appears that a specified source may have played an important role in a participant's ability to estimate the number of images to form an opinion. Together, the data in Table 1 shows that approximately 10% of data collected qualified as outliers.

The outlier removal formula was curated to take into account the amount of social media use and exposure the participants had. For the purpose of our study, we wanted to make sure the participants used an adequate amount of social media to form credible opinion formation thresholds, and also to exclude extraneous data that participants may have entered. This modification to the MAD technique will be used for outlier removal in future work related to this study.

2.6 Data Analysis Techniques

Jarque-Bera (JB) goodness-of-fit tests were initially used to determine if the data came from an unspecified normal distribution for each of the 12 conditions across the three sources (three questions asked during the experiment). The JB test results showed that the data were not normally distributed, which indicates that parametric analysis would not be appropriate. However, the exhaustive Quantile-Quantile (Q-Q) plot testing showed the data fit a log-normal distribution. Therefore, a log transform (the natural log was utilized) resulted in normally distributed data, confirmed with post transform JB tests. The parametric analyses were performed on the log transformed data with the final opinion formation thresholds reported as the inverse log transform of the statistics taken in the log transformed space (i.e., the means were transformed back into the original non-transformed space).

3. Results

All parametric analyses were performed on the log transformed data. The opinion formation thresholds are reported as the inverse log transformed values, resulting in averages in the original non-transformed space.

3.1 Factorial Analysis of Variance (ANOVA) Based on Data-type across Sources and Contexts

Separate mixed-measures ANOVAs were performed for each of the social media data-types (i.e., Images, Videos, and Messages) using social media source (i.e., Unknown, Like, and Different) as the within-participants measure, and context (i.e., Low, Medium, High, and None) as the between-participants measure. In some cases, the assumptions of sphericity were violated so Huynh-Feldt epsilon statistic is reported in such cases.

3.1.1 Source Analysis

The effect of source is presented in Fig. 3. There was a significant main effect of source on the approximate number of images required to form an opinion, $F(2, 243) = 16.06$, $p < 0.001$, $\eta_p^2 = 0.06$, $\varepsilon = 0.96$. The results indicated that more images were required to form an opinion based on Unknown and Like-minded social media sources. Additionally, there was a significant main effect of source on the approximate number of videos required to form an opinion, $F(2, 248) = 46.22$, $p < 0.001$, $\eta_p^2 = 0.16$, $\varepsilon = 0.86$, which indicated that more videos were needed to form an opinion from Unknown and Like-minded sources. There was a significant main effect of source on the approximate number of messages required to form an opinion, $F(2, 247) = 14.64$, $p < 0.001$, $\eta_p^2 = 0.06$, $\varepsilon = 0.87$, which indicated that Unknown and Like-minded sources required more messages to form an opinion. There were no significant interactions to report for these analyses.

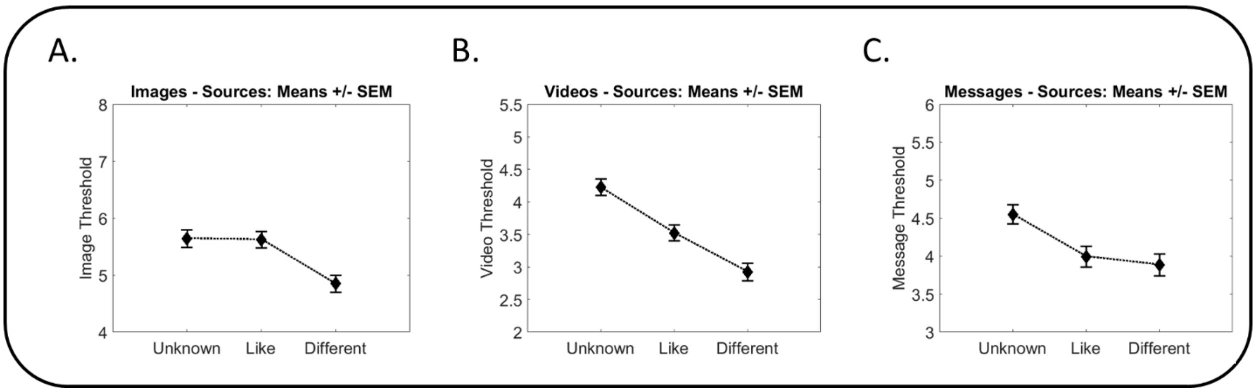

Fig. 3 Demonstration of the influence of source type over opinion formation thresholds. Sample averages for the three social media sources (i.e., Unknown, Like, and Different) are plotted with error bars representing the standard error of the mean (SEM). The y-axes show the opinion formation thresholds with specific data-types and the x-axes show the sources of social media: a) Images, b) Videos, and c) Messages.

3.1.2 Context Analysis

There was a significant main effect from controversy level for images, $F(3, 244) = 2.85$, $p = 0.04$, $\eta_p^2 = 0.03$. When context was absent (i.e., None) more images were required to form an opinion. However, when controversy level was Low, fewer images were needed to form an opinion. There was also a trending main effect of context on the approximate number of messages required to form an opinion, $F(3, 248) = 2.16$, $p = 0.09$, $\eta_p^2 = 0.03$. The results indicate that when context is absent (i.e., None) and controversy level is High, more messages are required to form an opinion. Similar to the results from social media source, there were no significant interactions to report for context.

3.2 Post-hoc Analysis

To further investigate the specific differences between contexts and sources, post-hoc tests were conducted using a Bonferroni correction for multiple tests. Interestingly, post-hoc tests did not find significant differences between contexts within each source for the Images data-type (see Figs. 3a and 4). In contrast, post-hoc analysis identified significant differences between the three sources for the Videos data-type (see Figs. 3b and 5). The results suggest that an Unknown source required significantly more videos to form an opinion than a Like-minded source (p = 0.01) and a Different-minded source (p < 0.001). In addition, a marginally significant difference was found between contexts Low and None for a Like-minded source (p = 0.09).

A trending significant difference was observed between the Unknown source and the Different-minded source (p = 0.07) for the Messages data-type (see Fig. 3c). Similarly, a trending significant difference was found between contexts Medium and High for the Like-minded source (p = 0.06; see Fig. 6). Finally, a significant difference was observed between contexts Low and High from an Unknown source (p < 0.01; see Fig. 6).

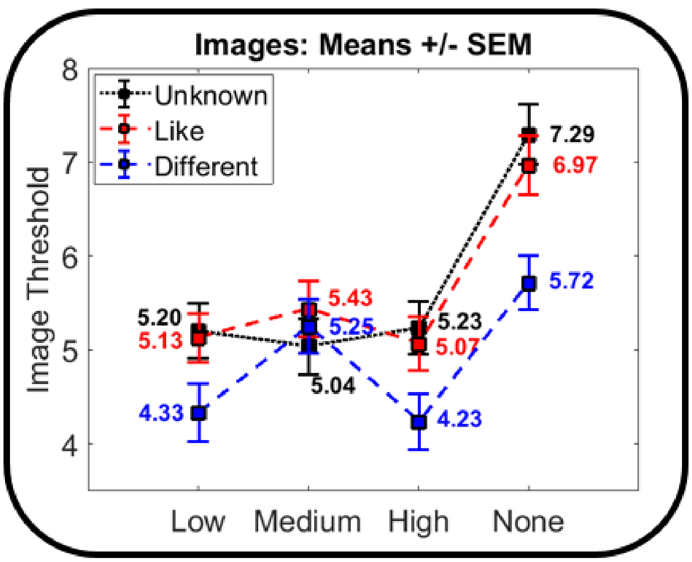

Fig. 4 Mean values per context and source for the Images data-type. The square boxes represent the sample means with color-coded values showing the precise mean value with error bars indicating SEM. Black shows the data from an unknown source (Unknown), red a like-minded source (Like), and blue a different-minded source (Different). The y-axes show the respective data-type threshold values. The x-axes show the four contexts.

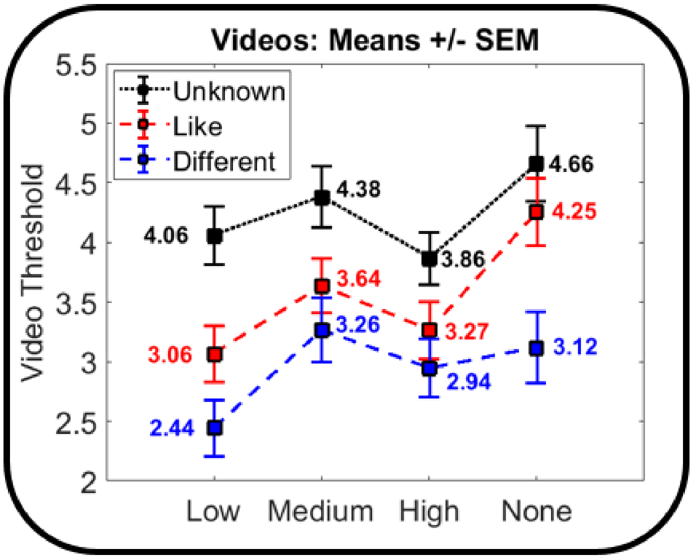

Fig. 5 Mean values per context and source for the Videos data-type. The square boxes represent the sample means with color-coded values showing the precise mean value with error bars indicating SEM. Black shows the data from an unknown source (Unknown), red a like-minded source (Like), and blue a different-minded source (Different). The y-axes show the respective data-type threshold values. The x-axes show the four contexts.

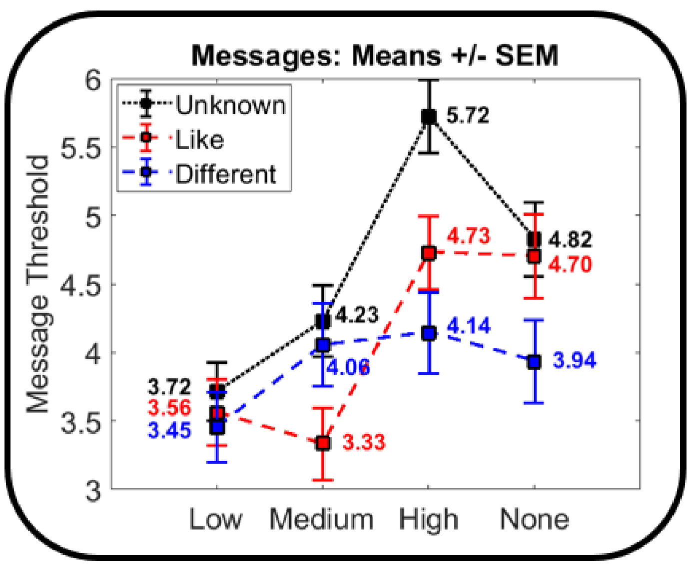

Fig. 6 Mean values per context and source for the Messages data-type. The square boxes represent the sample means with color-coded values showing the precise mean value with error bars indicating SEM. Black shows the data from an unknown source (Unknown), red a like-minded source (Like), and blue a different-minded source (Different). The y-axes show the respective data-type threshold values. The x-axes show the four contexts.

3.3 Opinion Formation Thresholds across Data-Types

Together, the results suggest that the opinion formation thresholds from social media can significantly depend on the source. For example, videos are significantly dependent on the source, with thresholds for an Unknown source ranging from 4 to 5, a Like-minded source ranging from 3 to 4, and a Different-minded source ranging from 2 to 3 (see Table 2). Furthermore, the results suggest that context has a marginally significant influence over opinion formation threshold when the information is posted by a Like-minded source (see Fig. 5). Moreover, the data indicate that an individual needs between four and seven social media images to form an opinion, independent of context and source (see Table 2). Finally, the results suggest that context had a significant influence over opinion formation threshold for the Message data-type in the case of an Unknown source, and the range of opinion formation threshold across contexts and sources for the Message data-type is three to six messages (see Table 2). The table shows the opinion formation threshold ranges based on a 95% confidence interval around the population means. Color-coded rows separate data-types (i.e., Images, Videos, and Messages), which show sub-rows corresponding to significantly different thresholds determined through post-hoc analysis with respect to source (i.e., Unknown, Like, and Different) and context (i.e., Low, Medium, High, and None).

Table 2 Opinion formation thresholds

Data-type	Source	Context	Threshold lower bound	Threshold upper bound
Images	All	All	4	7
Videos	Unknown	All	4	5
	Like	All	3	4
	Different	All	2	3
Messages	Unknown	Low	3	4
		Medium	4	5
		High	5	6
		None	4	5
	Like & Different	All	3	5

4. Conclusion and Discussion

In modern society, social media information has the power to shape the beliefs and perceptions of individuals and is freely available to anyone with access to the internet. Distinct information types (i.e., Images, Videos, and Messages) have differential persuasive influence over an individual's opinion formation, further depending on factors such as context and the information source. Furthermore, social media has become an information hub in a variety of domains (Kim et al. 2014; Westerman et al. 2014; Pirelli et al. 2016; Song et al. 2016), which is a reason why it shapes the formation of individuals' perspectives. Therefore, it is critical for society to understand the thresholds at which social media information influences the perspectives of individuals.

The current study aims to estimate a metric (opinion formation threshold) that can describe the point at which different discrete pieces of social media information change an individual's perspective from a neutral or naïve state to a formulated opinion. This line of research defines an individual's opinion formation as the establishment of a concrete belief based on an accumulation of evidence of the hypothetical information, given data-type, context (introduced as levels of controversy), and source. The opinion formation threshold per individual is the discrete number of distinct pieces of information per data-type (i.e., Images, Videos, or Messages) which that individual estimated and reported they would have needed to passively view (data consumption) in order to establish their belief or perceived formation of an opinion pertaining to the information with abstracted dimensions of context, source, and data-type. Whereas this experimental paradigm calculates opinion formation thresholds from population responses, it should be noted that this quantitative metric is based on participants' self-reported estimates/guesses. Therefore, the results and conclusions from this research should serve as a relative ratio or theoretical estimate for the selected dimensions associated with social media information. Further empirical testing with physical content would need to be done to confirm these results, but this work provides an expectation or basic population-based prediction for the amount of social media information that would need to be consumed before an individual formed an opinion.

The goals of the current study were to 1) calculate opinion formation thresholds for three distinct data-types (i.e., Images, Videos, and Messages), 2) measure the influence arising from different contexts (i.e., Low, Medium, High, and None) over opinion formation, and 3) determine how opinion formation is modulated by a social component of information source (i.e., Unknown, Like, and Different). The results from the current study indicate that 1) relative opinion formation thresholds can be compared across the data-types, contexts, and sources, 2) for the Messages data-type, context only appears to modify opinion formation thresholds from Unknown sources, and 3) data-type is an important factor in the social media opinion formation process. Together, these results provide a quantitative measure (i.e., opinion formation threshold) for predicting how social media information shapes the opinions of a population.

The identified and reported opinion formation thresholds suggest that a relatively small amount of social media data is needed for a population of individuals to form opinions irrespective of data-type, source, or context (see Table 2). The full range of opinion formation thresholds across data-type, source, and context is 2 to 7 pieces of information. This implies that a small amount of social media information has the potential to quickly influence a large number of people. However, based on the percentage of outliers (see Table 1), there are between 6% and 20% of people (depending on condition; the dimensions of the information) that simply would not form opinions from social media data. This interpretation is based on the percentage of participants that provided outlier responses, and these outlier responses can be interpreted as the participants conveying they would not form an opinion from social media data.

These results regarding opinion formation thresholds from passive social media consumption can be of immense importance in many areas of sociology and complex networks. In fact, results of this type can feed directly into stochastic models that simulate opinion spread throughout society. Examples include dosage-based models of opinion spread, which focus on the concept that individuals will remain in their current state until exposed multiple times to a new idea, at which point they change their state and adopt the new opinion (Dodds and Watts 2005). Thus, the results presented in this report give empirically measured values to the number of exposures necessary, allowing for the creation of more accurate models.

Furthermore, there exist computational models that deal with individuals that are particularly stubborn and difficult to change (Galehouse et al. 2014; Doyle et al. 2016; Niu et al. 2017), similar to the noted population of outliers that would not form an opinion (see Table 1). Using this new real world data, these models become far closer to mimicking the perceptions of real societies and allow for far greater predictive power in their execution.

Finally, future models can be developed using the information gained here; the results showing different thresholds for different data-types, sources, and contexts could be used to build new variants of previously studied models to capture specific facets of social interactions.

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Appendix. Exclusion Criteria and Demographics

Figure A-1 shows screenshots from the experiment illustrating exclusion criteria and demographic information.

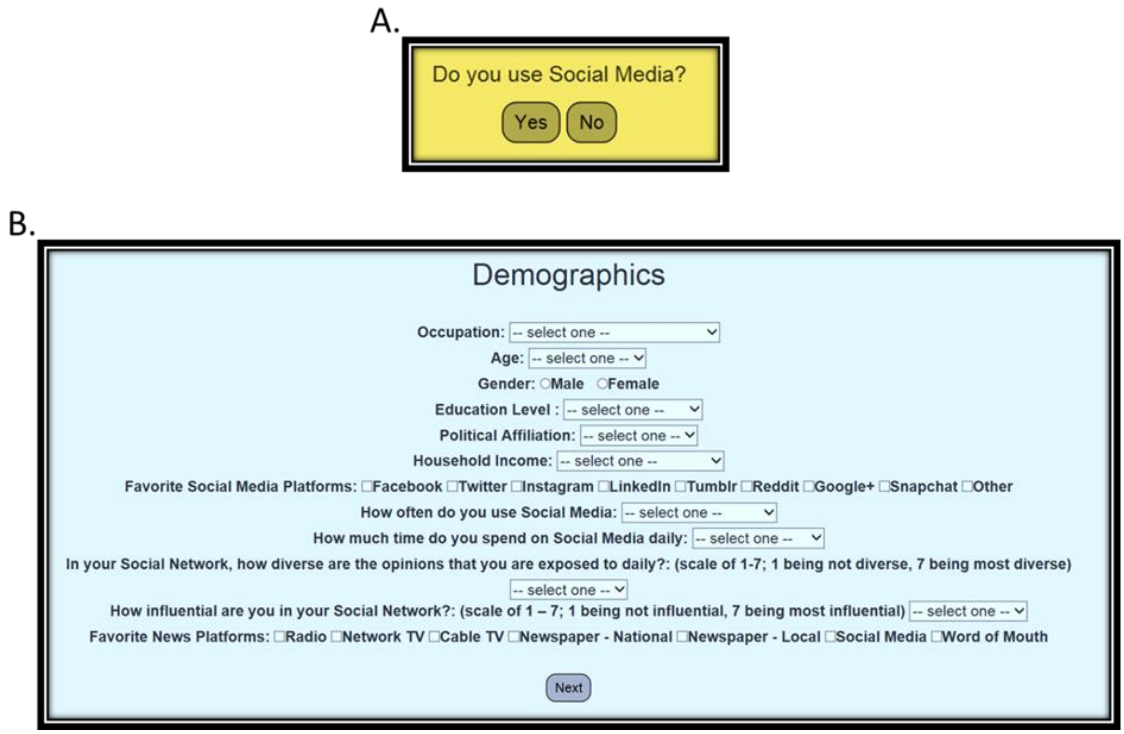

Fig. A-1 Screenshots from the experiment show a) how subjects were treated for exclusion, and b) the demographic survey consisting of 12 fields.

List of Symbols, Abbreviations, and Acronyms

ANOVA	analysis of variance
ARL	Army Research Laboratory
CCDC	US Army Combat Capabilities Development Command
JB	Jarque-Bera
MAD	median absolute deviation
MTurk	Amazon Mechanical Turk
Q-Q	Quantile-Quantile
SEM	standard error of the mean

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1 (PDF)	GOVT PRINTG OFC A MALHOTRA
1 (PDF)	CCDC ARL FCDD RLC IT D ASHER