ORIGINAL RESEARCH

Cultural Evolution and Digital Media: Diffusion of Fake News About COVID-19 on Twitter

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Abstract

Disinformation (fake news) is a major problem that affects modern populations, especially in an era when information can be spread from one corner of the world to another in just one click. The diffusion of misinformation becomes more problematic when it addresses issues related to health, as it can affect people at both the individual and population levels. Through the ideas proposed by cultural evolution theory, in this study, we seek to understand the dynamics of disseminating messages (cultural traits) with untrue content (maladaptive traits). For our investigation, we used the scenario caused by the Coronavirus Disease 2019 (COVID-19) pandemic as a model. The instability caused by the pandemic provides a good model for the study of adapted and maladaptive traits, as the information can directly affect individual and population fitness. Through data collected on the Twitter platform (259,176 tweets) and using machine learning techniques and web scraping, we built a predictive model to analyze the following questions: (1) Is false information more shared? (2) Is false information more adopted? (3) Do people with social prestige influence the dissemination of maladaptive traits of COVID-19? We observed that fake news features contained in messages with false information were shared and adopted as unblemished messages. We also observed that social prestige was not a determining factor for the diffusion of maladaptive traits. Even with the ability to allow connections between individuals participating in social media, some factors such as attachment to cultural traits and the formation of social bubbles can favor isolation and decrease connectivity between individuals. Consequently, in the scenario of isolation between groups and low connectivity between individuals, there is a reduction in cultural exchange between people, which interferes with the dynamics of the selection of cultural traits. Thus, maladaptive (harmful) traits are favored and maintained in the cultural system. We also argue that the local Brazilian cultural context can be a determining factor for maintaining maladaptive traits. We conclude that in an unstable (pandemic) scenario, the information transmitted on Twitter is not reliable in relation to the increase in fitness, which may occur because of the low cultural exchange promoted by the personalization of the social network and cultural context of the population.

Keywords Maladaptive traits · Misinformation · Machine learning · Cultural selection bias · Pandemic · Online information

Introduction

The exchange of information is an important aspect of social dynamics and can be understood as a synonym for culture, since culture is nothing more than information acquired from other individuals through social transmission via mechanisms such as imitation, teaching, and language [55]. The complexity in the transmission of information has enabled humans to become more competitive in the face of natural selection [29]. Evolutionarily, similar to biological transmission (through genetic material), the transmission of information can be understood by its ability to influence the adaptability of individuals (*fitness*) [73]. However, not all information transmitted is accurate and provides useful elements for *fitness*, resulting in the fixation and diffusion of maladaptive elements (elements that do not increase fitness) (e.g. [77]). The presence of maladaptive traits in the cultural system can harm individuals, especially when we take into account information that can harm the health of the population [39, 74].

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Table 1 Machine learning techniques used in similar studies on fake news and COVID-19

Technique	Database	References
Bidirectional encoder representations from transformers	Amazon Mechanical Turk	Ayoub et al. [11]
Random forest	Twitter	Madani et al. [52], Schroeder et al. [69]
Latent Dirichlet allocation	Twitter	Al-Ramahi et al. [6], Abd-Alrazaq et al. [1]
Hybrid (Naive Bayes classifier and support vector machines)	News websites	Hawa et al. [34]
Logistic regression	Twitter	Mahlous and Al-Laith [53]
Own model	FakeNewsNet; Twitter	Li et al. [51], Kaliyar et al. [40]
Long short-term memory	Twitter	Abdelminaam et al. [2]
Naive bayes	Twitter	Schroeder et al. [69]
Support vector machines	Twitter	Xavier et al. [81]

The dynamics of information within a cultural system can be understood and studied through the theory of cultural evolution (CE). Through Darwinian principles (inspired by biological evolution), CE seeks to explain the complexity of the transmission, diffusion, and fixation of information in cultural systems [56]. The transmission of information can be influenced by several factors, as pointed out in Mesoudi [55], for example: the content of the information, which can make it more attractive, the frequency of the information, that is, in certain situations individuals may adopt information because it is more or less common in the system; and whoever transmits the information, that is, people imbued with social prestige can influence others to adopt certain information. In addition to the transmission of information between people in the physical environment (e.g., conversations), the content of messages broadcast on digital media may contain elements that are maladapted. In other words, it may feature distorted information that does not match true facts (popularized as *fake news*), and which can have the intention of misinforming those who access it [48].

Fake news is shared through the same mechanisms used to share quotidian messages on social media. The messages are liable to various interactions by users that help spread them; for example, people can share a post made by another individual who is not necessarily part of their social circle [43]. Another mechanism is the "like," in which individuals can signal to others that they liked or sympathized with a specific idea. The tanning (act of enjoying the publication) symbolizes a mechanism for acceptance and adoption of shared content. The greater number of "likes" is perceived in digital media as a parameter for greater confidence [71], which, in turn, influences the adoption of behaviors in relation to the liked content, such as taking individuals to click on or engage with certain content [54, 63]. In addition, individuals who share content can also exert influence and change the attitudes of their followers, such as the intention to purchase a product [36].

The connectivity of people in digital media has brought more notoriety to the spread of fake news, as this problem was enhanced by the effects of the dynamic propagation of digital media itself [7]. The spread of fake news can directly affect an individual's survival, especially when the target of disinformation is directly related to health [30].

At the end of 2019 and beginning of 2020, the world faced the emergence of the COVID-19, a disease caused by the virus SARS-CoV-2 [42]. Owing to its high level of contagion, several mechanisms have been adopted to combat the spread of SARS-CoV-2. One of the main mechanisms was the adoption of social isolation measures [72]. The seclusion environment increased people's participation in digital media [80] and, consequently, the exchange of information about COVID-19 and the pandemic. In other words, the COVID-19 outbreak highlighted the spread of misinformation [15]. In view of the environment modulated by the effects of COVID-19, we considered this scenario to be ideal to investigate the aspects related to fake news (maladaptive traits) from the perspective of CE. Although CE has a large theoretical background on the dissemination of information, few studies have applied this theoretical basis to digital environments (see [3], despite an increasing number of digital media platforms have become crucial in the interactions between individuals [33]. Concomitantly with the increase in interactions on social media, the interest of study groups that seek to understand the dynamics of networks is growing. Many studies use machine learning techniques to understand social media phenomena, especially fake news that involves significant themes, such as COVID-19 (see Table 1).

Cultural evolution and digital media

In the digital age, communication between people has become extremely dynamic due to social networks that replicate the properties of real-life interpersonal communication [62]. In an experiment carried out by Milgram [57] to identify the number of ties of personal knowledge existing

between any two people, he inferred that people were separated from each other by an average of five intermediaries. Backstrom et al. [12] demonstrated that social networks can further reduce these intermediaries, that is, social networks favor the dissemination of information. This high rate of dissemination benefits the dissemination of any type of information, including fake news [17].

Previous studies revealed the existence of a cognitive and cultural mechanism that increases the attractiveness of distorted information. Acerbi [4] suggested some factors that may favor the success of these narratives on social networks. He found that the news content on websites that disseminate misinformation is mostly negative, and appeals to cognitive biases through the presence of gossip, threats, and information about celebrities. Despite the cognitive attractiveness of false information, evidence suggests that the act of sharing fake news is rare on social media platforms such as Facebook [31]. When individuals know that they are dealing with false information (for example, through news check notices), they tend not to share it [22]. Another factor that inhibits the sharing of false information is the possible damage to reputation and loss of confidence suffered by individuals who share fake news [8].

Concerns regarding the effects of fake news can be understood from an adaptive perspective, both at the individual and population levels. For example, fake news about health-related aspects can undermine individual responses to the adoption of prophylactic attitudes [15], in addition to inducing harmful behaviors (e.g., self-medication) that can lead to chronic intoxication [25]. Using the same reasoning about the effect of fake news on prophylaxis, we can also observe the same effect on population fitness. For example, the dissemination of fake news about vaccines leads a portion of the population to not get vaccinated and not to vaccinate their children, making them possible vectors and increasing the occurrence of diseases that were considered under control by health agencies [38]. In general, fake news can behave as a trait that is maladaptive for a good part of the population (except for the few people who benefit in some way from the spread of fake news).

When we analyze the generalities, the digital media environment shares similarities with the real environment in relation to the interaction between people and the exchange of information, which makes it possible to apply CE to digital media [3]. Therefore, CE can contribute to the understanding of contemporary cultural phenomena that involve the transmission of information in digital environments, such as the spread of fake news.

Questions/Hypotheses

After the emergence of COVID-19, the disease quickly became a pandemic, causing several countries to adopt socio-economic measures, such as financial aid and restricted movement of people, such as social isolation [32]. One of the main actions to prevent the spread of the virus responsible for COVID-19 has been the adoption of quarantines. Humans are extremely social organisms, and the restriction of physical contact between people has impacted society in several ways [21]. To continue socializing with other individuals and exchanging information, people have increased their participation in digital media [80].

The COVID-19 insurgency and its health effects have led to an unbridled search for information about the disease and the virus [37]. As a result, much fake news on COVID-19 has emerged [19]. Fake news has different effects on society, such as the individual adoption of harmful behaviors [67], the adoption of social behaviors that favor the prolongation of the COVID-19 pandemic [49], ant the disbelief in science and its ability to provide answers [24].

In situations of environmental imbalance, new difficulties can lead people to seek new information to face adversities [68]. We considered that the scenario caused by the COVID-19 pandemic could be a good model for the study of maladaptive traits from a cultural evolution perspective, especially in relation to digital media, by focusing on it, we could understand the main mechanisms that lead to diffusion of ill-adapted traits in cultural systems.

Therefore, using the theoretical framework of CE, we posed the following questions: (1) is there an association between the frequency of sharing information about COVID-19 and information containing maladaptive traits? (2) is there an association between the frequency of adoption information about COVID-19 and information containing maladapted traits? and (3) does social prestige influence the frequency of diffusion of maladaptive traits during COVID-19? To answer these questions we postulated the following hypotheses: (1) misinformation about COVID-19 has a lower frequency of sharing, given that false information containing health-sensitive information is, in general, rarely shared; (2) information with maladaptive features is less adopted because it presents a potential health risk; and (3) people with social prestige share maladaptive traits less frequently (in comparison to adapted ones) since individuals with prestige have more notoriety and could risk losing their prestige as a result of disseminating false information.

Despite the increasing studies on this subject, the case study we present here, to the best of our knowledge, is novel as it tests predictions from the cultural evolution theory to explain the spread of fake news on social media. We commenced from the idea of there being a possibility to prove that the same logic applies to virtual social systems. In addition, the observed scenario is distinct as the cultural system is in a state of instability (the pandemic). Therefore, in the theoretical approach, this research is novel.

Materials and Methods

Data Collection

Twitter Data

Twitter is a social network that allows users to send and receive personal updates from other contacts (in texts of up to 280 characters, known as "tweets"). Through tweets, it is possible for users to interact with each other (commenting, liking, or sharing messages). We chose Twitter because the interaction between users is essentially through texts, in addition to the fact that the company provides free access to its database. To have access to the messages and general data about the messages, we acquired an application programming interface key (API key). The key was acquired by registering on the Twitter developer platform (https://developer.twitter.com), in which we submitted our project and objectives.

In possession of the API key, we built a search key with the following hashtags: "#coronavirus OR #covid OR #covid19." That is, the selected tweets needed to have at least one of these hashtags. In addition, we imposed other requirements such as (1) tweets that are in the Brazilian Portuguese language, and (2) only original messages, excluding retweeted (duplicate) messages to avoid multiple replications of just one tweet. We excluded identical messages to prevent messages triggered by robots from contaminating our analyses. For the formulation and regrowth of the search key, we used the functionalities of the Rtweet package [41]. The exclusion of messages triggered by robots was done by building an algorithm in the R development environment [64] that compared all tweets.

Our search retrieved 337,403 messages between April and June 2020. After the exclusion of repeated messages, 259,176 tweets remained. The collection took place during this period, as it was the beginning of the adoption of measures against COVID-19. After May of the same year, there was a progressive decrease in the daily tweets in the hashtags of our search key. With a considerable number of tweets, we decided to end the collection and finalize the database.

Data on the News

We considered in this work a maladaptive trait as a synonym for fake news, as the establishment of information that does not contribute to fitness [55], and for not fake news scientifically based messages and opinions.

To classify the maladaptive traits contained in the tweets, we created a news repository for COVID-19. Part of the repository was built using the data available in .CVS format at https://chequeado.com/latamcoronavirusportugues/. The purpose of the site was to check the reliability of news about COVID-19. The website is a collective effort by 34 organizations from 17 Ibero-American countries. The Portuguese version was led by Agência Lupa (https://piaui.folha.uol.com.br/lupa/).

To build the other part of the repository, we use the *"Web Scraping"* method, which consists of building an algorithm that visits websites and "scrapes" information of interest to the programmer [18]. For this study, it included the title (brief summary of the news), the description/body of the story (for the full understanding of the news subject), the date (to check the news's contemporaneity), and the news URL (to have the original news source). We used this method for both news items that pointed to fake news as well as non-fake news.

Web scraping was carried out at three sites: https://www.saude.gov.br/fakenews, https://g1.globo.com/fato-ou-fake/, and https://g1.globo.com/welfare/coronavirus/. We used the following criteria for the choice of sites: (1) volume of news available; (2) compilation of news in an organized manner at the electronic address; (3) availability of pre-classified news (e.g., in title) or that could easily be classified later through content of news.

The data were filtered based on the criterion of being related to COVID-19; the data that did not meet this criterion were removed. Finally, the repository consisted of approximately 12,200 entries, of which 3100 were classified as fake news and 9100 were classified as non-fake news.

Data Processing

Deep Learning

To identify fake news in tweets, we used a method called deep learning, more precisely, the construction of an artificial neural network (ANN) [60]. Deep learning is a machine learning branch (machine learning) that allows a machine to be fed with raw data and automatically find the representations necessary for the detection or classification of a certain pattern [50]. ANNs are models that "teach" the machine certain patterns. The model is based on biological neural networks, and depending on the stimulus received by the neuron, an action potential will be generated, if the action threshold is exceeded, there will be a response [60]. Because of the nature of our data (i.e., texts), we used natural language processing techniques (NLP). NLP aims to improve the understanding of natural language through the use of computers and the semantic representation of documents to improve the classification and retrieval of information [13], thus optimizing our ANN. Therefore, the following procedures were performed on the texts

(Supplementary Material S1: we removed the punctuation, symbols, and numbers from the messages, we put all the texts in lowercase; and we removed stopwords. Stopwords are common words in a language that do not add meaning to phrases, such as prepositions [82].

Our repository had an imbalance between classes: 75% of non-fake news and 25% of fake news. There is hardly a balance between classes in nature [20, 45, 79]. Class imbalance can affect the performance of the model [76], however, there are some ways to solve this problem. We used oversampling, a technique in which minority class entries are randomly duplicated to obtain the same number of entries in both classes [58].

After processing the textual standardization of the messages, we randomized the entries with the function sample of the R development environment [64], and then divided the repository into two: a bank to train the model (training bank) with 70% of the entries, and a bench to test the model (test bench) with 30% of the entries. The proportions of the fake and non-fake classes were kept in balance (50% fake and 50% non-fake) in both banks.

The construction of ANN took place in the R environment using the Keras package [9]. Keras is a deep learning API written in Python (also codified in R), running on top of the machine learning platform, TensorFlow (package available on R). It was developed with a focus on enabling fast experimentation.

Through the Keras package, we build a multilayer perceptron (MLP) as a learning module. A multilayer perceptron is a feedforward network with at least three layers: input layer, hidden layer, and output layer, as depicted. In MLP, except the input layer, other layers use nonlinear activation functions.

MLP uses supervised learning called backpropagation or training. The MLP consists of a minimum of three layers with nonlinear activation functions, making this a deep neural network (DNN). Every node in the MLP contains certain weights (wi), which are connected to the nodes in the following layers. MLP learns in its learning phase with the change of weights after the processing of every node. Based on the output of the unit compared to the expected result, the error is calculated and the weights then get updated through the backpropagation method [10].

The function of neurons is defined by:

$$f(x) = \sum_{i=1}^{m} \left(W_i \times x_i \right) + b,$$

m is the number of neurons in the previous layer, w is a random weight, b is a random bias, and x is the input value.

In our model, the layers were sequentially stacked to build the classifier as described in TensorFlow and RStudio [78].

The first layer takes the integer-encoded vocabulary and looks up the embedding vector for each word index. These vectors are learned as the model trains. Next, a layer returns a fixed-length output vector for each example by averaging over the sequence dimension. This allows the model to handle inputs of variable lengths, in the simplest way possible. The fixed-length output vector is piped through a fully connected layer with 16 hidden units dense and activation function (relu). The last layer is densely connected with a single output node. Using the activation function (sigmoid), this value is a float between 0 and 1, representing a probability or confidence level.

The equations of activation function are defined by:

$$relu(x) = \max(0, x),$$

$$sigmoid(x) = \frac{1}{1 + e^{-x}}.$$

The algorithm works as a biological neural network, in which the stimuli are captured and pass through an action potential system. In our ANN, the stimuli were the words. Each word was converted into a single number. The model uses the training bench's pre-classified fake and non-fake messages to adjust weights to learn patterns and be able to predict. After training the model, we used a test bench to check its accuracy and obtained a value of 92%. We used the model to predict the likelihood of messages containing fake news and the likelihood of messages not containing fake news. The entire step-by-step on data processing for prediction is exemplified in Fig. 1. We categorized the probabilities of containing and not containing fake news in three ranges: high, with a probability greater than 80%; low, odds less than 30%; and intermediate, odds greater than 30% and less than 80%.

Twitter Variables

In this study, we used the number of retweets of messages as the equivalent to the number of shares in a cultural system. Although the number of shares is a continuous variable, we chose to categorize it for the following reasons: (1) non-parametric tests are not well suited to a high number of samples [26], (2) the frequency of 0 and 1 represented 80% of the distribution. We categorized the data into three groups: low frequency of shares, less than 30 retweets, high frequency, greater than 200 retweets, and intermediate frequency, greater than 30 retweets, and less than 200 retweets.

To check if messages with maladaptive traits were better evaluated, we used the number of likes. In the scenario of CE in virtual environments, we can understand tanning as an indication of the adoption (in the sense of welcoming and/or acceptance) of cultural traits. The "tanned"
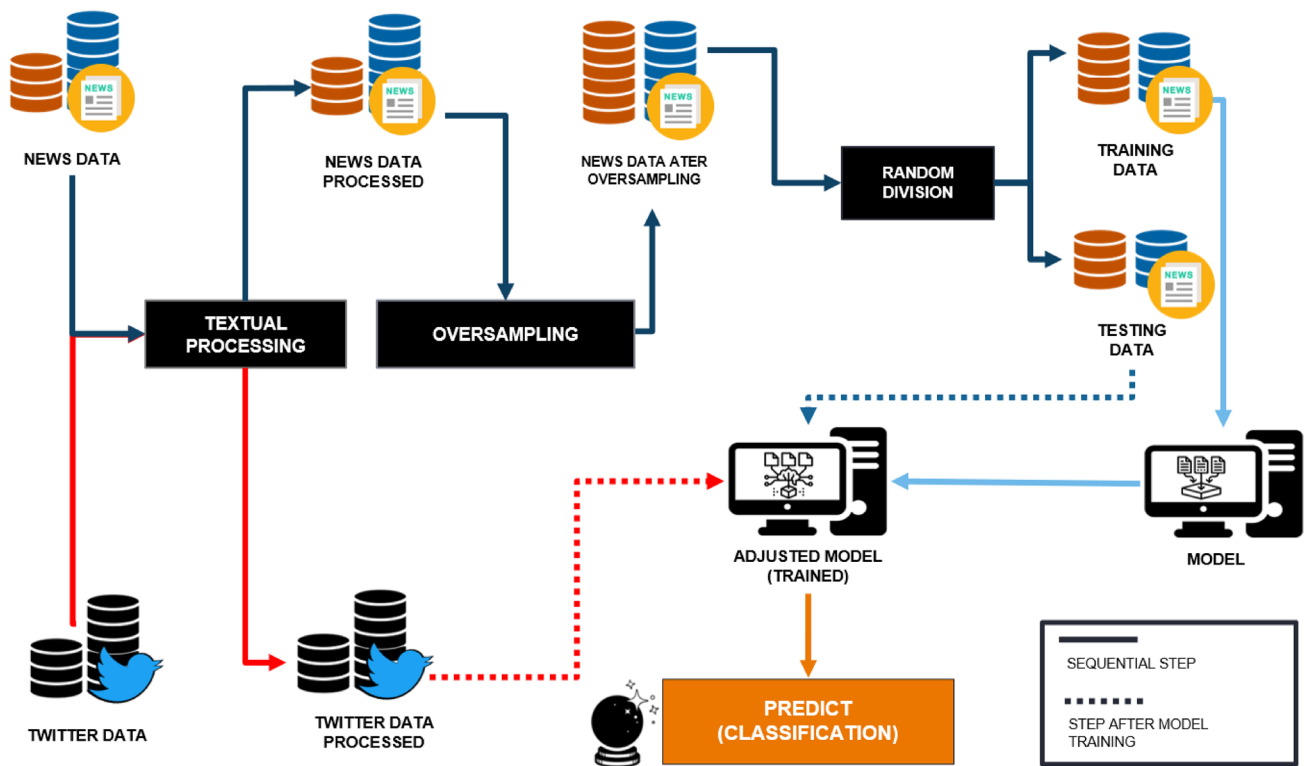
Fig. 1 Schematic of the procedural steps for classification and prediction of messages

variable showed a behavior similar to the "sharing" variable. Therefore, we adopted the same categorization procedures: low frequency of likes for messages with less than 30 likes, high frequency for messages with more than 200 likes, and intermediate frequency for messages with more than 30 likes and less than 200 likes.

To identify whether the model that transmitted the message influenced the diffusion of maladaptive traits, we used as a criterion the presence of the "verified" seal to separate the groups. This seal is given to accounts/profiles of public interest or that are prominently recognized. There are several criteria for an account to be granted the status of "verified," with the majority of them belonging to main employees and government offices, companies, brands, organizations, artists, athletes, activists and other influential personalities.

Data Analysis

We used the chi-square test of independence to test our questions, because in addition to our categorical data, the test does not require normality of the data. For a result with a p value < 0.05, we performed post hoc tests of the residues to observe the statistically significant combinations. All tests were performed in R development environment [64]

Content × Sharing

To answer our first question, we created two contingency tables (Supplementary Material S1). The first table with a model predicts the probability that the message contained fake news, with the frequency of sharing. The second contingency table was built with the model's predictions of the probability that the message contained non-fake news, with the frequency of sharing (Supplementary Material S2).

Content × Likes

To answer our second question, we built two additional contingency tables (Supplementary Material S2). Similar to what was done for the first question, the first contingency table contained the probabilities that the messages contained fake news, along with the frequency of likes. The second contingency table was built with the model's predictions of the probability that the message contained non-fake news, with a frequency of likes.

Content × Status

To understand the influence of celebrities on the diffusion of maladaptive traits we separated messages from verified accounts from those from unverified accounts. We then used

the frequency of sharing messages from verified and unverified profiles and built two contingency tables (Supplementary Material S2). In the first table, we relate the frequency of sharing and verification status with the probability that the messages contain fake news. In the second table, we compare the frequency of sharing and verification status with the probability that the messages contain non-fake news (Supplementary Material S2).

Results

Are Texts that Contain Maladaptive Features More Widespread?

In both models tested (the probability that the message contains fake news and the probability that the message does not contain fake news) (Tables 2, 3), the variables tested were dependent ($p < 2.2e-16$) and exhibited the same behavior in the post hoc test (Supplementary Material S3). Messages with fake and non-fake news are also shared.

Are Messages that Contain Maladaptive Traits Adopted More?

In both models tested (the probability that the message contains fake news and the probability that the message does not contain fake news) (Tables 2, 3), the variables tested were dependent ($p < 2.2e-16$) and exhibited the same behavior in the post hoc test (Supplementary Material S3). Messages with fake news and non-fake news were also adopted (liked).

Does the Transmitting Model Influence the Diffusion of Maladaptive Traits?

In both models tested (the probability that the message contains fake news and the probability that the message does not contain fake news) (Tables 2, 3), the variables tested were dependent ($p < 2.2e-16$) and exhibited the same behavior in the post hoc test (Supplementary Material S3). These results suggest that maladaptive and adaptive traits are equally widespread, regardless of the model that transmits the message.

Discussion

The maladaptive traits of COVID-19 are shared and adopted as neutral/adaptive traits. We observed that maladaptive and adaptive features were transmitted equally by both models. The literature on maladaptive traits shows that these can be transmitted in medical systems, despite inefficiency or impairment [77]. Regarding virtual environments, our findings differ from those of other studies. For example, Guess et al. [31] found that sharing fake news is relatively rare. In another study, Chung and Kim [22] found that, when people

Table 2 Comparison of variables by group in relation to the probability of messages containing fake news

Characteristic	Sample size n	(%)	Low probability of the message containing fake news	Average probability of the message containing fake news	High probability of the message containing fake news	Chi-square independence
Number of shares						
≤ 30	255,526	98.6	191 490	12 257	51 779	$\chi^2(4) = 115.66$
> 30 < 200	2988	1.2	2521	103	364	$p < 0.001$
≥ 200	662	0.3	538	25	99	$n = 259,176$
	259,176	100				
Number of likes						
≤ 30	247,413	95.5	184,788	11,992	50,633	$\chi^2(4) = 414.64$
> 30 < 200	8682	3.3	7205	277	1200	$p < 0.001$
≥ 200	3081	1.2	2556	116	409	$n = 259,176$
	259,176	100				
Number of shares per model						
Celebrity ≤ 30	29,435	11.4	24,399	1036	4000	$\chi^2(10) = 10,527$
Non-celebrity ≤ 30	226,091	87.2	167,091	11,221	47,779	$p < 0.001$
Celebrity > 30 < 200	1916	0.7	1664	54	198	$n = 259,176$
Non-celebrity > 30 < 200	1072	0.4	857	49	166	
Celebrity ≥ 200	531	0.2	440	22	69	
Non-celebrity ≥ 200	131	0.1	98	3	30	
	259,176	100				

Table 3 Comparison of variables by group in relation to the probability of messages containing non-fake news

Characteristic	Sample size n	(%)	Low probability of the message containing non-fake news	Average probability of the message containing non-fake news	High probability of the message containing non-fake news	Chi-square independence
Number of shares						
≤ 30	255,526	98.6	52,610	12,222	190,694	$\chi^2(4) = 162.57$
$> 30 < 200$	2988	1.2	367	101	2520	$p < 0.001$
≥ 200	662	0.3	101	25	536	$n = 259,176$
Number of likes						
≤ 30	247,413	95.5	51,472	11,945	183,996	$\chi^2(4) = 437.78$
$> 30 < 200$	8682	3.3	1194	287	7201	$p < 0.001$
≥ 200	3081	1.2	412	116	2553	$n = 259,176$
	259,176	100				
Number of shares per model						
Celebrity ≤ 30	29,435	11.4	4035	1065	24,335	$\chi^2(10) = 10,533$
Non celebrity	226 091	87.2	48,575	11,157	166,359	$p < 0.001$
Celebrity $> 30 < 200$	1916	0.7	201	51	1664	$n = 259,176$
No celebrity $> 30 < 200$	1072	0.4	166	50	856	
Celebrity ≥ 200	531	0.2	72	20	439	
Non-celebrity ≥ 200	131	0.1	29	5	97	
	259,176	100				

are aware that the information is false, they tend not to share it on social networks. This suggests that, when people do share, they may not be aware of or do not believe that the information they share is false.

The experiment carried out by Segovia-Martín et al. [70] can also help us to understand our findings regarding the diffusion of traits in the system. They found that content bias is a predictor of population convergence in a single cultural variant (which tends to be more adaptive), and convergence in certain cultural traits is affected by the connectivity of individuals and populations. For example, highly connected populations tend to converge on a single variant with a greater degree of adaptability. However, some factors, such as egocentric bias and population isolation, can affect the convergence dynamics of the features. They propose that convergence tends to decrease because of the egocentric bias (attachment to their own cultural trait), since the individuals who would maintain their own cultural variants make it difficult to converge, as well as the isolation of populations (or subpopulations), due to less cultural exchange. Despite the digital environment offering the highest degree of connectivity for human interactions, the formation of "social bubbles" is common in digital media. Social bubbles on social networks are formed by three factors [61]: homophilia, association with friends with similar ideas on the social network, and selection of the individual's own content and algorithms for personalizing content suggested to the user. In other words, social bubbles are subgroups that have less diversity of information (cultural exchange) [61],

which can lead individuals to not proactively discuss ideas with different people or groups of opinions and reject ideas opposite their own [75]. In other words, social bubbles can induce selfish bias and can be interpreted as subpopulations. Then, paralleling the cultural model of Segovia-Martín et al. [70] to our study, we can infer that the reason for the lack of difference in the diffusion of adaptive and maladaptive traits is the egocentric bias and the low connectivity caused by social bubbles.

Regarding the adoption of cultural traits, we can understand our results from the perspective of the cognitive attractiveness of content biases.[1] Bebbington et al. [16] showed that the human brain is more easily attracted to messages with negative content in the social transmission of information. According to Rozin and Royzman [66], negative events are more threatening (e.g., a catastrophic and irreversible event) than positive beneficial events, have greater information complexity (e.g., situations of threat, freezing, withdrawal, and escape mediated by negative feelings) and if they develop more quickly and require a quick response (e.g., imminent life threat), which would justify the cognitive attractiveness of this type of content. Kumar et al. [46] found that fake news is characterized by mostly messages with negative content. In the same sense of cognitive

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[1] Content bias refers to the sensitivity of individuals to the intrinsic characteristics of the traits, which are cognitively more attractive [5, 70].

attractiveness for information content, it was found that information related to survival tends to be prioritized in the human brain (see review [59]. Information on COVID-19 is intrinsically related to the survival of individuals [65]. Thus, the maladaptive traits of COVID-19 can be adopted due to the negative bias, while better adapted traits are adopted by the survival bias. Therefore, because COVID-19 is a new agent that destabilizes the system, individuals can try to collect all types of available information, which can be another factor that contributes to the maintenance of both types of traits in the system.

The transmission of information through models intrinsically depends on the prestige and credibility of other individuals [35]. In our study, we found that prestige did not influence the diffusion of maladaptive traits. Altay et al. [8] found that people's concern about damaging their reputation can lead to a decrease in the sharing of fake news. This may suggest two things to us: that in our system, individuals are not afraid of losing prestige and/or may not be losing prestige. We can again use the concept of social bubbles (subpopulations) that we used earlier to understand how these two phenomena would occur. If we assume that "social bubbles" favor a selfish bias and have a low cultural exchange, they can prevent individuals from losing prestige and spread both adapted and maladaptive traits. Then, the social bubble would act as a buffer, shielding the individual from the loss of prestige. The disclosure of this bubble can be demonstrated by the intense polarization of ideas [28, 47]. The ideological issue promotes the conformity of ideas or behaviors through the feeling of belonging to a group [23]. This same ideological issue can influence the rejection of technical and scientific information (negationism) [44], that is, we can observe the egocentric bias and the decrease in the exchange of cultural traits in the system. Therefore, the models that transmit these bubbles would not suffer sanctions, since the "social bubble" would accept the diffusion of both adapted and maladaptive traits of a model belonging to the group. Another phenomenon that can occur inside the bubbles and explains some of our results is the compliance bias generated within them. The formation of bubbles is generated by people who share similar opinions, so there is already a cultural pre-uniformity formed within social bubbles. Therefore, it is reasonable to think that a frequent cultural feature in the system can be even more widespread or adopted.

Another factor that can help us understand our findings is the Brazilian social issue regarding COVID-19. Only tweets in Brazilian Portuguese were collected. Therefore, it is possible that some peculiarities of the country's context may influence our findings. For example, the federal government in the figure of the government's head has openly encouraged the use of treatments that do not have scientifically proven efficacy, which can lead to intoxication (promotion of ill-adapted traits), as well as taking a stand against the adoption of indicated behaviors by the scientific community as prophylactics for COVID-19 [14]. The position of the head of state and government has a prestige inherent to the position, therefore, having a great deterrent power, since his words reach the majority of individuals in the country. The federal government has adopted a position similar to presidential ideologies, resulting in an institutional position encouraging treatment with doubtful effectiveness and encouraging behaviors contrary to those recommended by international experts [27]. Therefore, it is possible that the position adopted by the Brazilian government may have affected our findings.

Conclusion

In an unstable (pandemic) scenario, the information transmitted on Twitter is not reliable in relation to the increase in fitness for most people, which may be due to the low cultural exchange promoted by the personalization of the social network and the cultural context of the population. This emphasizes the dangers caused by the polarization of ideas.

From an adaptive point of view, having different ideas (traits) in the system is beneficial, as scenarios can change, and other traits are more likely to give an advantage in the face of adversity. With the development and spread of digital media, it is essential to reflect on the content we receive/consume, its sources, and contrasting ideas. With the volume of information on the network increasing, bottlenecks and personalization of the information that we acquire through social media will be inevitable, as we will be unable to screen everything.

It would be interesting for future studies to investigate whether there are individuals who benefit from the formation of social bubbles and propagation of fake news, as this phenomenon can act as a means that favors the maintenance of fake news. This is because individuals who benefit can be catalysts and maintainers of false information in the system. Therefore, it will be useful to examine their identity, as well.

We also suggest that future studies focus on other digital media platforms to understand whether digital media in unstable scenarios does not provide an increase in fitness during the dissemination of information. We also suggest that this idea should be replicated in stable environments to gain a better understanding of the phenomenon.

Limitation of the Study

The chi-square test is used in an attempt to understand the behavior of fake news and non-fake news in an unstable cultural system. However, the test has some limitations.

The chi-square distribution is a series of distributions that vary according to their degrees of freedom. The chi-square test is designed to test a statistically significant relationship between nominal and ordinal variables arranged in a bivariate table. In other words, it tells us whether two variables are independent of each other. The chi-square statistic obtained essentially summarizes the difference between the frequencies observed in a bivariate table and the frequencies expected if there was no relationship between the two variables. However, the chi-square test cannot establish a causal relationship between two variables. Therefore, we suggest that further studies can indeed study the phenomenon's cause-and-effect relationships.

Availability of Data and Materials The data associated with this research are available at supplementary material.

Code Availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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