e-Health for Older Adults: Navigating Misinformation

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Abstract: In this position paper, we advocate for the design of more progressive online social networks and their web pages for the user base of older adults, arguing that in order to address the issue of misinformation, strategies attuned to this population of users in particular are needed. We discuss challenges that arise with misleading health information and with websites that support questionable positions with fake reviews (often generated by bots). We also discuss the contribution of search engine results to the difficulties that this population faces when navigating misinformation. We propose an approach where more interaction with users is promoted, and where education about the perils of the online world can be supported, as an additional tool for reducing misinterpretations which may lead to significant negative outcomes. The algorithms which we propose come from the computer science subfields of artificial intelligence, human-computer interaction and information retrieval. The novel stance is insisting on solutions that fit the demographic in question especially well, instead of relying on one-size-fits all approaches, which may disadvantage users who are older adults.

1 INTRODUCTION

In this position paper, we introduce some new directions for a series of concerns regarding e-health and older adults, for the specific challenge of assisting with online misinformation. We first consider misinformation as it arises in social networks, examining both how older adults may contribute to providing misleading content, and also why this base of users requires special consideration when developing solutions for provide assistance in coping with challenging content. With this important background in hand, we then comment on the specific case of social media posts regarding healthcare, providing insights into why this context in particular requires special consideration when considering older adult users. Our next subtopic explores fake reviews on health-related products on websites and discusses why older adults in particular may need specific assistance. We first discuss a collection of reviews about healthcare, discovered online in April 2020, identifying the characteristics that strongly suggest questionable content. Based on research regarding older adult attitudes towards online information in general, we then make some specific recommendations, highlighted in italics. We also advocate creating automated solutions for improving online experiences, so that possible harm from misinformation is mitigated. An important thread for our discussion is exploring current approaches for detecting whether online reviews are fake, using machine learning. We point the reader to a later subsection of the paper where we discuss further how to attune these solutions to older adults.

A third contributor to misleading content online is the output of search engines. We discuss concerns that arise due to these browsing efforts, reflecting as well on what may be most relevant for older adults, specifically when the topics at hand are those of healthcare. The strategy that we propose for providing better assistance to this user base for this particular challenge is to conduct detailed user studies in order to carefully learn what poses the most difficulty. The engagement of participants yields further insights into the specific problems to address with online misinformation and the strategies that may hold the most promise in order to assist users in this demographic.

We move forward from here to a section of the paper devoted to examining the use of techniques from artificial intelligence multiagent trust modeling, outlining their promise both in assisting with detection of misinformation and in delivering help to older adults in particular. The methods which we outline enable reasoning both about the specifics of the user and the particular content at hand, in order to propose strategies for improving online experiences. We preface

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this discussion with some insights into the user base of older adults and what may be most important for them when addressing untrustworthy health information. As part of our final reflection for the future, we consider more concrete steps forward using computer science methods to improve the state of the world. We also highlight the treatment of health information and raise the current concern of Covid. In our conclusion, we advocate for a combination of intelligent processing of online information and a strategy of better education, going forward. It is important to note that each online user is an individual; we are not claiming that all older adults will fit the same profile. All the same, certain challenges that have been shown to be more prominent for this user base merit consideration. And while older adult users may enjoy distinct benefits online due to the wisdom of their age, since failing to address healthcare misinformation may have critical outcomes, we choose to focus on steps to deflect concerns.

2 THE CENTRAL CONCERNS FOR OLDER ADULTS WITH ONLINE MISINFORMATION

2.1 Social Networking

When considering misinformation in online social networks and the specific concern about misleading healthcare posts, research shows that this may be more prevalent in certain platforms. For example, Ebola misinformation was present in more than 80% of Instagram posts but fewer than 50% of Tweets (Guidry et al., 2017). There is also an issue with the spread of rumors and how this changes over time. As an example, reports on narcolepsy as a side effect of a flu vaccine in the Nordic countries were first depicted as rumors, but later few cases were confirmed after years of research and this is still contested (Sturkenboom, 2015). Acting on health misinformation might also need urgent actions from health organizations to stop the spread and share correct information. Detecting health rumors in a timely fashion can help public health officials tackle them before they spread. In the case of the Ebola outbreak, some of the rumors circulating the Internet, such as that drinking salty water was an effective protective measure, led to several deaths (Oyeyemi et al., 2014).

One promising approach is focusing on this important issue of rumor spread in social media, proposing methods for detecting the origins of misinformation using a combination of crowdsourcing and expert advice, examining features of the messages. Algorithms to assist in detecting misinformation and rumour spread have been designed specifically for concerns with health within Twitter (Ghenai and Mejova, 2017). While this research also examined specific health issues (e.g. Zika fever, cancer), a range of possible health-related topics could also be considered by the methods presented in this paper.

Since some research has shown that older adults may actually quite benefit from using social media (Myhre et al., 2016) in terms of improved working memory and cognitive function, it would be valuable to encourage these users to participate in online communities. But two problems arise. The first is that older adults may be responsible for the spread of misinformation. For example, in a study of registered voters on Twitter (admittedly only a small sample of the older adult users), Grinberg et al. (Grinberg et al., 2019) found that people over 65 shared roughly 4.5 as many false news stories on Twitter as people 18 to 24. Older adults were also found to have shared more fake news and hoaxes in Facebook (Guess et al., 2019), nearly 7 times as many articles from fake news domains than younger users, and also 3 or 4 times as many fake news links. The second problem is that older adults are more susceptible to misinformation, compared to younger adults (Wylie et al., 2014). As to why these users may be more prone to believe incorrect information, studies such as (Ghosh and Iyengar, 2019) suggest that feelings of isolation and loneliness may be important factors in willingness to believe the misinformation. This research suggests that more specific attention on the user base of older adults is merited, when trying to address online misinformation. The importance of doing so becomes all the more essential when considering healthcare posts with fake reviews, as we discuss in the section below.

2.2 Fake Reviews

A recent study (Shao et al., 2019) suggests that credulity is the factor that increases vulnerability to fraud in older adults where credulity refers to a propensity to believe things that are unproven or unlikely to be true. Slower cognitive processing and increased trust might also be reasons why fraud among older adults is efficient (Bailey and Leon, 2019). Liao et.al (Liao and Fu, 2014) conducted a study to understand how age affects credibility judgements of online health information. The results showed that older adults pay less attention to credibility content cues (e.g. high ranked medicine with research evidence, explanation of treating mechanisms, comprehensive and accurate information, professional writ-

ing) compared to younger adults. Different from younger adults, older adults further tend to ignore the contextual website features during credibility judgment (such as nice layout/color/information structure, with reference/contact information/third party endorsement). When looking at user reviews, older adults were helped in making better credibility judgments when these reviews were consistent with content cues. We are encouraged as well by the work of (Stewart et al., 2014) that suggests how credibility indicators can be promoted for older adults.

From this study, we conclude that older adults might benefit from explicit, prominent guidelines to better perform credibility judgements. On the design perspective, website designers might use pop-up checklist that "reminds" users to ask critical questions relevant to the credibility of information and to pay attention to Web-specific features, which may help older adults to naturally adopt more effective credibility judgment when consuming online health information.

2.2.1 Older Adults and Healthcare

We discovered several examples of reviews of healthcare products on Amazon in April 2020 which we suspected were fake. The first was for an essential mineral supplement "Pure" which has few words ("hair grew back"), and claims huge benefit ("bald cure"). At times we saw review text with strong titles ("Five stars" or "Great product") that was incoherent, possibly autogenerated, including "I gave this to my son since I have the mugs that are copper he likes it" and "This is the very best Melatonin in the market today. Buy up while you can" (where the product was not even melatonin-based). Generic wording at times seemed canned, as well. This happened with a review for a fingertip pulse oximeter which claimed "I need this instrument very much to detect the physical condition of me and my family". Stilted writing and fearmongering were also elements which heightened our concern about the reviews. This study of possible fake reviews points to the value of algorithms (explored in the next subsection) which delve further into the linguistic style of reviews and which may be able to detect irrelevant content.

von Helversen et al. (von Helversen et al., 2018) considered the differences in how younger and older adults assessed products based on three attributes: product attributes, average ratings, affect-rich (emotional) user reviews. In the absence of any ratings or reviews, they found that older adults were more likely to carefully consider the product attributes. However, they still struggled to determine the better product just by looking at the attributes, which may be affected by aging-related declines in their decision-making abilities. They also found that younger adults were strongly influenced by average consumer ratings and in the absence of user reviews would most likely choose the product with a higher average rating unless there was jarring difference between the attributes of the product. In comparison, average ratings had no such effect on the decisions by older adults, which they found to be surprising. They postulate that it's possible that older adults simply don't care about what other people think or that the user interface for average ratings may be difficult for older adults to understand or see. As for user reviews, they found that younger adults were strongly affected by both affect-rich negative reviews and affect-rich positive reviews. In contrast, older adults were not at all affected by affect-rich positive reviews but strongly affected by affect-rich negative reviews. They claimed that this is consistent with the socio-emotional selectivity theory since older adults want to focus on emotional goals and thus want to avoid negative emotions that may be associated with choosing a product.

Below we provide some of our key proposals in italics. *The researchers conclude and we recommend that rating systems be adapted for older adults by having better visibility of all negative reviews and more clarity regarding average ratings.* It is of course also important to prevent the injection of fake, vivid, negative reviews. The researchers also observed and we find it important to emphasize that the next generation of older adults may be more internet-savvy. It is also important to note that the authors' baseline reviews were skewed towards positive statements since they were more typical than neutral reviews. *We therefore advocate that another study should examine whether these results are repeatable. If they are, then platform owners such as Amazon should make use of content moderation to be more circumspect with strongly positive reviews that may be fake.* However, freedom of speech still needs to be balanced; users should not feel that there is undue censorship.

2.2.2 Automating the Assistance

It is important to note that fake reviews arise online in part because they are generated by automated procedures, commonly referred to as bots. For example, this significant study examined how artificial intelligence technology could be used to populate websites with fake reviews (Yao et al., 2017). This work then examines how to address this practice using technology. In fact, several researchers have designed machine learning algorithms to detect fake reviews and we suggest also using these methods as part of the effort to assist older adults.

The work of Ott et al. (Ott et al., 2011) examines linguistically analyzing the content of reviews online in order to identify those which may be suspect. Specifically, their findings suggest the importance of considering both the context (e.g., BIGRAMS+) and motivations underlying a deception, rather than strictly adhering to a universal set of deception cues. Several other approaches for detecting fake reviews have been developed over the years. The performance of different methods is examined in (Hájek et al., 2020). The work of Sun et al. (Sun et al., 2013) makes us aware that various spamming techniques can still be used to thwart fake news detection algorithms. And the research of Mukherjee et al. (Mukherjee et al., 2013b) critiques just how effective methods being used today by some of the current platform owners turn out to be, examining what is happening in the context of Yelp.

We also assembled a set of papers aimed at detecting fake reviews which introduce deeper AI techniques for the analysis. The techniques spanned supervised learning (supporing binary classification), unsupervised learning (to address lack of labelled data) and semi-supervised learning; both text and behaviour features were considered. The approach in (Mukherjee et al., 2013a) formulates detection as an unsupervised clustering problem based on user behaviours, using Bayesian methods. The work of (Li et al., 2017) shows the AI methods of hidden Markov Models, exploiting bimodal distributions and behaviour features. Some of the methodology used in linguistic processing of text is revealed in (Shuqin and Jing, 2019), following a semi-supervised learning approach. Examining the contribution of temporal features is the core idea of the next paper examined (Liu et al., 2019), as a specific element of interest. We also analyzed a supervised learning proposal that focuses on text features, culminating in a machine classification process (Jia et al., 2018). A useful literature review in the area is offered in (Wu et al., 2020); this paper makes clear that effective methodology and useful datasets are both important.

Some of the central issues that need to be addressed are as follows. First of all, obtaining ground truth data is a challenge. As explained above, one approach is to use crowdsourced labelling towards this end, but the accuracy of these methods to date for fake reviews has faced various challenges (Fornaciari et al., 2020). With respect to feature detection, our observation is that using behaviour features for fake reviews needs to focus on the review account behaviour, such as how many reviews were posted per day. This is distinct from user behaviour analyses that arise in studies such as (Ghenai and Mejova, 2017). We explore how some of this feature analysis can be tuned to older adults in particular, in Section 3.

2.3 Older Adults and Search Engines

Even if search engines return the most relevant documents, sometimes these relevant documents contain incorrect information. The presence of incorrect information might cause harm when making health-related decisions. In a prior study (Ghenai et al., 2020), the authors showed that there is a significant influence of search results on people's decisions when determining the efficacy of a medical treatment. When search results were biased towards correct information, people tended to answer health related questions with high accuracy. On the other hand, when the search results were biased towards incorrect information, people's accuracy dropped. The consequences of the presence of incorrect information in search results are dire especially when dealing with serious illnesses. For example, a search user is diagnosed with cancer, and turning to a web search engine, finds documents offering many treatments for sale, but many of these treatments will have no effect or even a negative effect on the health of a cancer patient. If a user is provided with incorrect treatment information, the searcher may not seek known effective treatments or may reject such beneficial treatments in favor of unhelpful treatments.

The prior study (Ghenai et al., 2020) was biased towards highly educated young computer savvy part of the population due to the recruiting process. How would the effect of search results differ when dealing with a different set of population with potentially high risk of being influenced with the incorrect information such as older adults? In 2010, it was reported that 45% of older adults over the age of 65 go online to search for health-related information (Fox, 2010). While older adults often have lower health literacy than younger adults (Czaja and Lee, 2012), many of them are novices in Internet searching and health-related websites (Becker, 2004). These factors raise the concern of how incorrect online health information effect older adults' health-related decisions.

We advocate conducting a new study in order to investigate how search results affect older adults when determining the effectiveness of a medical treatment. The central recommendation is to assist older adults with challenges resulting from search engine results by first conducting a hands-on investigation in order to properly ascertain the preferences and concerns of this user base. We advocate combining surveys, interviews in person, audio-recording, video-recording and recording eye movements using an eye-

tracking devices. Only older adults capable to using a computer to do online search (independently or with help) will be able to participate. Each participant also needs to confirm that they are 65 years of age or older.

With older adult users, any online questionnaires will need to take into consideration vision function, cognitive function and memory function; it would be best as well to try an array of ages and to survey both males and females. An important study (Seo et al., 2020) has also highlighted that certain segments of this older population are even more vulnerable to online misinformation. This then suggests a comprehensive assembly of participants with different user profiles.

We acknowledge that during the Covid pandemic, it will now be more difficult to gather together with participants in person. But we would still like to learn how older adults may be misled about this important subtopic. *We recommend trying to first understand which topics regarding health these users tend to search for the most and what platforms they use the most for health information gathering.* It would also be useful to determine, for Covid19, whether features that social media plaforms have deployed in order to mitigate this use (e.g. linking explicitly to trusted sources) are helpful to older adults. We propose conducting an online survey in order to get responses from our users. We also feel it would be valuable to conduct a longitudinal study where we conduct the survey multiple times during a given time period, to see if opinions change over time. We are also aware of important research on how best to design surveys that operate with older adult users and have some recommendations following these results (displayed in italics), as well. We recommend that *researchers need to consider the technical dexterity of the users and that responses rates to surveys may be increased if privacy protection measures are heightened.* A very interesting study (Chin et al., 2018) focused specifically on polling older adults with respect to healthcare information. The authors conclude that at times new websites arise which provide clearer advice to patients. *One useful strategy may be to display both old and new websites when health information has been updated, in order to emphasize the new contributions for the older adult population.*

3 THE POTENTIAL OF AI TRUST MODELING

In order to examine in closer detail how algorithms for judging trustworthiness of agents in multiagent systems may be of use in order to assist older adults online with healthcare misinformation, we first conduct a deeper investigation of how this particular user base differs from others, when considering trust in other parties. One observation in the literature is that older adults have smaller social circles, being less likely to build new online contacts of their own initiative (Steijn, 2014). This suggests that their conclusions when presented with healthcare information online, may have a tendency to agree with other users having similar backgrounds. In this way, the effects of misinformation may acccumulate. Another distinguishing viewpoint of the older adult community outlined in (Lüders and Brandtzæg, 2017) is that at times they regard the Internet more as a functional tool than as an avenue for social interaction. An outcome may be less critical thinking of the content that is provided.

It is very important to treat each online user as an individual and not to make generalizations based on common habits that may be observed. Nonetheless, when providing assistance online to someone identified as an older adult, some options may be provided which will facilitate beneficial outcomes. *Especially for the consideration of online healthcare information, all users would benefit from including known experts in the medical field in their social circle. Older adults may acquire more discrimination of online content, if they were shown some statistics of how many other users within their platform have disagreed with the opinion that they may choose to promote (e.g. retweet).* Some of the online statistics that are not obviously displayed can become more prominent. In part, this suggestion aligns with earlier recommendations of ours about fake reviews (Section 2.2), to enable older adults to be more aware of true negatives rather than focusing on positives. *In a similar vein, the information in online social networks, when directed to users identified as older adults, can draw out more explicitly the origin of the advice that is being provided (e.g. if a medical organization known worldwide has initiated the information).*

Two central approaches for reasoning about trustworthiness of online sources using multiagent trust modeling have emerged recently. The first outlines how discussions which emerge following a post in a social media environment such as Reddit can provide important clues as the reputation of the post that launched the discussion (Parmentier and Cohen, 2019). The second sheds light on how clusters of users with similar behaviours may receive personalized recommendations for whom to trust within a review-based context, using Yelp as the exemplar (Parmentier and Cohen, 2020). This is based on a multi-faceted set of trust indicators such as how often

a trustee's ratings agreed with that of the trustor.

In order to move forward with algorithms such as these, if assisting the user base of older adults in particular, there are some key ideas which hold some promise. The Reddit study explored the contributions of specific features in the text such as negative language or sentiment. But one interesting feature which seemed to be particularly helpful in identifying questionable reputation was the difference in scores within the ensuing discussion of a post. We have already mentioned that older adults may need more assistance with negativity when reacting online. As such, scenarios where older adults are involved in the discussion may well be ones with significant disagreement amongst users. Further study of this particular indicator of user reputation may be quite fruitful, in order to provide assistance to older adults. The Yelp study located clusters of users based on their patterns of trusting others. But we may be trying to assist a set of users already identified as all being older adults. We may know the general features of this set of users, such as ones we have drawn out in this paper regarding attention on negative reactions. This may then suggest new trust indicators to be used within the multi-faceted trust model which may then assist in grouping together older adult users within the same clusters. In addition, what is known beforehand about these users can be considered to be a prior on the Bayesian reasoning employed within the proposed multi-faceted trust modeling. Then the personalized attention that is delivered can become appropriate explicitly for this user base.

4 LOOKING TO THE FUTURE FOR OLDER ADULTS AND ONLINE MISINFORMATION

In this paper, we have reported on some challenges which arise when trying to assist older adult users with online misinformation about healthcare. We have made clear that different contexts are relevant and important: social media, fake reviews and less helpful search engine results. We have also explained why older adult users may require special consideration in each of these scenarios. And we have tried to emphasize the additional concerns which arise when the discussions centre around healthcare. For each of the specific areas in which we would like to see improved experiences for older adult users, we have highlighted some specific recommendations: actions to take, including the use of various automated, intelligent algorithms and the importance of doing deeper explorations of the actual needs and preferences of the user base, online. Looking to the future, it would be valuable to consider some more dramatic efforts for more benefical outcomes for our older adult users, towards their healthcare decisions. Several of these suggestions emphasize improved interactions with this user base.

A first suggestion is to offer additional support when the various technologies are being used. An ambient help system which does not interrupt but allows for additional guidance may be useful to install, both with respect to search engine use and in navigating posts in online social networks. The work of (Matejka et al., 2011) serves as an inspiration for this step forward. Some current efforts to engage older adult users (Yu and Moffatt, 2019) have also shown that the importance of being careful with these users when it comes to layout preferences and privacy considerations. In the case of healthcare, where messages may seem mixed and difficult to interpret, one creative suggestion to support older adults is to consider integrating friendly voice assistants. We feel this solution may be appealing, in much the same way that robotic companions have been accepted (Bemelmans et al., 2012). In general, we are suggesting that a somewhat different emphasis on what to support and consider for this user base may be required.

We also have specific plans for advancing from solutions on detecting rumours about healthcare in Twitter (Ghenai and Mejova, 2017). Taking Covid-19 as a case study (an issue of critical concern to older adults), we can collect a set of tweets and then classify them into rumors or non-rumors. Later we can scrutinize the source of the rumour tweets to better understand the origins of this particular misinformation campaign. We can also collect Covid-19 articles from the RSS feeds of already labelled media sources, as was suggested in a recent research challenge (ICWSM 2020 dataset challenge). After identifying sources which contain suspected misinformation, we can look further into whether certain domains are more responsible for the spread. This then brings us into the important concern of examining influence spreaders within the networks (Starbird et al., 2018). Since many studies to date have focused on the spread of news misinformation, we would aim to study more carefully whether the results differ when the focus is on health misinformation.

With respect to Covid-19, it would also be instructive to learn whether opinions change over time, as new sources of information are presented to users. Towards this end, we would aim to have a longitudinal study (same survey during different time periods) of older adult users. The specific exploration

of Covid-19 is quite enlightening, as international collaborations between fact checkers has been established for this particular topic: 90 professionals from 39 countries have debunked 495 falsehoods in 15 languages. The #CoronaVirusFact/#DatosCoronaVirus alliance has published six international reports in English and created a special search list on Twitter (poy.nu/2019CoronaVirusFacts) to help citizens easily get the latest verified content online.

Moving from (Ghenai and Mejova, 2018) to consider COVID-19 to detect misinformation, we raise these points. First, Twitter is currently doing a great effort to keep its content rumor-free regarding COVID-19. As a result, when collecting data, we might not find a large amount of tweets containing COVID-19 rumors due to stricter regulations regarding the pandemic. Having fewer data might affect the performance of the model. Second, (Ghenai and Mejova, 2018) did not consider the geographic distribution of rumors in Zika or in the cancer study. However, in COVID-19, we believe that we need to consider the geographic location when building the model. Many conspiracy theories and rumors might be different in each location. The misinformation tracking models in (Ghenai and Mejova, 2018) did not look at temporal changes of rumors. Keeping track of time when building the model will be important for COVID-19, as regulations and rumors tend to change rapidly.

5 FINAL REMARKS

This position paper has drawn attention to the fact that the user base of older adults merits special consideration, when developing technological solutions to assist with misinformation about health that may occur online. We make clear that different contexts of use arise and need to be examined: social media, fake reviews and search engines. We also clarify that for these online experiences, healthcare is a prominent topic in focus for this base of users, who may also be particularly vulnerable. Through some specific recommendations about what to present and what to highlight for these users and through some original suggestions for moving forward with technologies that we have developed to date, with greater focus on this user base, this position paper provides some important messages and some concrete starting points for progress. A predominant theme to this message is enabling older adults who are online to be better educated about potential misinformation. As such, combining the steps forward outlined in this paper with independent outreach to these individuals, making them aware of valued sources and the importance of careful scrutiny of online content, is also an essential part of the solution, in our view.

While what we discover now about older adults may not be true tomorrow for the next generation of these users, continuing to conduct dedicated user studies will assist in understanding this demographic; healthcare will always be an important issue for this user base and helping to navigate misinformation should therefore continue to be an ongoing concern.

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