Tackling Fake News on Facebook

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With the advent of widely circulated and easily produced news on the internet, the emergence of fake news has become increasingly prevalent. Fake news is intentionally incorrect or misleading content, in an article purporting to be true, especially with the intent of inciting a particular reaction (Weedon, Nuland, & Stamos, 2017). As the saturation or circulation of fake news increases, it demands an equal and opposite effort to combat it. Deception is not only ethically problematic; external effects of deception can be socially, politically, and financially damaging. In the context of fake news, it has been shown to be an effective vessel for political propaganda and troubling ideologies (Starbird, 2017).

Since there is no editorial oversight in place on social media, it lends itself easily to the propagation of fake news. This is a problem worth addressing, so we started by identifying which specific platform we would target with a potential solution to the fake news epidemic. Over 60% of Americans get their news on social media, and the majority of them do so on Facebook (Gottfried & Shearer, 2016). Combined with the fact that Facebook is overwhelmingly the world's largest social network, with 1.28 billion daily active users during March 2017 ("Facebook Newsroom: Company Info," 2017), it seemed like the appropriate platform to target.

Fake news has recently posed a significant challenge for Facebook. Recent evidence shows that top fake news stories during the 2016 US presidential election outperformed top real news on Facebook (Silverman & Singer-Vine, 2016), and 75% of Americans who recall a fake news headline believed the story to be true (Silverman, 2016). This issue partially stems from the fact that people rarely verify the information they obtain on the internet (Flanagin & Metzger, 2000). Some have considered the fake news problem on Facebook so severe and permeating that they regard it as a deciding factor in the election of US President Donald Trump (Read, 2016). While an extraordinary claim, scientific inquiry has shown it has at least some plausibility (Gentzkow & Allcott, 2017).

Facebook has acknowledged the issue of fake news on their platform, and they have even begun to enact measures to alleviate it. These changes include an easier way to flag news stories as false and the integration of feedback from third-party fact-checking organizations into the News Feed (Mosseri, 2017b). If enough users flag a story as false, then it will be sent to an independent fact-checker, such as Snopes and PolitiFact, for verification. If deemed to be false by the organization, it will be flagged, and its visibility will be reduced in the News Feed.

While it is commendable that Facebook is attempting to mitigate the fake news problem, it does not seem to be working (Levin, 2017). Even if an article is debunked, the "disputed" flag often does not appear, and reliance on manual fact-checking by a select few organizations means that only a fraction of fake news can be adequately debunked and labeled. One of the most critical issues, however, is that the manual process takes too long given how quickly fake news spreads. If a third party debunks a fake news article, there is an approximate 13-hour lag between its initial release and the release of the third party response (Shao, Ciampaglia, Flammini, & Menczer, 2016). This is not accounting for the additional delay caused by Facebook's implementation, where the content must first be flagged by users and then reviewed by at least two fact-checking organizations. This process is far too slow; it has been shown that a news article is viewed mostly in its first 36 hours, and it can peak in views in just a few hours (Dezsö et al., 2006), so once Facebook responds to the fake news, most of the damage has already been done. The issue is compounded by the fact that there is no available data to show that Facebook's flagging and tagging policy reduces views and shares of fake news articles. Considering the shortcomings with

Facebook's existing attempts to tackle fake news and the inherent limitations of manual approaches to inhibiting its spread, an algorithmic solution would be ideal (Chen, Conroy, & Rubin, 2015).

While there is existing research on algorithmic solutions to fake news detection, with some methodologies being particularly compelling (Conroy, Rubin, & Chen, 2015), we identified a significant gap in knowledge on how to implement these solutions in Facebook. Since knowing how to apply a solution is equally as important as having it, we focused our efforts on building the interface of an effective algorithmic solution on Facebook.

Our project addresses the interface design of a fake news detection tool that would operate on a Facebook News Feed, along with feasibility and implementation concerns. We have pursued a design that is motivated by research in interfaces, credibility enhancement, and deception detection. We have also tested our design in an initial user trial experiment and further refined it based on our preliminary results.

Interface Design

To design a meaningful interface, it is important to establish what algorithmic system of fake news detection we will use. Our review of the existing literature indicated that using Conroy et. al.'s hybrid approach of both linguistic analysis and network analysis holds promise in detecting fake news effectively (Conroy et al., 2015). Compared to the linguistic approach, the "linked data" network effect methodology is more useful for visually representing the algorithm's function: a key component of our interface design. Using a knowledge base of "factual statements," it is possible to calculate the probability of a certain statement being true based on predicate relationships and semantic proximity to other statements. The shorter the knowledge graph path in the network, the higher the chance of the statement being true. Therefore, if it takes many nodes and a long chain of semantically proximal topics to connect the predicate with the subject, it is unlikely the statement is true. For example, consider the false statement "Barack Obama is a Muslim" in the context of a knowledge base such as Wikipedia. The subject "Barack Obama" will face many degrees of separation with the predicate "is a Muslim" on Wikipedia, and therefore the likelihood that the statement is true diminishes with each degree of separation (i.e. each node in the knowledge graph path). The shortest path from the Wikipedia page for "Islam" to the Wikipedia page for "Barack Obama" takes a total of seven intermediate pages, suggesting the two are quite unrelated. This visual effect (fig.1), combined with the linguistic analysis and other network effects, provides the algorithmic foundation with which we will build our interface.

Displaying the algorithmic foundation within the interface is not only important for transparency, but also important for establishing credibility for our system. In our interface, we visualized the network effect described previously by showing a graph of linked images illustrating the relation between two topics in an article, and the nodes that separated them. For the other aspects of our interface design, we turned to further literature review to ensure our design choices were as research-motivated as possible.

Our interface is intended to be integrated into the Facebook News Feed on mobile platforms. We chose to design the tool for Facebook's mobile application due to the popularity of mobile platforms for accessing social media and news. The majority of Facebook's users only access it through mobile (Facebook, 2016). Also, we designed our tool for mobile platforms because mobile news consumption has increased considerably in the past few years. From 2013 to 2016, the percentage of Americans who accessed news on a mobile device has grown from 54% to 72% (Mitchell, Gottfried, Barthel, & Shearer, 2016). Furthermore, these users prefer to get their news through mobile: in 2016, the majority of Americans who got news through desktop or mobile platforms preferred the mobile platform (Mitchell et al., 2016). The popularity of mobile platforms, combined with the trend of increased mobile usage, informed our decision to design for Facebook's mobile application. As users scroll through their News Feeds, their only immediate tools for judging credibility are the features of the interface they see (Morris, Counts, Roseway, Hoff, & Schwarz, 2012). Currently, these features are essentially limited to a news article's headline, photo, and source. Therefore, we saw the need for a conspicuous visual indicator of how the detection algorithm evaluated a news article. Our interface places a symbol next to the headline of each news article appearing in the Feed in order indicate the credibility of the article.

Furthermore, research has shown that visualizations of credibility assessments are effective at improving a user's perception of validity when displayed in search results, not on web pages themselves (Schwarz & Morris, 2011). As a News Feed resembles a list of search results for news articles, we utilized this information as motivation to design our tool for the News Feed directly rather than for the source news articles**.**

We chose to label the articles using three different levels of credibility: "accurate," "questionable," and "inaccurate." Each of these corresponded to the small symbol that was placed next to the title of each article. For articles labeled "accurate," we used a green check mark; for "questionable," a yellow question mark; and for "inaccurate," a red 'X.' In choosing these colors, we took into consideration human perception and techniques to transfer meaning to users. We chose red, green, and yellow as a metaphor for traffic lights to utilize the common association of these colors with stop, go, and standby (Dix, Finlay, Abowd, & Beale, 2003). Furthermore, we chose to use a simple, colored icon because of the speed at which users access content on Facebook. On average, users consume a single piece of content on their mobile News Feeds in only 1.7 seconds, and it takes only 0.25 seconds of exposure for them to recall the content from the Feed (Graham & Simo, 2016). Therefore, we knew it was necessary to have a simple icon that wouldn't take much time for a user to process.

Upon tapping this symbol in the Feed, a small pop-up box appears that contains information about how the algorithm determines the credibility of the article. Visualizing the algorithm discussed above was important in achieving our transparency and user trust goals. Additionally, research showed us that icons are not able to stand on their own to convey information and that they must be paired with a written explanation, especially when first seen by a user (Haramundanis, 1996). Therefore, in the design of our pop-up, we included a visualization of several nodes linked together, representative of the network graph utilized by the algorithm. We also included brief interpretation of the graph regarding how it indicates an article's credibility to facilitate user understanding and trust.

Research also showed us that upon simply reading misinformation, people may later mistake it for accurate information. This is the problem that users currently face with fake news on Facebook: without any indication of if an article is credible, the user is at risk of misinformation. However, bringing attention to accurate information can reduce this influence (Rapp, Hinze, Kohlhepp, & Ryskin, 2014)**.** Given this memory encoding, we created one version of our interface in which the article titles contained a red strikethrough. Presenting the title as inaccurate on a user's first glance encourages encoding it as misinformation. For some users who scroll through their News Feed quickly, they may be unable to read this crossed-out title at all, preventing the misinformation from ever being encoded. Our visualization is a secondary measure of correcting misinformation for users. While they would ideally not even read the title of an article marked as fake news, in the case that they did, users would be able to click our icon and find the evidence for or against the credibility of the article.

Experimental Methods

To validate that our interface design is an effective approach to conveying the credibility of articles, we designed and administered an experiment. The purpose of the experiment was to test our Facebook design implementation against a control - a typical Facebook timeline without any alterations.

To run this experiment, we needed to simulate a Facebook News Feed that implements our interface. We did this using the online prototyping software Proto.io. We first aggregated a collection of screenshots from a real News Feed, including real news articles, questionable news articles, and fake news articles. We combined these into a simulated News Feed in Photoshop. Once imported into Proto.io, we were able to add scrolling and display it on a smartphone using the Proto.io app. This is how we built our control News Feed.

For the experimental News Feed, we added the credibility icons next to the news article titles and designed the pop-up interface that contains the visualization of the algorithm. Once we imported this into Proto.io, we were able to add interactive components to the icons to make the pop-up box appear. When displayed on the Proto.io app, both of these simulated News Feeds looked similar and functioned almost identically to the real Facebook News Feed, which was important for the ecological validity of our experiment.

The experiment was designed to test whether our interface design had an effect on an individual's assessment of credibility on Facebook news articles. More explicitly, we wished to test whether an individual could accurately identify a single questionable or problematic article from a newsfeed out of eight total articles. Seven aggregate tests were designed and evaluated (Table 1).

Experiment 1	All accurate articles	One questionable article	One problematic article	One problematic article with strikethrough
Test - Interface	5 individuals	5 individuals	5 individuals	5 individuals
Control - No interface	5 individuals	5 individuals	5 individuals	N/A

Table 1. Experiment design.

For each category of interest, the eight articles were placed in the same order for both the test and the control, and the questionable and problematic article (if applicable) was placed in the same position. A total of 35 individuals participated in the experiment, as five people were tested within the scope of each category. In an attempt to minimize bias within the experiment, each category required five distinct individuals. Unfortunately, for the purpose of this experiment, individuals were not selected randomly, but rather by convenience; as such, all individuals that participated in the experiment were college students. However, in the future, it is crucial to not only have more variability in the demographic of individuals tested but also to select users randomly.

Before the experiment, we used a script to introduce users to the task without explicitly mentioning fake news, and we ensured the users understood that we were testing the interface and not their performance. During the experiment, individuals were tasked with scrolling through their respective Facebook News Feeds (displayed through the Proto.io app on one of our smartphones) and rating the articles on a scale of 1-5 of how credible they perceived the article to be. In addition, they were asked to rate how certain they felt about the rating that they provided for the credibility of each article, also on a 1-5 scale (Table 2). After each individual had finished reviewing the articles, we asked them a series of questions from a questionnaire to gain a qualitative understanding of the existing News Feed, our interface, and their current tactics for dealing with fake news on Facebook. We compiled these answers into a document. At the end of the experiment, we gave users an experiment debriefing, where we told them our project goals and answered any additional questions.

	1	2	3	4	5
Credibility	Not at all credible	Somewhat credible	Moderately credible	Mostly credible	Completely credible
Certainty	Not at all sure	Somewhat sure	Moderately sure	Mostly sure	Completely sure

Table 2. Credibility and Certainty Scale

A randomized block design was used to analyze whether our interface implementation had an effect on individuals assessing the credibility of accurate articles. As such, each of the eight articles was treated as a distinct block - each of which were to be tested for two treatments (with the interface and without the interface). To interpret the results, an ANOVA table was constructed and examined.

To analyze whether individuals could accurately identify a questionable and problematic article, a simple independent samples design was conducted. The null hypothesis was defined as $\mu_I = \mu_N$, and the alternative hypothesis was defined as $\mu_I > \mu_N$ (where I stands for interface and N stands for non-interface) at the 0.05 level of significance. Because the sample sizes were inherently small, a small sample size test was necessary - as it was not feasible to assume that the difference in means is asymptotically normal. The tests for the accurate articles and the questionable/problematic articles were separated with the purpose of analyzing whether the interface had an effect on identifying not only the questionable/problematic articles but also the accurate articles. Accordingly, the data for both categories were stratified such that the means and the standard deviations could be accurately calculated. In other words, the data for all seven of the accurate articles were combined to find the appropriate mean and standard deviation.

To detect whether the variance of the interface data and the non-interface data were equal, it was additionally necessary to conduct an F-test of population variance. Based on the results, we could continue with the according T-test. If the results of the F-test found that the variances were equal, we could continue with a small samples t-test with unknown variances which would require us to find a pooled sample variance. However, if the results of the F-test found that the variances were not equal, it would be necessary to conduct a Behrens-Fisher test to find the corresponding degrees of freedom and subsequently assess the hypothesis.

Results/Outcome

Due to the limitations that the first experiment iteration had, our results left something to be desired. After conducting the experiment, the data was aggregated based on the different categories of accuracy for the articles in the News Feed (the accurate articles, the questionable article, and the problematic article). Consequently, the tests for credibility and certainty were conducted. We will discuss the results for each of the tests below.

First, the results from the randomized block design describe that there is not a significant difference between individuals identifying credible articles with our interface and without our interface. Our data relating to identifying the credibility of articles described a p-value of 0.97, incredibly greater than the level of significance that we selected to analyze our results, 0.05. We found similar results with the results of certainty ratings with a p-value of 0.96. However, we firmly believe that additional testing with increased individuals could lead to more favorable results. The most interesting result of the block design, however, was that the articles had a significant difference in credibility ratings with a p-value of 0.0044. This is a concerning result, as our hope is for users to be able to determine an article to be credible if it is indeed credible - no matter the source. However, the corresponding certainty rating was not found to significant at the 0.05 level (a p-value of 0.0609) which meant that individuals were found to be sure about their certainty even though they were found to be incorrect in their inclinations.

Additionally, we found that there was not a statistical significance for individuals assessing the credibility of questionable and problematic articles with our interface compared to those not using our interface (Table 3).

Credibility	Accurate articles	Questionable articles	Accurate articles	Problematic articles
T-statistic	0.270	0.166	0.326	0
T-value	1.682	12.706	1.682	12.706
Result	Fail to Reject	Fail to Reject	Fail to Reject	Fail to Reject

Table 3. Results of credibility for "Questionable" News Feed and "Inaccurate" News Feed

Furthermore, there was not a statistical significance for individuals assessing the certainty of such articles with and without the use of our interface (Table 4).

Certainty	Accurate articles	Questionable articles	Accurate articles	Problematic articles
T-statistic	1.096	0.589	0.0948	0.630
T-value	1.682	12.706	1.682	12.706
Result	Fail to Reject	Fail to Reject	Fail to Reject	Fail to Reject

Table 4. Results of certainty for "Questionable" News Feed and "Inaccurate" News Feed

Despite this lack of statistically significant quantitative results, we did find some trends in user responses from the questionnaire portion of our experiment. First, users used several indicators for judging credibility of an article, the most prominent being assessment of the reputability of the source. If the website was reputable, they were more likely to give the article a high credibility score, whereas if it was an unfamiliar source, they rated it with low credibility. Of those who were shown the interface without the implementation of our tool, most expressed interest having a tool like this in their feed. However, some were skeptical about the extent of its functionality and whether they could trust it. For users who were tested with the implementation of our tool, there were mixed results about whether or not they found it useful in assessing credibility. However, the majority of users had trouble understanding the supplemental pop-up box explaining the algorithm behind the interface. Users did not understand the brief description and also could not make sense of the pictures in the graph were or their significance. Regarding the functionality of the tool, one piece of feedback we received was that users did not believe satirical websites such as The Onion should be placed in the same credibility category as accurate articles.

Both the qualitative and quantitative results are somewhat concerning, as it suggests that our interface prototype may not be effective at fulfilling its purpose. However, given that this is our first iteration of the design and experiment, we firmly believe that further improvements may show more significant results. We wish to couple the quantitative results with the qualitative results we received to formulate a new design.

Limitations

Our project, in its first iteration, has come across some limitations. The first limitation that we faced was a time constraint. Given the limited amount of time that students have within a quarter, our group only had time for one iteration of the prototype, of which only one round of user testing was conducted. We ended up having even less time than expected since our group pivoted ideas as we progressed in our literature reviewing, initially aiming to create a news comparison tool, and later pivoting to a fake news detection tool. Ideally, our group would have conducted further iterations of the interface and its design, as well as additional user testing in the hopes of obtaining more favorable results. Furthermore, there were a few flaws in the experiment design that we identified while initially conducting the experiment. For instance, two of the News Feeds contained an article from The Onion, a satirical publication website, which created a confounding variable in assessment of fake news. Additionally, we found that it was unnecessary to generate three different News Feeds. Given that we tested distinct individuals rather than using the same individuals to assess all three different interfaces, we could have used the same News Feed across all our trials, swapping out the single accurate, fake, and questionable news articles as necessary.

Future Work

Given the feedback from our user testing, as well as additional research we have done since creating the initial prototype, there is certainly room for improvement in our original design. One aspect we would be interested in investigating is the effect of color on perception of credibility. In our initial prototype, we used green as a metaphor for the "Go" traffic light. However, research shows that the color blue is seen as a "secure" color and is also linked to trust (Labrecque & Milne, 2012). Therefore, in preparation for future user testing, we would like to make a version of our interface with a blue check icon, which we would use to assess whether the blue or the green color is more effective in convincing users of our credibility ratings.

During user testing trials, several users were confused about the network graph visualization we included in the pop-up box. For this reason, we drafted several low-fidelity prototypes of different visualizations of this graph to decide how best to convey its meaning to users. One specific idea we prototyped is displaying a straight, horizontal graph overlaid on a spectrum of credibility. The graph is divided into three sections corresponding to the three different colors we chose for credibility. For example, a chain of two nodes would remain in the green region, while a chain of seven nodes would extend past the green and yellow regions and into the red, indicating the relationship between length of path of the nodes and credibility. Furthermore, since users did not understand our original high-level explanation of an interpretation of the network graph displayed above it, we would slightly change the wording of it. For example, to explain the credibility of a fake news article: “There are many degrees of separation between Topic X and Topic Y, so they are not closely related. Therefore, the information presented in this article is most likely false." We would label the start and end nodes in the graph with "[Topic X]" and "[Topic Y]" to reinforce the correct interpretation of the graph.

The next iteration of our experiment design would address all of the shortcomings of our first. Namely, we wish to standardize the accurate articles by using the same articles across all of the categories that we want to test. By doing so, we minimize the potential variability of credibility ratings of accurate articles. This was one of the main problems that our team faced because, in order to analyze the impact of our interface, we aggregated all of the accurate articles in each Facebook News Feed that we tested to conduct the statistical analyses. Initially, we had anticipated that we would compare the results of the accurate articles to the results of the inaccurate/questionable articles. However, this was quickly found to be flawed, as we are not testing whether individuals can identify problematic/questionable articles and accurate articles correctly. Ultimately, this is our goal, but the experiment is meant to test whether our interface was influential in assisting users to classify the articles.

With that in mind, we propose to test ten accurate articles using a block design to test whether individuals view a significant difference between articles using our interface as opposed to the standard Facebook News Feed. Additionally, it is compulsory to increase the number of questionable and problematic articles within each respective news feed. Our first experiment simply had one of each type of article, which made the data less reliable due to its small sample size. Thus, we propose to include five questionable and five inaccurate articles to couple with the standard ten accurate news articles. The analyses of the data that we would collect from this new experiment design would remain the same, and an F-test (to assess population variance) for the questionable and problematic articles can be properly conducted. Finally, we wish to increase the sample size of our experiment by increasing the number of trials conducted and testing a larger number of individuals. By doing so, we can increase the amount of data we collect, and hopefully, be rewarded with results that are consistent with our hypotheses.

Feasibility

Given that the implementation model for fake news detection we have created is designed for Facebook, we foresee some factors Facebook would need to consider if they were to adopt this model. We think this tool would be most useful if it were a native part of the Facebook interface. It is difficult for a third-party to augment Facebook's mobile app, so we consider adoption by Facebook itself the optimal way to reach as many users as possible. Even if the design were adopted for Facebook's desktop interface, it would still be most effective as a native part of the interface because other means such as browser extensions are inherently less accessible to the total Facebook user base. While our project did not focus on the back-end implementation, there is much promising research in the field, and Facebook will be able to progress this research even further. Algorithmic approaches to fake news detection fall well into their stated goals for tackling the problem through building new products (Mosseri, 2017b). Once part of Facebook, A/B testing will refine the interface and ease integration into the News Feed, aided by the fact that our interface, with its small icons, is minimally invasive. Given the scale of Facebook's user base, A/B testing could refine the interface much faster and more accurately than our user testing.

A potential problem with this approach is Facebook's current stance on the extent to which they are willing to contribute efforts to deal with the problem of fake news. They have said they "cannot become the arbiters of truth"(Mosseri, 2017b), so we fear they will reject our solution, as it places the responsibility of identifying truth on them. However, we are careful in the design of our interface to not make absolute claims to acknowledge the fallibility of an algorithm; we labeled articles that the algorithm identified as fake news as "most likely false." Therefore, we believe our interface still falls within Facebook's requirements. Alternatively, since Facebook already outsources its fake news detection to third-party services like Snopes, our model would be a familiar solution for them as an independent, third-party service. Adopting our model would allow them to gain the benefits of the automated fake news detection tool but without the burden of responsibility associated with making controversial decisions about the validity of news.

Finally, as a way for users to better understand how our interface works, Facebook can add an instructional guide to their existing resources for combating fake news. One of their recent initiatives involved a link at the top of the News Feed to their tips and tricks for identifying fake news (Mosseri, 2017a). If our design were implemented, this would be an ideal location to place information to introduce users to our interface.

Figures

Fig. 1: Network Graph linking "Obama" and "Islam"

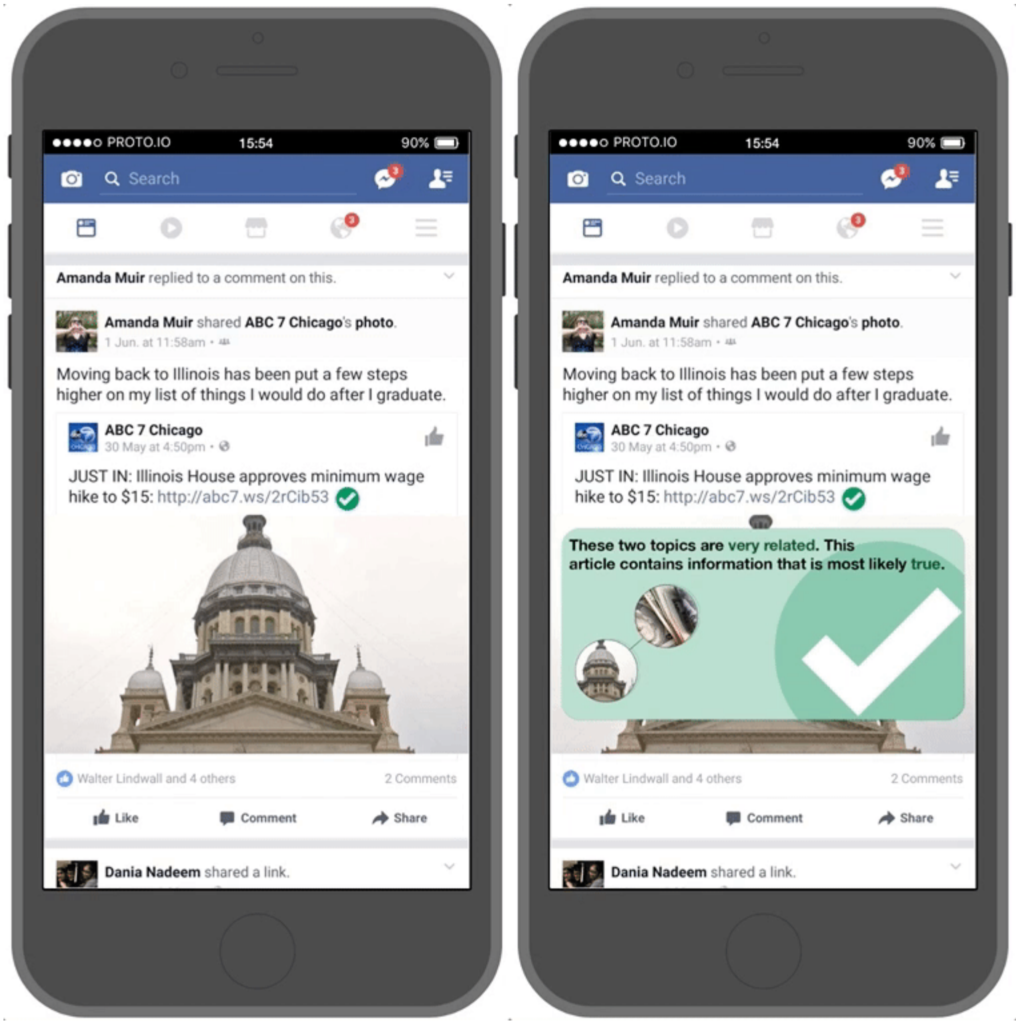

Fig. 2: First iteration of fake news detection interface for News Feed. The first screenshot shows the interface for a credible article, which a user can see while scrolling through their News Feed. The second screenshot shows the algorithm visualization that is visible when the user taps on the icon, showing why the article was marked as credible.

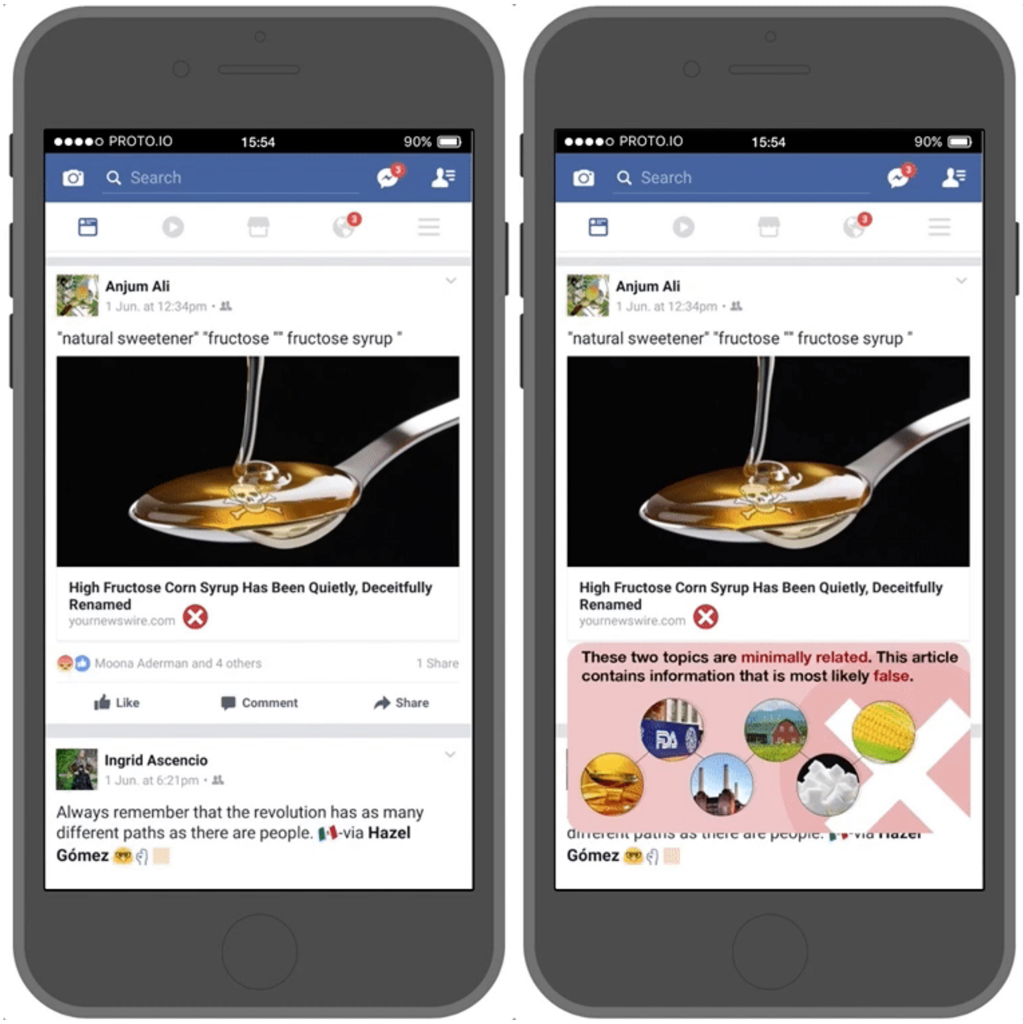

Fig. 3: First iteration of fake news detection interface for News Feed. The first screenshot shows the interface for a fake news article, which a user can see while scrolling through their News Feed. The second screenshot shows the algorithm visualization that is visible when the user taps on the icon, showing why the article was marked as fake news.

Fig. 4: Second iteration of fake news detection interface for News Feed. The first screenshot shows the interface for a credible news article, which a user can see while scrolling through their News Feed. The second screenshot shows the algorithm visualization that is visible when the user taps on the icon, showing why the article was marked as credible. This iteration was designed in response to further research and our experiment, showing us we needed a more visible implementation on the News Feed with a clearer explanation in the visualization.

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