Panic Buying and Fake News in Urban vs. Rural England: A Case Study of Twitter During COVID-19

Abstract

This paper explores the potential association between the spread of fake news and the panic buying behavior, in urban and rural UK, widely accessible on Twitter since COVID 19 was announced by the WHO as a global pandemic. It describes how consumer's behavior is affected by the content generated over social media and discuss various means to control such occurrence that results in an undesirable social change. The research methodology is based on extracting data from texts on the subject of panic buying and analysing both the total volume and the rate of fake news classification during COVID-19, through crowdsourcing techniques with text-mining and Natural Language Processing models. In this paper, we have extracted the main topics in different phases of the pandemic using term frequency strategies and word clouds as well as applied artificial intelligence in exploring the reliability behind online written text on Twitter. The findings of the research indicate an association between the pattern of panic buying behaviour and the spread of fake news among urban and rural UK. We have highlighted the magnitude of the undesired behaviour of panic buying and the spread of fake news in the rural UK in comparison with the urban UK.

1. Introduction

The emergence of the novel coronavirus (SARS-CoV-2) in December of 2019 has quickly led to a global pandemic claiming hundreds of thousands of deaths worldwide already (Roser et al., 2020). In the absence of an effective treatment or vaccine, researchers have pointed out that managing the pandemic response would require leveraging insights from the social and behavioral sciences, particularly with regard to non-pharmaceutical interventions and containing the spread of fake news and misinformation about COVID-19 (Depoux et al., 2020; Habersaat et al., 2020; Van Bavel et al., 2020).

In fact, the spread of misleading information about the virus has led the World Health Organization (WHO) to warn about an on-going "infodemic" or an overabundance of information— especially misinformation—during an epidemic (World Health Organization, 2020 in van dar Linken, et al. (2020); Zarocostas, 2020). This infodemic makes it harder for people to find trustworthy and reliable information when they need it.

Specifically for COVID-19, misinformation could have led to a higher number of cases and deaths, since people could have followed inadequate procedures to prevent contagion or treat the disease. The worldwide dashboard from WHO, as of October/2022, show more than 600 million confirmed cases and more than 6.5 million deaths due to COVID-19 (WHO, 2022). Since the number of cases and deaths could be affected by the spread of good or bad information, the study of consumer behavior during the COVID-19 pandemic, especially taking into account the dissemination of information through social media, may shed light to relevant insights related to technology advances and social challenges.

In this article, we ask four critical questions to help better inform societal response to the infodemic, namely; (1) what is the scope and reach of fake news about COVID-19

in the general population during COVID-19 period?, (2) what is the scope and reach of panic buying behaviour during COVID-19 period?, (3) what evidence is there to suggest that fake news about the virus is encouraging the public support for—and the adoption of— panic buying behavior?, and (4) how can insights from the digital divide be leveraged to effectively manage societal response to help limit the spread of influential fake news and limit the panic buying behavior?

These questions are relevant and timely issues for understanding better the social phenomenon related to panic buying. We use data from the United Kingdom, including posts on social media, to explore issues related to fake news, consumer behavior, and digital divide. More specifically, regarding the first question, fake news, especially during health crises may lead to inadequate sanitary behavior or treatment procedures that could cause higher number of deaths. From a societal perspective, the second question, panic buying can result in price surges and product shortage, making more vulnerable people to bear more severe consequences of the pandemic. The third question aims at investigating evidences of relationship between fake news and panic buying, advancing the implications of the first two questions. Finally, the fourth question aims at further investigating the main elements of the research, including the perspective of digital divide. In particular, we tackle the potential different effects of fake news in different public profiles in relation to access to technology, The remainder of the article is organized as follows. Section 2 discusses the extant literature around the key themes of the paper: panic buying, fake news and digital divide. Section 3 presents the research methodology adopted in the paper, followed by the presentation of findings in Section 4. Section 5 discusses the association of fake news, panic buying during COVID 19 amongst twitter users, in context of the digital divide in the UK. Finally, Section 6 presents the conclusion, limitations, future research agenda, and implications for policy and practice.

2. Literature review

2.1 Panic Buying

2.1.1 Issues in panic buying

Crises and disasters proved to change consumption and consumer behavior (Forbes, 2017; Peck, 2006; Sheu and Kuo, 2020). This change could comprise undesirable incidences such as herd mentality, variations in investment decisions and in purchasing habits, particularly panic buying (Loxton et al., 2020).

Panic buying is the act consumers undertake through purchasing larger amounts of products than they used to buy when they perceive a disaster, product's shortage, or high price increase (Yoon et al. 2017; Yuen et al. 2020). Panic buying could lead to a shortage in necessities and medical supplies because this behavior can be widely spread (Thomas, 2014), which in turn leads to additional unavailability of resources that can exacerbate the impact, creating further panic buying (Hall et al., 2020). A serious consequence of such behavior lies in preventing vulnerable groups to acquire their basic needs (Besson, 2020). Previous research showed contradictory findings concerning the role of consumers in increasing the unavailability of goods due to the higher demand (Tsao et al., 2019; Quarantelli, 1999).

Panic buying was clearly witnessed during the early stages of COVID-19 when consumers started to stockpile medical supplies, groceries, hand sanitizers, and even toilet paper (Barr, 2020; Collinson, 2020) implying empty shelves in many stores (Cogley, 2020; Mao, 2020). These changes in consumption are due to the "interplay between shifts in both consumer demand and availability of supply" (Hall et al., 2020), and the extent of this consumption displacement varies through the stages of a disaster (preparedness, response, recovery, post-event planning and mitigation) (Anderson et al., 2020).

Moreover, Non-Pharmaceutical Interventions (NPIs) adopted to face COVID-19 such as limiting people's mobility and personal contact have exacerbated the problem through affecting consumption displacement occurrence over four dimensions: (i) where (spatial aspect): limiting the movement of the consumers; (ii) when (temporal aspect): time variation for enabling/disabling access to different merchandises; (iii) what and why: types of products demanded based on psychosocial influence; and (iv) how: changing the way and process of purchasing (Hall et al.,2020).

The scientific literature identifies a number of factors that lead to and fuel panic buying. First, when consumers perceive a future shortage in certain products that would affect their lifestyle, they may anticipate the purchase to avoid regret not possessing it in the future (Yoon et al., 2017; Yuen et al., 2020). Second, due to the risk perceived by consumers during times of crises and uncertainty of their durations, consumers tend to make irrational decisions and change their buying patterns (Slovic et al., 2004; Sim et al., 2020). A third reason for panic buying is attributed to the loss of control consumers feel, which drives them to acquire more products to regain a sense of control and stress alleviation (Ballantine, 2013). Furthermore, consumers can be influenced by others' opinions and behaviors in their society (Yuen et al., 2020). Another factor that drives panic buying behavior lies in the encouragement of some governments to prompt citizens to accumulate goods to avoid their reliance of government's aid (Kulemeka, 2010). In addition, the fear of a complete store shutdown and lockdown posed by governments shortens the operating hours of stores and limits the shopping time and location for citizens (Islam et al., 2020), making consumers more willing to stockpile products. In a nutshell, the reasons behind panic buying are all a consequence of a change in behavior of the individuals, communities, and governments when a disaster occurs.

2.1.2 Understanding Consumer's panic buying behavior

Various studies attempted to depict the consumer's decision-making process that leads to panic buying (e.g., Campbell et al, 2020, Prentice et al, 2022, Sing et al, 2021, Huan et al, 2021). The study from Billore and Anisimova (2021) provides an extensive literature review on panic buying and the paper from Cruz-Cárdenas (2021) performs an analysis of the literature on COVID-19, consumer behavior and society. Particularly, taking into account the changes in society, especially due to technological advances, the content generated on social media provides a rich source for researchers to analyze the behavior of consumers during crises. Hence, the extant literature offers many frameworks developed to examine how consumers' spending behavior increases during times of crises.

A thorough review of the relevant literature revealed that the Theory of Planned Behavior (TPB) developed by Fishbein and Ajzen (2011) is widely referred to in understanding pandemic-driven consumer behavior (Wang et al., 2022). For example, through gathering both quantitative and open questions from consumers in Germany, Lehberger et al. (2022) concluded that stockpiling behavior is due to three main drivers: attitude, subjective norms, and fear of future unavailability. Furthermore, through an online survey on 371 respondents from Malaysia, Tan et al. (2021) proved that attitude and subjective norms have an impact on panic buying unlike the third construct in TBP: perceived behavior control that was not found a predictor of panic buying. Moreover, the findings of Tan et al. (2021) showed that online news influence attitude, subjective norms, and Perceived Likelihood of being Affected (PLA). They noted also that PLA affects subjective norms as individuals tend to be attributed to close groups when perceiving a risk.

In addition, Laato et al. (2020) proposed a model based on the Stimulus Organism-Response (SOR) framework developed by Arora (1982) to examine the relations among: online information source exposure, information overload, perceived severity, cyberchondria, self-isolation intention, intention to make unusual purchases, self-isolation, self-efficacy, and purchasing self-efficacy. The authorse tested their research model through conducting an online survey with 211 Finnish respondents. Their findings show a strong link between self-isolation intention and intention to make unusual purchases. In addition, exposure to online information sources has an impact on cyberchondria and on information overload, which in its turn affects cyberchondria. Moreover, both intentions to make unusual purchases and to self-isolate are a result of perceived severity and cyberchondria. . In addition, exposure to online information sources has an impact on cyberchondria and on information overload, which in its turn affects cyberchondria. Moreover, both intentions to make unusual purchases and to self-isolate are a result of perceived severity and cyberchondria. The SOR framework was also referred by Islam et al. (2020) in combination with the Competitive Arousal model to build a framework in which they used the same online survey method but on respondents from the US, China, India, and Pakistan. They concluded that external stimuli, such as limited quantity and time scarcities, fuel consumers' arousal, which drives them to impulsive and obsessive buying. Furthermore, Li et al. (2021) extended the SOR model and combined it with the dual-system theory to understand how consumers are driven into panic buying. Their analysis of data collected from 508 residents in Singapore showed that impulsive buying decision results from reflective thinking and environmental stimuli (such as, perceived susceptibility and severity of the crisis, social norm, and social influence). Such environmental stimuli can affect consumers' perceptions of scarcity and affective response (panic and fear of products' unavailability).

Panic, stress, and anxiety were also highlighted by several research such as, Sneath et al. (2008) and Barnes et al. (2020). Based on life event theory, Sneath et al. (2008) developed a model and tested it through collecting data from 427 US Gulf Coast residents who were affected by Hurricane Katrina. Their findings showed that both perceived lack of control and loss of possession lead to stress. Accordingly, stress results in a depressive state. Being depressed, people's behavior tends towards compulsive and impulsive buying. It was proven also that age, gender, income, and insurance coverage do not moderate the relationship between depression and impulsive buying. They stated that when a disaster occurs, impulsive buying prevails as a rational behavior rather than compulsive buying. It is worth mentioning that impulse buying is not always associated with emotions as there exists sometimes a cognitive aspect that moderates the relationship between impulse buying trait and consumers' buying behaviors (Rook and Fisher, 1995). Barnes et al. (2020) through the use of the Compensatory Control Theory (CCT) have conducted a study to prove that anxiety and fear feelings negatively affect consumers' perceived control, which in its turn increases purchasing behavior especially in case of utilitarian's low quality. In their study, they relied on big data set gathered from Twitter users in Italy. Over and above general depression, stress, and anxiety (negative affect), Gallagher et al. (2017) highlighted the specific effect of Anxiety Sensitivity (AS) on compulsive buying. Their study on a sample of 437 Canadian undergraduates concluded that two of the three dimensions of AS: Cognitive concerns (e.g., fear of losing control) and Physical concerns (e.g., fear of having a heart attack) have an impact on the tendency to buy compulsively. Interestingly, the third dimension of AS, Social concerns (e.g., fear of public ridicule) was not proved pivotal in compulsive buying behavior.

Governments' planning and intervention during crises and their influence on consumer behavior were also highlighted by Prentice et al. (2022), Loxton et al. (2020), Nakano et al. (2021), etc. They concluded that panic buying was to a large extent a reaction to the legislations and restrictions set by governments. Based on the scarcity principle, crowd psychology and contagion theory, Prentice et al. (2020) gathered data from 341 consumers from the USA and Australia who experienced panic buying, and concluded that public health risk mitigation measures enforced by governments to control the virus spread (such as, lockdowns and social distancing) were perceived as a sign for resource scarcity. In addition to the influence of the government, Loxton et al. (2020) employed the volume and timing of consumer spending patterns of American and Australian markets and proved that the behavior of consumers during COVID-19 is the same during other crises in terms of panic buying, herd mentality, and consumption's priority (based on Maslow's Hierarchy of Needs Model). However, others see that COVID-19 amplified panic buying behavior due to internalization, isolation measures, absence of vaccine for a long time and uncertainty about duration of the pandemic and the extent of effectiveness of the vaccine (li et al., 2021; Loxton et al., 2020; Dulam et al., 2021). Nakano et al. (2021) proved a strong association between the timing of two government policy settings and two corresponding waves of consumers' panic buying of 173 product categories in Japan. In addition, they embraced a segmentation approach to understand the difference in behavior among different consumers in terms of demographics and psychographics. Their study relied on data collected through 3 different sources: extracted purchase data, device log data from television and mobile devices, and survey feedback from 968 respondents.

The work of Nakano et al. (2021) pinpointed key critical aspects: the time factor and the demographic, psychology, and personal traits of consumers. First, the influence of the stage of both the pandemic and corresponding reaction of the government on the hoarding approach of the consumers, such factor is confirmed by the studies of Hall et al. (2020) and Dulam et al. (2021) that state that the over purchasing decision making process during crises is phase dependent. As for the difference in buyers' personal characteristics, Bentall et al. (2021) developed a psychological model of over-purchasing derived by the animal foraging theory that combines the different variables that lead to over-purchasing. Based on data collected from online surveys on 2025 respondents from the UK and 1041 ones from Ireland. Their findings proved that panic buying is affected by household income, presence of children at home, psychological distress (depression, death anxiety), mistrust of others (paranoia), and ability to reflect about reassuring messages. Interestingly, their results revealed that over-purchasing occurred in Ireland more than the UK and in Urban more than rural areas. Individual differences were also researched by Dulam et al. (2021) through the use of the agent model to examine how the mental, emotional, behavioral states of the consumers are important predictors of their purchasing decision over a 6-stage decision-making process: need recognition, information search and processing, factor valuation, decision, purchase, and purchase evaluation. They developed a simulation tool and tested it through conducting a questionnaire survey on 2000 households following the distribution and count of demographic data in Japan. Furthermore, the simulation tool created by Dulam et al. (2021) studied consumer behavior in accordance with the supply chain, as smoothing the supply chain process would primarily have a positive outcome on reducing panic buying (e.g., Lee et al. (1997) and Sterman and Dogan (2015). Their conclusion stressed on the necessity of an effective policy setting to mitigate the impact of over-purchasing on the supply chain, and of situation-dependent rationing measures. Understanding consumer behavior during crises and its impact on the supply chain was also investigated by Zheng et al. (2020) who emphasized on consumer's social learning behavior to anticipate supply disruption risk. Therefore, retailers could optimize their inventory strategies based on the extent of social learning that a second group of consumers acquire from the initial panic intensity of a first group.

It is important to highlight that this social learning effect can be aggravated by social media, which is a major player in influencing consumer behavior. Social media platforms have been impacting society costumes and also buying patterns. Particularly, as suggested by Appel et al. (2020), Specifically, during the Covid-19 pandemic, the guidelines for social distancing and the lockdown enforcements implied more information interexchange through social media Naeem and Ozuem (2021a).

Nowadays, social learning is evidently more intense due to the existence of social media. Social media enabled the propagation of news and ideas to wider groups -as the number of Internet users is increasing continuously (Arafat et al., 2020)- who are influenced by the views and perceptions of their related friends and acquaintances. As such, social media had a prominent part in fueling consumers' buying panic intention (Appel et al., 2020). Lockdown measures and social distancing resulted in more engagement and socialization over social media (Muqadas et al., 2017; Naeem and Ozuem, 2021a). Undoubtedly, social media has connected people together during the pandemic, facilitated information sharing, and has exerted a social change nurturing a "constructive voice behavior" (Bhatti et al., 2020) through online ratings, social motivation, influencers, etc. (Alalwan, 2018); Hence, shifting from individual to collective consumers' purchasing activities (Thomas et al., 2020), and assisting consumers in making better buying decisions (Alalwan, 2018; Baker Qureshi et al., 2019). On the other hand, the social change carried out by social media has sometimes led to negative consequences. The ease of generating and propagating content resulted in an uncontrolled immense spread of fake news. Since the start of the pandemic, social media became a rich medium for broadcasting plenty of rumors, misinformation, and news' magnification because people are usually attracted to shocking content (Cogley, 2020; Hou et al., 2020; Mao, 2020). Therefore, social media has increased fear and anxiousness, which has driven consumers to change their buying patterns and to stock-pile different utilitarian products (Naeem, 2021).

2.2. Fake News

In the information age, the volume of data made available from official and non-official entities grows more and more during the pandemic. Rather than increasing transparency and assisting citizens and governments in decision-making, increasingly more accessible information about COVID-19 – yet contradictory - seems to confuse even more people, delaying the improvement of recovery whether in health or economics terms. Avoiding the spread of misinformation and fake news in the first place could therefore shunt the reluctance to follow governmental guidelines. Misinformation and fake news can amplify humanity's greatest challenges. A salient recent example of this is the COVID-19 pandemic, which has bred a multitude of falsehoods even as truth has increasingly become a matter of life-and-death; people share false claims about COVID-19, in part, because they simply fail to think sufficiently about whether or not this content is accurate when deciding what to share (Pennycook, et al., 2020).

Users nowadays receive information mainly through the internet, especially during the COVID-19 when most people have to stay at home. These users receive such information through an ever more advanced algorithm of public and content selection, regardless of the media they choose. This process is known for direct or indirect creating the so-called “information bubbles”, in which users receive only, in a consistent manner, one type of information. This variation can go from political opinions to social engineering desires.

One consequence of this during Covid-19 is that users can be sometimes confused with the amount of information being spread, especially when it seems to be sharply divergent from media to media with potential bias. The information during Covid-19 is worldwide being broadcasted in an decentralised means, and fake news is increasingly more difficult to set apart from trusted news. Traditional media, such as television, printed newspapers and radio, continue to play a significant role. However, user-generated content and even official sources on social media are having a more significant share now than ever before. This decentralised content generation can be referred to as crowdsourcing and has a vital role in understanding social behaviour (Chamberlain et al, 2021). Decentralised content generation is not only a phenomenon that has an impact on better understanding the data, but also a necessary mean of information sharing. Government and private sector heavily depend on the use of the social media platforms for rapid information sharing, and during COVID-19, this dependency has only increased (Chan et al, 2020). Analysing such contents during the pandemic has proven to be effective (Lopez, Vasu and Gallemore, 2020) for understanding users’ trend of social media. Not surprisingly, rumours and misinformation are a topic of great interest in understanding such behaviour during the pandemic (Tasnim, Hossain and Mazumder 2020).

It is unclear exactly how people start endorsing fake news, but their high level of circulation online is a recognized contributing factor, as seeing an information makes people more likely to believe in it, and seeing it several times re-enforce the view that it could be true, a psychological phenomenon called the illusory truth effect, (Roggeveen and Johar, 2002; Unkelbach, Koch, Silva, & Garcia-Marques, 2019).

Being able to avoid fake news during the pandemic could not only help the individual receive the best information for their health by taking the best choice possible but could also make governmental guidelines clearer and easy to follow, hence more effective.

The WHO has classified the information overload about COVID-19 as an "infodemic". The infodemic has become such an important subject with some effort made to help people classify information in categories as information; misinformation; disinformation and malinformation (Baines, D. & Elliott, R. J., 2020). This undesired information is formed by fake news, rumours, and conspiracy theories, promotion of fake cures, panic, racism, xenophobia, and mistrust in the authorities, among others (Alam, et al., 2020).

Some evidence show that it is possible to analyse user behaviour by analysing tweets. A research project, for instance, has analysed 1000 posts and concluded that although false information was more frequent than legit ones, these received less retweets, indicating users could to some degree use this kind of information to filter news (Pulido, Cristina M., et al.,2020).

Other researchers analysed other social medias and found that the level of misinformation varies according to the social media platforms, having pointed that twitter is among the biggest social networks the one with the most questionable sources (Cinelli, M, et al., 2020).

There is, still, demand for analysis that can go beyond the simple true and fake classification, which could perhaps translate some deeper political nuances and use information beyond text to allow a better automated analysis of content being produced online during the pandemic (Knight, J., et al., 2020).

There are examples of successful uses of Twitter to forecast off-line behaviour, for example, film box office gross (Asur and Huberman, 2010; Hennig-Thurau, Wiertz and Feldhaus, 2015), book sales (Gruhl, et al., 2005), and music sales (Frick, Tsekauras, and Li, 2014). Therefore, Twitter data is an appropriate context to find the association between fake news trend and panic buying off-line behaviour.

The digital divide has been a major focus of online research;(Blank, 2016). Digital inequality can take many forms that have been explored in the United Kingdom as well as elsewhere, (Blank, 2016). In Britain, the Oxford Internet Survey (OxIS) has charted 10 years of trends in the online population (Dutton & Blank, 2011, 2013). These studies document that British Internet users have been younger, better educated, and wealthier than the off-line population since the earliest wave in 2003. Some differences between the online and off-line populations have disappeared, such as the gender gap which was important in the early 2000s but disappeared by 2011. Students have been the most likely to use the Internet, although employed people have been closing the gap. Retired people are least likely to be Internet users. Disabled people are about half as likely to use the Internet as nondisabled, although this gap has been declining. Black and Asian minorities are more likely to use the Internet than Whites. Urban–rural differences are not significant, ;(Blank, 2016). We further discuss the recent developments regarding digital divide in the UK and consider its potential impact in the context of fake news and off line behaviour for the digitally excluded population in the UK.

2.3 Digital Divide

Digital divide refers to "inequalities in access to internet, extent of use, knowledge of search strategies, quality of technical connections and social support, ability to evaluate the quality of information and diversity" (DiMaggio, 2010, p 310). Rural communities are normally located remotely from main cities and hence are in greater need of better digital connectiveness to facilitate a better of quality of life, yet this is not always the case (Salemink et al., 2017). A common finding in the extant research conducted on digital exclusion and inequalities in the Western countries show that rural telecommunication infrastructure is inferior to urban areas (Philip et. Al., 2017; Gerli and Whalley, 2021). Given its profound impact on population's quality of life, digital divide has been investigated extensively over the last two decades in the UK and indeed occupied a considerable policy space (Serafino, ,2019). Despite that, global media had a tendency to portrait digital connectivity, especially in the

West, as pervasive and abundant, this is not always the case, for example in the UK the ONS (2019) figures have shown that despite a significant improvement in the number of adults who have either never used the internet or have not used it in the last three month, still there is 5.3 million adult who falls within this category. This is a worrying figure as this means that this population could miss out on a number of benefits from being connected to the internet such as earning potential, employability benefits, retail transaction benefits, communication benefits and time saving in accessing government and banking services (Serafino, 2019). This area of concern has been targeted by government policy on two dimensions: the socio-economic and technological infrastructure (Sparks,2013). Where the earlier is addressed through enhancing stakeholders' ICT skills, digital literacy i.e especially in rural areas, the latter is addressed by further investing in psychical infrastructure supporting connectivity to the internet (Blank and Groselj, 2015; Gerli and Whalley, 2021). Here, policymakers in the UK have designed a number of initiatives to address these forms of digital divides for example: The UK Gigabit Programme or 'Project Gigabit' which is a £5 billion government infrastructure project focusing on delivering a fast and reliable digital connectivity for the entire country (Department for Digital, C., Media & Sport, 2021) Notably this massive investment was also underpinned by the government's 'Barrier Busting Task force' which was initiated in 2017 to address any barriers preventing "the fast, efficient and cost-effective deployment of gigabit-capable broadband and improved mobile coverage, including next generation 5G technology." (Department for Digital, C., Media & Sport, 2021). Previous initiatives focusing solely on rural areas were also introduced in 2017: Rural Gigabit Connectivity Programme. Yet the digital challenges to rural population remain.

Despite the above-mentioned efforts to address the digital divide, one would argue that these inequalities have manifested since the onset of the COVID-19 pandemic, as more than half of the UK participants surveyed by the ONS in 2018 has shown that they use the internet to look for health related information (Watts,2020). As such and even if this figure has improved by March 2020, it means that a significant part of the population must have suffered the bitter consequences of the digital divide. Moreover, during lockdowns the digital divide has reportedly negatively affected mental health and general wellbeing of those digitally excluded (Watts, 2020). In the same vein, young adults who have grown up in a relatively digitally driven environment, where using the internet is not a matter of preference but rather a lifestyle and a platform for communication that has taken-over conventional methods of communication (making landline calls or even mobile phone calls). Whereby mobile phones are mainly used as smart devices to communicate via social media. This group who are living in rural areas in the UK face digital connectivity difficulties in the form of a relatively poor internet services which excludes these group from participating in online activities as their fellow urban dwellers (Philips et. al., 2017). Other groups are also impacted as the ONS survey in 2018 shows that 60% of the internet users use it for social networking (Serafino, 2019).

Furthermore, the impact is not only limited to health and social communication, but also, to commercial transactions. In the ONS 2018 survey, 65% of the internet users indicated that they use it to find information about goods (Serafino, 2019). In fact, commercial transactions and use of social networking platforms became interrelated, with the rise of e-word of mouth (e-WOM) where users' opinions such as friends, peers and family regarding products or services can influence other users' decision of buying (Castellano and Dutot,2017). A negative side though to this digital engagement can also lead to viral spread of misinformation (Naeem, 2021). However, taking into consideration the digital divide along with non-internet users in rural areas, one could reasonably argue that the impact of e-WOM as well as spread of misinformation could be less prevalent due to digital exclusion and hence this population could potentially be protected from the adverse effects of participation in social networking platforms such as "fake news, hatred and creating racism during epidemics and civil unrest" (Kadam and Atre, 2020). Having said that, with the progression and successful rolling out of high-speed internet and programmes to enhance the digital skills of rural dwellers, this picture could change and along with reaping the benefits of being digitally connected, unintended consequences can include being exposed to the adverse effects noted above. However, taking into consideration that in some cases the digital skills courses could be too far from rural areas, expensive or of a questionable quality (Parliament.UK,2019) could be translated to a persistent users' problems that can widen the exposure to these adverse effects of digital connectivity.

Of note, digital divide observed between urban and rural areas can also be reflected on social media usage and which platform to use, as these decisions can be socially constructed (Hine, 2020). In fact, digital divide on Twitter can be slightly different from the traditional notion of digital divide (Blank, 2015). More specifically, research has shown that Twitter users are young, well-educated, single and wealthy elites (Blank, 2015). However, while this profile is useful to know as it gives insights to engagement of these segments with Twitter, Blank (2015) warns that “twitter data is not proxy for research on the population as a whole or even the subset of the population that is online. Instead, Twitter users reflect the interests, values, skills, priorities, and biases of elites” (Blank, 2015, p.13). Reasons for not using Twitter are more likely socio-cultural rather than technical/financial (Hine, 2020). Moreover, Twitter users are 12-38 % more likely to participate in an activity than non-Twitter users. This shows that a prudent interpretation is needed when Twitter data is analysed and especially in terms of generalising findings based on Twitter data to the general population of internet users or offline individuals. For example, using Twitter data to forecast election results would lead to inaccurate or possibly wrong conclusions (Huberly, 2015). Fortunately, there are some exceptions to using Twitter to forecast off-line behaviour and as such generalise to the population to which these users are part of, such as in the case of commercial products (Blank, 2015).

Against the above background, this paper attempts to investigate the scope and reach of fake news and the association with panic buying behaviour in the context of an existing digital divide in the UK.

3. Research Methodology

3.1 Model and data

The data analysis step in this paper took place in two stages. Initially, uncharacterized posts were collected from the social network *Twitter* from England. The collection, carried out through the use of API, collected data between March 2020 and October 2021 and used posts related to *panic buying* as search criteria. This search method uses *Twitter*’s mechanism of search for returning the associated posts that meet the search criteria.

The search was performed at the following locations from a manually entered list of 51 Towns: *Bath, Birmingham, Bradford, Brighton and Hove, Bristol, Cambridge, Canterbury, Carlisle, Chelmsford, Chester, Chichester, Coventry, Derby, Durham, Ely, Exeter, Gloucester, Hereford, Kingston upon Hull, Lancaster, Leeds, Leicester, Lichfield, Lincoln, Liverpool, London, Manchester, Newcastle upon Tyne, Norwich, Nottingham, Oxford, Peterborough, Plymouth, Portsmouth, Preston, Ripon, Salford, Salisbury, Sheffield, Southampton, St Albans, Stoke-on-*

Trent, Sunderland, Truro, Wakefield, Wells, Westminster, Winchester, Wolverhampton, Worcester, York.

Because the search depends on the location chosen by the user, the search was also performed by Counties (totalling 34 counties) to ensure a larger number of posts, since the search selection criteria restrict our results, hence why we search for more posts. The list used consisted of: *Somerset, West Midlands, West Yorkshire, East Sussex, Bristol, Cambridgeshire, Kent, Cumbria, Essex, Cheshire, West Sussex, Derbyshire, Durham, Devon, Gloucestershire, Hereford and Worcester, East Riding of Yorkshire, Lancashire, Leicestershire, Staffordshire, Lincolnshire, Merseyside, London, Greater Manchester, Tyne and Wear, Norfolk, Nottinghamshire, Oxfordshire, Hampshire, North Yorkshire, Wiltshire, South Yorkshire, Hertfordshire, Cornwall.*

This location was used to cross-reference the data with the official classification database for assessing the level of rurality of the results obtained: *Rural Urban Classification (2011) of Counties in England*[1]. The classification, according to the source, is based on a numerical scale ranging from 2 to 6, with 2 being Predominantly Rural and 6 being Predominantly Urbanized. No county is classified, according to the source, as 1.

The total number of posts collected in the specified period was 1602 posts. Because it is not a value considered expressive, the distribution along the rurality classifications was not balanced and for this reason the group with 2-3 classifications were analyzed as being rural and 4-5-6 as being urban classifications. Possible implications of this scenario are discussed on the implications and future research section.

For further classification as to the veracity of the information (*fake news* classification) we used the textual database *LIAR Dataset*[2] (Wang, 2017). The LIAR Dataset consists of small statements manually classified for truthfulness, which range from pants-fire (most false option) to true, and deal with different topics. Other information in the dataset includes the authorship (speaker), context, state, political party (when applicable) and others. The ratings were then aggregated into two main groups, namely True statements and False statements.

[1] Source: Office for National Statistics licensed under the Open Government Licence v.3.0
[2] " liar, liar pants on fire": A new benchmark dataset for fake news detection.

This procedure aims at classifying collected panic buying twitter-posts in a binary fashion. An example of the aggregation process is shown in table XX.

Original Label	Used Label	Statement
True	True	Building a wall on the U.S.-Mexico border will take literally years.
Mostly-true	True	Marijuana is less toxic than alcohol.
Half-true	True	Obamacare was the Republican plan in the early 90s.
Barely- true	False	Hillary Clinton said gun confiscation would be worth considering.
False	False	Half of children struck by cars near schools are hit by parents driving children to school.
Pants-fire	False	Evidence shows Zika virus turns fetus brains to liquid.

Despite the simplification process in forcing binary classification, the results obtained by the authors of the database (Original Label), when training a supervised model was approximately 0.27 (Wang, 2017), possibly evidencing that there is an excessive subdivision of the original data. Thus, it is expected that the results of this step will only guide the analysis of the volume of data collected on panic buying, hence it is beneficial to have a more comprehensive classified sample.

We then used the model for classification on the data collected from *Twitter* regarding panic buying, from the first step. Results are presented on the end of this section comparing the volume of posts containing panic buying issues with the results of this veracity classification, both in total values and aggregated by urbanization groups 2-3 (rural) vs 4-5-6 (urban).

3.2 Natural language processing overview

Before classifying the text as *fake news*, we need to adapt both the text used in the training (coming from the *LIAR Dataset*[2]) and the collected posts themselves in order to classify them later. This process of textual analysis is commonly called *Natural Language Processing* (NLP). The following is a summary of the main points adopted in this step.

In this work, the representation of words in the *bag-of-words*[3] (Zhang et al., 2010) format was adopted. This representation is the transformation of sentences into numeric vectors that

[3] Fixed-length representation of individual tokens, disregarding the relationship with neighboring tokens and order.

enable the computer to perform the mathematical operations of classification. The first step is the separation of words into *tokens*[4] and the application of preprocessing (cleaning), followed by numerical conversion into vectors and finally the relative calculation of the frequency of each term in the vocabular (*term frequency-inverse document frequency* or *tf-idf*). The following is an example of this for two sentences: *Today I read a Panic Buying news* and *Today winter starts*:

The phrases

Today I read a news article about Panic Buying

and

Today begins winter

become respectively

today	*I*	*read*	*news*	*article*	*about*	*panic*	*buying*

and

today	*begins*	*winter*

in the standardized token conversion. The conversion into vectors of the first sentence follows

today	*I*	*read*	*news*	*article*	*about*	*panic*	*buying*	*begins*	*winter*
1	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*0*	*0*

and for the second sentence

today	*I*	*read*	*news*	*article*	*about*	*panic*	*buying*	*begins*	*winter*
1	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*1*

Another important step is the correction by the inverse frequency of terms in sentences. This means that we penalize words that appear with high frequency in several posts. This follows for both sentences, respectively

today	*I*	*read*	*news*	*article*	*about*	*panic*	*buying*	*begins*	*winter*
1/2	*1/1*	*1/1*	*1/1*	*1/1*	*1/1*	*1/1*	*1/1*	*0/1*	*0/1*

and

today	*I*	*read*	*news*	*article*	*about*	*panic*	*buying*	*begins*	*winter*

[4] Individual part of a sentence having semantic value.

1/2	*0/1*	*0/1*	*0/1*	*0/1*	*0/1*	*0/1*	*0/1*	*1/1*	*1/1*

In this way we can work with a large volume of data in an optimized way such that allows us to analyze the relationship of each word in the same vector space with the entire vocabulary. Other data cleaning processes involve eliminating *stopwords*[5], limiting the vocabulary to words with a frequency of appearance of less than 70% of the documents, and maintaining only alphanumeric words with at least two characters.

3.3. Machine learning

The model adopted in the training of the *fake news* classification model is relatively simple (especially regarding *deep neural networks*), but of great effectiveness for classification activities, being a frequent choice for *NLP* text analysis (Kim et al., 2006)(McCallum and Nigam, 1998). The model, called *Multinomial Naive Bayes* and belonging to the class of supervised models, is said to be naive because it considers that all observation pairs are independent for a given class y (in this case, corresponding to being false or not).

In text analysis, this could mean not analyzing the relationship between neighboring words, which would be a detriment in context analysis. However, this does not usually happen due to the adoption of *n-grams*[6] and, mainly, by statistical approximation of the likelihood function for a high number of tokens in the corpus, as shown below for the dependent variables (our n *tokens*, or n words) x_1 through x_n :

$$P(y|x_1, \dots, x_n) = \frac{P(y)P(x_1,\dots,x_n|y)}{P(x_1,\dots,x_n)} \tag{1}$$

Using the naive conditional independence assumption

$$P(x_i|y, x_1, \dots x_{i-1}, x_{i+1}, \dots x_n) = P(x_i|y), \tag{2}$$

for all i, this relationship is simplified to

$$P(y|x_1, \dots, x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1,\dots,x_n)} \tag{3}$$

Since $P(x_1, \dots, x_n)$ is constant given the input (it depends on the corpus used for training, and not on the single sentences to be classified), we can use the following classification rule:

$$P(y|x_1, \dots, x_n) \propto P(y)\prod_{i=1}^{n} P(x_i|y) \tag{4}$$

$$\Downarrow$$

[5] words or terms irrelevant to the context
[6] Combination of n words into a single *token*, e.g. *social_media*.

$$\hat{y} = \arg\max_{y} P(y) \prod_{i=1}^{n} P(x_i|y), \quad (5)$$

And this way we can know which class has the highest probability of appearing, considering the individual contributions of each word relative to the class.

To implement the *MultinomialNB*[4] model, the *Scikit-learn*[7] package in the Python programming language was used, using the *tf-idf* inverse frequency count correction (Zhang, 2004). This model is similar to the one presented previously, parameterized by the vectors $\theta_y = (\theta_{y1}, \dots, \theta_{yn})$ where θ_{yi} is the probability $P(x_i \mid y)$, with the difference of adding a smoothing parameter α in order not to bias the model with words that are infrequent ($= 0$) in the test phase but may appear in the classification phase.

$$\hat{\theta}_{yi} = \frac{N_{yi}+\alpha}{N_y+\alpha n} \quad (6)$$

The parameter choices for the function are as presented in the *Parameter Tunning* subsection.

3.4 Parameter tunning

The grid search method was used to search for the optimal combination of parameters to maximize classification accuracy. Two normalization methods were tested in the *df-idf* calculation: *L1-regularization*[8] vs *L2-regularization*[9]. Finally, for the α parameter *Laplace smoothers* ($\alpha = 1$) and *Lidstone smoothers* ($\alpha = 10^{-1}$, $\alpha = 10^{-2}$, $\alpha = 10^{-3}$ and $\alpha = 10^{-4}$) were analyzed. All results used factor 3 *cross-validation*, totalling 10 candidates and 30 fits. The criteria for accuracy was measured with *F1-Score*[10].

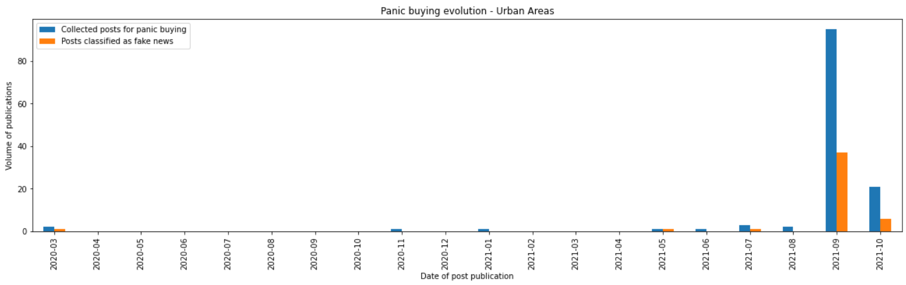
With an average accuracy of 86% for the fake news training dataset, the optimal parameters chosen to classify the panic buying posts were $\alpha = 10^{-2}$ and *df-idf* with *L2-regularization*.

4. Findings and Results

After applying the previous model to the panic buying posts, we were able to compare how many of the collected posts could be classified as fake news according to this model. On

[7] https://scikit-learn.org/stable/modules/naive_bayes.html#multinomial-naive-bayes
[8] L1 is just the sum of the weights
[9] L2 is the sum of the square of the weights
[10] Harmonic mean of the model's precision and recall

average, 33% (535) of the collected posts were classified as *fake news*. As the collected posts were collected with the information of the location, we can cross-reference this data with the rural and urban areas classification and analyse how both groups behave. The results for urban areas are presented on figure X.



On average, 88% of all posts found in the urban areas occurred between January 2021 and October 2021 (second half of the analysis). A considerable part (68% of all urban posts) happened only in the month of September 2021.

It is possible to generate a word cloud from the peak in September 2021 to have a better look at the contents of what might be causing this wave of posting (Figure X).

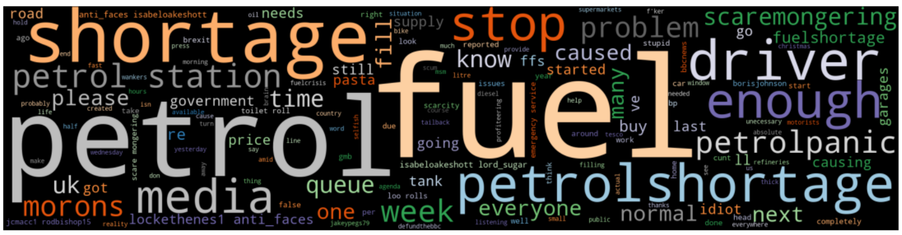
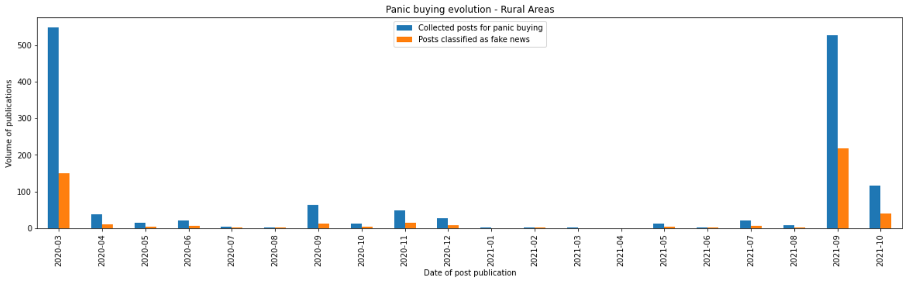


Figure 1 - Word cloud - Urban, September 2021

Words like fuel, shortage, petrol and driver show a strong relationship to the origin of this peak, indicating that they originated from a connected sharing pattern. Quantitative results for the rural cases are presented in figure X.



Unlike the urban case, the rural scenario shows 41% of its posts in the first half of the analysis, and 59% in the second half of the analysis. Two high-intensity periods of posts occurred in mid-March 2020 and September 2021, with total percentage of rural posts at 33% and 49% respectively, with other posts distributed over the remaining months. The relative high volume of collected posts only coincides between rural and urban posts in the month of September 2021. It can be seen that when evaluating fake news about panic buying, these results appear to coincide with relevant waves of cases of covid-19 which occurred in the UK: in March to May 2020 and in September to October 2021 (Hasell et al., 2020).

Similarly, we generated word clouds for the posts collected in the observed peak months of March 2020 and September 2021 (figure X and X).

Figure 2 - Word cloud - Rural, March 2020

Commented [HK1]: Do not include the figure of covid cases, since we do not have permission for use it

Commented [LG2R1]: Professor, at the right bottom it says CC BY. I could also remove if still desired.

Short description: CC BY: This license allows reusers to distribute, remix, adapt, and build upon the material in any medium or format, so long as attribution is given to the creator. The license allows for commercial use.

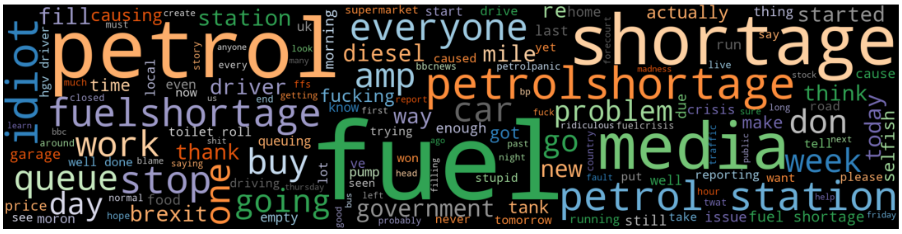


Figure 3 - Word cloud - Rural, September 2021

While the results from the word clouds indicate a difference between the causes of the two peaks (predominantly linked to supermarkets in the first moment, and petrol in the second), the peaks are similar in the month of September 2021 between rural and urban posts. However, one can observe that, in the word cloud of rural areas, the words founds are relate to the Covid-19 event, whilst in urban areas ththe words are more associated with transport and energy.

While this analysis is useful for assessing association, it is not able to assess the causality effect between rural-areas and fake-news or panic buying content spread. This is due to the fact that indirect unmeasured causes may lead to these differences, such as those that characterize rural and urban areas in the first place. In other words, what defines rural (or urban) areas is never a single characteristic, but multiple factors that co-influence the outcome.

However, when looking at the statistical association, total collected posts present a correlation of 98% when looking only at the second half of the data (from January 2021). If we look only at the first half (from March 2020), the correlation drops to 88%. Although correlations are relatively high, this can be due to the fact that many months present little to no posts on both cases. The quantitative and qualitative results seem to present a direct relationship with key events in the UK, evidencing possible cause and effect, here measured between (unknown origin) cause and posts, as further discussed in the next section.

5. Discussion

Findings revealed that fake news posts constitute around one third of panic buying ones showing a significant existence of rumors on social media associated with panic buying. This mandates the need to set measures to reduce fake news propagation.

Moreover, comparing rural and urban activities on Twitter highlights primarily that there are more posts on panic buying as well as more posts on fake news in rural areas. Remarkably, in March 2020, high posts on panic buying were observed (but relatively lower percentage of fake news than in September 2021) unlike urban areas where posts barely include panic buying or fake news posts. Throughout the duration from March 2020 to September 2021, posts on both subjects are remarkably less (or sometimes were not existing) in urban areas compared to rural ones.

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The outcome of this study illustrates that rural areas are more engaged in social media and users in these locations exchange information about panic buying and fake news. The study also shows a significantly higher volume of fake news posts at the onset of the COVID-19 pandemic in March 2020 as shown in figure (x) in rural areas compared to urban areas. The findings also show a significant association of these fake news to panic buying posts on Twitter. Moreover, we can see that the word clouds in rural areas in March 2020 show further evidence on this panic buying behaviour as reflected on the keywords appearing on tweets and related to panic buying such as 'toilet rolls', 'Coronavirus'; 'food', 'shop' along with mentioning of many super market chains such as 'Sainsbury's' and 'Asda'. Whilst in urban areas posts classified as fake news or those indicating a panic buying behaviour were minimal. Here, when Bentall et al. (2021) examined the buying behavior of consumers during the pandemic, they found that over-purchasing is higher in urban than rural areas. We argue that these results show the impact of the digital divide on fake news circulation and panic buying. As we noted earlier, fewer tech savvy users in rural areas are potentially less likely to question fake news and hence engage in more panic buying. As such, this could be due to the gap in ICT readiness that exists between urban and rural areas (Asfar and Zainuddin, 2015; Gilliggan, 2005). Being at an early stage of readiness when it comes to the use of the Internet, could make users in rural areas less experienced in scrutinizing overstated statements or fake news before sharing them. However, we must be cautious in interpreting these results taking into consideration that in rural areas and due to their location, they can understandably be more fearful of product unavailability as well as of contracting COVID-19 where access to healthcare at times of a pandemic could be more challenging (Whelan et. Al. 2021). And also taking into consideration that social media content does not necessarily or fully reflect the off-line reality. Moreover, whether panic buying behavior is high on social media or physically in rural areas, in both situations, it is vital to understand the context and culture of social media users living in these locations to have an in-depth insight about their attitudes and activities toward panic buying.

Gilliggan (2005) highlighted interesting insights about the lifestyle of people living in rural areas and its effect on their adoption and use of technology. He noted that people living in rural areas experience scarcity in a number of resources such as, information, goods, and services than cities' residents. Large retail stores, being usually far from their homes in addition to less developed network of transportation, makes it hard for them to obtain all the products or services they need. Mobility restrictions limit them also from obtaining adequate health services, meeting with others out of their physical circle, or even having access to plenty of leisure options. Consequently, they could rely more on mobile devices as a mean for maintaining their relationships with others and for getting a wider exposure and better access to resources. This could explain the fact that the number of mobile subscribers in rural area is higher than urban ones in several countries including the UK (Oftel, 2002). The context in which consumers exist was therefore considered in a number of studies that investigated panic buying. As an example, through applying the Stimulus-Organism-Response model (SOR), Islam et al. (2020) and Li et al. (2021) confirmed that the environment is pivotal as a stimulus that can affect consumers' feeling towards impulsive buying.

In the same vein, our analysis in September 2021, shows consistent results where engagement with fake news and panic buying in rural areas is significantly higher than in urban areas, yet, on this occasion there was a noticeable increase in urban areas behaviour compared to March 2020. This could be due to more employees returning to work from office instead of working from home. Hence, the lack of petrol could have a huge impact on their daily lives. Moreover, this is in line with the extant literature where "The sudden increase in buying of essentials creates imbalance between supply and demand, and this exerts more pressure in rural areas and people with low income (Arafat et al., 2020)" and once again means that rural areas feel more pressure and fearful of the impact of lack of a necessary commodity like fuel on their daily lives.

This paper contributes to the extant literature on consumer involvement on social networking sites. More specifically, the study offers novel findings on the intersectionality between fake news on social media platforms, panic buying and digital divide. Interestingly, the paper shows that whilst significant efforts and resources are devoted to address the digital divide in the UK, more effort is needed to address the ICT readiness in rural areas. As not doing so with enough speed/ effectiveness could lead (as our findings show) to users in rural areas being more prone to the adverse effects of being connected on social media platforms. This contribution is related to a very peculiar circumstances i.e. covid-19 and hence we acknowledge that this might have exacerbated the negatives. Still, this underlines the importance for more attention to addressing the ICT readiness in rural areas especially with a greater reliance on the virtual world as we move forward.

One of the contribution of our paper lies in distinguishing the differences and similarities between both rural and urban inhabitants with regard to the interrelations between the above three concepts, as most studies concentrate on urban areas (Gilliggan, 2005). In this context, our paper represents one step in studying the impact of fake news generated and spread over social media platforms on panic buying, comparing results from different geographical areas, which can imply distinct behaviors, uses, and experience with social media. Further studies are planned to develop a framework that encompasses other dimensions that could influence consumers' over-purchasing patterns, and how these dimensions could be understood differently based on different consumers' contexts and personal traits.

Overall our study has highlighted important subtle dynamics related to the concepts of fake news, panic buying, and digital divide. Here, the study has shown that more panic buying and fake news were observed in rural areas, with a more severe impact at the onset of the Covid-19 pandemic. The same behavior was not observed in urban areas. This result suggest that the digital divide and other socio-cultural constructs may have relevant roles in panic buying. Some constructs may include for example digital skills, users' level of awareness, economic conditions, supply of products and services in rural or urban areas, and the ability to scrutinise and moderate the information on social media. The severity of panic buying and fake news were somehow lower in September 2021 compared to March 2020. Therefore, there is relevant time dimension related to the nature of the event and the perceived implications or associated risks.

Rural dwellers must have perceived much higher risk associated with getting Covid-19 at a time when the world knew nothing about the virus in comparison with a time when there would already be a vaccine. The existence of a vaccine could have mitigated the perceived associated risks, Understandably, these associated risks are lower when the issue in hand is related to an energy crisis (despite its significant impact of daily life). Similarly, and in terms of the volume of fake news, the digital divide could be observed in terms of a higher level of fake news consumption in rural areas

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during the onset of the pandemic in March 2020. Our study has also documented a higher level of panic buying in rural areas during the sampled periods, which goes against the extant literature. This highlights the impact of the digital divide on fake news circulation and panic buying. Here, the study emphasises the importance of understanding the socio-economic and demographic realities in relation to the ongoing digital divide, as these seems to affect SNSs users' behaviour.
The study offers an important theoretical contribution regarding a subtle interplay between the concepts of digital divide, panic buying and fake news within the context of social media and shows a correlation between these constructs.

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From a practical perspective, the study highlights that while social networking sites (SNSs) offer many opportunities for equality and inclusion, it opens the doors for unintended consequences that varies subject to the socio-economic context in question. Hence, more effort is needed in order to enhance social media governance where more safeguards are enabled to spot and spot/stop circulation of fake news. This can happen by further collaboration between SNSs companies and government agencies and relevant charitable and NGOs to identify features and characteristics of urban v. rural communities. From a managerial perspective, SNSs companies could then introduce these advanced features to protect users and minimise circulation of fake news.

The study has also important policy implications, as it highlights that addressing the fake news and any negative consequences of engaging with SNSs, especially in more deprived areas, this can only be achieved through better social media governance. Hence, policy makers need to bring various stakeholders including social media users, social media operators, legislators, non-governmental organisations to have a conscious dialogue on how to improve SNSs governance without affecting freedom of speech and other rights enjoyed in democratic societies. Indeed, careful consideration for digital divide and related skills gap should be a top priority.

6. Conclusions, Limitations, and Future Research

Our analysis demonstrates that despite a significant effort is being made to improve digital connectivity of rural areas in the UK, at time of crises, this connectivity could mean being more prone to experience adverse effects of being connected i.e. inability to spot fake news and engagement with a panic buying behaviour. These adverse impacts may require more effective training strategies and digital awareness, particularly in relation to social media platforms which constitutes an integral and crucial part of our daily lives. It is equally important to raise awareness about the shortcomings and even dangers of engaging with social platforms.

As Covid-19 is a global phenomenon that has a significant socio-economic effect, it opens a venue for plenty of studies aiming at understanding how social change in general and consumers' behavior in particular can be shaped by technology. Consumer buying behavior is a complicated and multidimensional concept especially in the existence of social commerce

(Aragoncillo and Orus, 2018; Abdelsalam et al., 2020; Naeem, 2021); mandating further studies in this field of research.

Our paper seeks to provide a contribution in this direction. While there is a body of literature that investigated the effect of social media on panic buying, there is scarcity of studies in examining their association with fake news. The only study that combined the three concepts related to fake news, panic buying, and social media was from Naeem and Ozuem (2021b) that tried to understand how fake news over social media platforms affect consumers' emotions and rationalities driving them to panic buying intentions and actions.

One possible limitation for the research is the data collection step. One reason for this relies on the fact that we depend both on what we input for the twitter's search engine Application Programming Interface (the actual list of towns and counties being used is not extensively elaborated for the UK) as well as on the inner workings of the search engine itself, which could theoretically handle posts from urban and rural areas differently, hence resulting in a difference in proportion between urban and rural areas relative to the actual total number of posts generated on the platform. One general solution for this issue could be the development on future endeavours of a broader collection process, both including more areas of search for twitter as well as the collection from other sources, such as local news outlets.

A second limitation present on this work is the lack of available good and robust databases for training fake news classifiers. The current databases available on this subject for research are either reference specific and do not generalize well for the identification of universal fake news or do not have an adequate volume for training and generalization. The one used on this work seems to have a sufficient balance in quality and total volume, however it's outdated examples could reflect in a decrease in accuracy. The research could profit from future investigations of the real accuracy of the developed classification model, most likely through a manual classification and comparison of a sufficient sample as well as the collection and structuring of an updated version of the LIAR Dataset, containing e.g. COVID-19 content.

The propagation of fake news can lead to threats of panic buying of groceries, which consequently increases the anxiety of vulnerable people leading to depression and anxiety that provokes further panic buying practices (Naeem and Ozuem, 2021b). Moreover, rumors and misinformation could cause supply chain disruption (Loxton et al., 2020). Fake news also poses a serious challenge to businesses, for maintaining their operations under the COVID-19 restrictions enforced by the authorities. Conflicting information concerning the pandemic's prevention and treatment, and unclear statements regarding government regulations encourage people to stockpile leading to price rise and to scams' occurrence (Dang, 2021). Naeem (2021) pointed out to the ambiguities caused by the late or ineffective response of the government to people's concerns and to the weak communication and integration between governmental and non-governmental institutions, which reduce the trust of citizens towards their governments (Naeem and Ozuem, 2021b) opening rooms for influencers and non-professionals to post false or inaccurate information (Din et al., 2020) indulging them in additional panic buying behavior. Therefore, prompt responses, better institutional cooperation and unified communication strategies are vital to address panic buying during crises. Furthermore, it is recommended that governments and civil societies collaborate in shaping the required policies to address the negative consequences of fake news. Din et al. (2020) stressed on the importance of education and knowledge of societies that enable individuals to possess a critically thinking of the credibility of the flooding online content they encounter. Rather than being a source for disseminating fake news, social media could realize remarkable benefits through providing people with valuable and timely information (Donovan, 2020). Arafat, et al., (2020) have claimed that the identification of fake news and ignoring them or reporting about it to appropriate authority may also be beneficial in the prevention of panic buying.

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