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Emergency preparedness during the COVID-19 pandemic: Modelling the roles of social media with fuzzy DEMATEL and analytic network process

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ABSTRACT

While the utility of social media has been widely recognized in the current literature, minimal effort has been made to further the analysis of their roles on disruptive events, such as the COVID-19 pandemic. To address this gap, this work comprehensively identifies the 16 prevalent social media roles in disaster preparedness during the COVID-19 pandemic. Furthermore, an integrated fuzzy decision-making trial and evaluation laboratory (FDEMATEL) and analytic network process (ANP), hereby termed the FDANP methodology, is used to perform the causal analysis of social media roles and to systemically measure the priority of these roles in emergency preparedness. Among the identified roles, those considered top priority are social media roles concerned with the information dissemination, personal health concerns disclosure, and opinion expression.

1. Introduction

With the spiraling pandemic of the (COVID-19), many countries are integrating suppression and mitigation strategies to delay the outpourings of patients in healthcare facilities and flatten the demand for hospital beds while defending the most vulnerable population from infection. National response strategies employed by countries include layers of contact tracing and quarantining, promotion of public health protocols (i.e., including handwashing, respiratory etiquette, and social distancing), and postponing operations of nonessential establishments [1,2]. The careful implementation of these measures throughout the population is crucial for public health.

Schillinger et al. [3] pointed out that mass communications influence population health by shaping discourse about exposure to risk and disease, influencing the adoption of health-promoting social measures, linking people to health services, and providing education and motivation that influence behaviors. An emerging observation by Briscese et al. [4] in Italy shows that the intention and willingness of people to participate in self-isolation efforts are significantly reduced if surprised by information beyond their expectations (i.e., hypothetical extensions). Thus, compliance to isolation measures depends on two factors: (1) how authorities communicate the duration, and (2) the match between such announcements and people’s expectations [4]. It is observed that how individuals respond to the government’s call in preventing transmission is equally important, if not more important, to government actions [5]. Thus, the observation of Briscese et al. [4] is a crucial insight for communication efforts.

Nowadays, digital media and communication technologies play a significant role in addressing major public health and development issues. There is currently a global recognition of the power of digital media in transforming various sectors of society, especially public health delivery [6]. In particular, social media have revolutionized the way people disclose their personal health concerns and express opinions on controversial public health issues. It has become a powerful platform for...
debates on science and health without the time and location constraints [3]. Social media are computer-mediated technologies that enable creating and sharing of information, ideas, career interests, and other forms of expression via virtual communities and networks [6]. More than 2.9 billion individuals use social media regularly, and many for long periods. However, the current understanding of how these platforms could be leveraged by governments to optimally support emergency response, resilience, and preparedness is not well understood [7].

Various works identified different roles that social media play in emergency preparedness during COVID-19. Finset et al. [8] reviewed the essential factors that should be considered in fighting the COVID-19 pandemic. Although their work recognizes the contribution of social media as an effective health communication medium, there were limited discussions about its role in emergency preparedness during the pandemic. On the other hand, Schillinger et al. [3] investigated the effects of social media on public health. From a developed continuum model, six social media roles were established: (1) contagion, (2) vector, (3) inoculant, (4) surveillance, (5) disease control and mitigation, and (6) treatment. However, their work is limited in scope, which may not be sufficient from a general viewpoint as the development of the framework is highly dependent on the authors’ interpretations. Although their analysis is not on COVID-19, Kumar et al. [6] used the Delphi and decision-making trial and evaluation laboratory (DEMATEL) approach to investigate social media’s roles in polio prevention in India. While their work claims to provide some measures of the identified roles, they failed to produce such measures and only provided inference from their developed graphs via causal analysis. Thus, there is a need to employ more appropriate approaches in achieving such a goal.

The unprecedented availability of digital devices and platforms prompted different development institutions to design and implement a range of social media interventions for social and behavioral change [7]. Despite the significant efforts made in understanding social media roles in emergency preparedness during a crisis, limited efforts have been made to comprehensively establish these roles during COVID-19, as well as their corresponding relationships. A deeper understanding of the dynamics inherent in social media roles is imperative to develop leverage strategies to employ social media more effectively as tools for emergency preparedness, especially during emergencies like the COVID-19 pandemic. Furthermore, limited information is available about measuring the roles of social media in emergency preparedness in response to epidemics or pandemics, although measuring such roles could facilitate the design of appropriate communication strategies to the public and enhance community perceptions of response mechanisms. Note that social media roles can be viewed as interdependent elements whose function, in this context, is to regulate the impact of COVID-19 through emergency preparedness initiatives. Thus, to provide a rigorous analysis leading to identifying appropriate intervention strategies, the research inquiry should go beyond describing and enumerating social media roles towards explaining them. While studies occasionally indicate the importance of a dynamic perspective and consideration of causal interdependencies, these topics are rarely explored in evaluating social media roles during the COVID-19 pandemic. These gaps became the major departure of this work.

This work aims to achieve two main objectives: (1) to determine the causal relationships of social media roles and identify those key roles, and (2) to systematically measure the priority of these social media roles on emergency preparedness. To address these objectives, an integrated fuzzy DEMATEL (FDEMATEL) and analytic network process (ANP), briefly termed as the FDANP methodology, is adopted in this work. It begins with the identification of social media roles in emergency preparedness against COVID-19. They are obtained from the available COVID-19 literature through a comprehensive review. From these identified social media roles, a cause-effect evaluation model is constructed via the FDEMATEL method proposed by Lin and Wu [9] in an attempt to reflect their causal relationships and cluster these roles into a net cause and net effect. Clustering social media roles into the net cause and net effect would provide insights into the overarching nature of these roles. Developed by the Science and Human Affairs Program of the Battle Memorial Institute of Geneva between 1972 and 1976, the DEMATEL method espouses a network analysis based on graph theory where system elements represent the vertices, and the causal relationships of these elements define the edges. Due to the inherent uncertainty of eliciting judgments within the DEMATEL approach, fuzzy set theory is synthesized with the DEMATEL. The fuzzy set theory proposed by Zadeh [10] offers a computational framework in computing information with vagueness and uncertainty, which is prevalent in toolboxes that require expert elicitations such as the DEMATEL. The use of FDEMATEL is widely reported in previous works, with applications in urban water management [11], reverse logistics [12], managing consumer behavior [13], sustainable food supply chain [14], and even in emergency management [15,16]. Note that this list is not intended to be comprehensive. To obtain a measure about the systematic impact of social media roles, alternatively viewed as their importance in emergency preparedness initiatives, the analytic network process (ANP) [17] is employed along with the FDEMATEL. This process of integrating FDEMATEL and ANP, popularly known as FDANP, has been demonstrated in various recent applications, e.g., air traffic congestion [18], sustainable food manufacturing [19], location selection [20], among others.

This work attempts to contribute to the domain literature in the following ways. First, it comprehensively establishes a list of social media roles in emergency preparedness during the COVID-19 pandemic. Second, it employs a systematic approach to illustrate the interrelationships between social media roles. Third, it measures the priority weights of the social media roles, representing their importance in emergency preparedness actions. Lastly, it rationalizes the causal relationships of social media roles to provide managerial insights considering the Philippines as a case in point, a setting that has never been examined before in this context. The succeeding sections of this work are arranged as follows: Section 2 details the different social media roles from a comprehensive literature search. Section 3 provides relevant preliminaries of fuzzy set theory, DEMATEL, and the ANP. Section 4 presents the case study background, the required computational procedure of the FDANP. Section 5 discusses the results, while Section 6 espouses the policy insights derived from them. Lastly, Section 7 presents the concluding remarks of this work along with suggestions for future research.

2. Social media roles and their interdependencies in disaster preparedness during the COVID-19 pandemic

2.1. The roles of social media in emergency preparedness during the COVID-19 pandemic

To obtain the different social media roles, a rigorous review of the domain literature was implemented. A systematic search using the following operators and keywords: TITLE-ABS-KEY(“Novel coronavirus” OR “Wuhan coronavirus” OR “Wuhan pneumonia” OR “SARS-CoV-2”) AND TITLE-ABS-KEY(“COVID-19” OR “2019 nCoV” OR “COVID-19” OR “Wuhan coronavirus” OR “Wuhan pneumonia” OR “SARS-CoV-2”) AND TITLE-ABS-KEY(“Social media”), was performed in the Scopus database. The resulting papers are reviewed, and the social media roles were obtained and discussed in the following sections. Note that for each social media role, a corresponding code (i.e., SMR1, SMR2, ..., SMR16) is attached for easier reference.

2.1.1. Promotes public participation against COVID-19 (SMR1)

Schillinger et al. [3] highlighted social media as a potential engine for grassroots movements to develop a common cause and advocate and implement measures to combat the COVID-19 pandemic. For instance, social media has been essential in raising pediatric advocacies, which aids childcare despite lockdown restrictions [21]. Chen et al. [22] detailed the strategies employed by government agencies worldwide using social media to encourage citizen engagement in COVID-19 crisis
management. Citizen engagement resulted in the development of programs initiated through social media. Among these programs include the "Social Distancing Narratives" which aims to shift the risk perception of the COVID-19 pandemic [23]. Chen et al. [24] also emphasized that during the COVID-19 outbreak in China, social media platforms became spaces of active public engagement, in which citizens expressed care and solidarity, engaged in claim-making and resistance, and prompted negotiations with authorities. In this regard, social media provides a platform for discourse about the balance between protecting the health and preserving individual freedoms, an essential input in public policy development [3].

2.1.2. Links multidisciplinary teams of experts worldwide (SMR2)
As a ubiquitous communication platform, social media is essential in linking multidisciplinary teams and health professionals across borders [25]. For instance, social media has been utilized in hosting a virtual hackathon composed of medical students, clinicians, scientists, and engineers to work for solutions for COVID-19 as recommendations to companies [26]. Stokel-Walker [27] indicated that social media facilitates the collaboration of health experts from different countries to rapidly establish treatment norms, document treatment options, and provide and share COVID-19 information. Several social media programs and campaigns were also jointly initiated by medical professionals worldwide in response to the COVID-19 pandemic, like #GetMePPE for personal protective equipment (PPE) shortage for healthcare workers and other essential workers, and #COVIDSTEMI for sharing and viewing various COVID-19 case status and conditions [25].

2.1.3. Provides virtual alternatives to physical activities (SMR3)
While COVID-19 lockdowns restricted business operations, social media was explored to deliver targeted content, products (e.g., masks, gloves, alcohol), and purchasing opportunities in the online market [3]. It also played a significant role in the production and distribution of PPEs despite the travel constraints caused by lockdown measures. For instance, the #GetMePPE campaign initiated in social media helped suppliers and distributors connect with customers who need medical PPEs [25]. Social media has also served as an alternative venue for physical activities [28]. For example, public forums and meetings have been widely organized on Facebook during lockdown [29]. Virtual education is also made possible by various social media platforms, such as Google Hangouts, Zoom, Whatsapp, Microsoft Teams, among others. Medical consultations with cancer patients are also widely performed on social media [30], which made social media instrumental in keeping high-risk individuals (e.g., cancer patients) from COVID-19 infections [23].

2.1.4. Facilitates the development of COVID-19 policies (SMR4)
Social media for healthcare research have been published annually, providing insights for public health surveillance or helping develop health policies [31–33]. Furthermore, social media accelerates the dissemination of scientific information, which is essential in expediting well-informed public health policies [34,35]. Although some scientific journals expedite the review and publication procedure for COVID-19-related articles, the process can still take several months or weeks at best. The timeliness of scientific information is crucial to public health response. In this aspect, social media plays a vital role by providing experts an avenue to publicize their perspectives in real-time. To transform the community, scientists have frequently updated scientific knowledge and perspectives on their personal Facebook accounts [34,36,37]. For instance, the Facebook posts by Tran Xuan Bach—an Associate Professor of John Hopkins University based in Hanoi—have attracted nearly 13,000 views and hundreds of shares from the public [34]. Policymakers could mine this data from social media to explore popular discourse about the pandemic and the measures set in place to mitigate it.

2.1.5. Facilitates robust response to COVID-19 (SMR5)
The high transmissibility of COVID-19 requires coordination and global cooperation to quickly implement targeted responses and mitigate the pandemic [38]. With this, social media plays a vital role in increasing the collective capacity and action of global and local bodies through effective communication to the public [39]. Sahni and Sharma [40] emphasized that social media platforms serve as a way for disaster management, outbreak prevention, and emergency response staff to easily communicate and access critical information collected by organizations, such as the World Health Organization (WHO) and Centers for Disease Control. This way, social media communications support outbreak preparedness for a robust public health response [3].

2.1.6. Facilitates COVID-19 research (SMR6)
Critical analysis of emergencies can be obtained from social media [41] through data generated and used in enhancing research and development activities [42,43]. Osterhoff et al. [44] demonstrated that social media aids data gathering, communication of scholars, and recruitment and engagement of research respondents on COVID-19 studies. The utility of social media platforms can efficiently and effectively recruit large and diverse samples of survey respondents, especially during a global health crisis such as COVID-19, compared to other methods of recruitment, which are no longer safe, practical, economically feasible, or even legal [45,46]. Thus, social media creates a research community that brings researchers together from distinct fields like machine learning, data science, biomedical informatics, medicine, pharmacology, and public health to help develop initiatives against the coronavirus [47].

2.1.7. Repository for social health data (SMR7)
Reliable data archive and sharing are essential to jump-starting innovative research in combating COVID-19 [47,48]. With people forced out of public spaces, many conversations about this phenomenon now occur online through social media platforms, such as Facebook, Twitter, Instagram, and YouTube [24]. Some social media functions such as 'mentions' and 'hashtags' allow government agencies to convey information more efficiently, which implies that these platforms' functionalities and activities help respond to COVID-19-related events [24]. Also, information shared through digital media such as websites, blogs, and social networking sites helps collect and monitor health-related data during national disasters or emergencies [35]. In this sense, utilizing a real-time information sharing system in various social media platforms is essential as it provides real-time content analysis in several languages globally, contributing to the public health response needs [49].

2.1.8. Rapid information dissemination (SMR8)
The need for access to timely and reliable information about disease symptoms and their prevention is crucial, especially during a pandemic. Finset et al. [8] denoted that social media is often seen as a fast and effective platform for searching, sharing, and distributing real-time health information among the general population. Social media facilitates health professionals in providing accurate information to their patients and the public or highlighting available medical resources [50]. Thus, social media is one of the primary sources of disseminating coronavirus information [51]. While acknowledging that social media may draw a negative impact (e.g., misinformation), Chan et al. [42] pointed out that its potential use in COVID-19 prevention is still viewed positively, especially if it is responsibly and appropriately used in providing rapid and effective dissemination routes for crucial information.

2.1.9. Facilitates the prevention of misinformation (SMR9)
The major drawback of social media amidst a major public health dilemma, such as the COVID-19 pandemic, is its potential to be used as a platform to convey misinformation and fake news [35]. The increased social media presence creates landscapes for widely available
information, data, advice and inopportune, misinformation, specula-
tion, and conspiracies [23]. Actions have been taken to counter
health-related misinformation about COVID-19 circulating on social
media. Some of these actions include identifying emerging trends and
prevalence of health information, evaluating its influence on health, and
developing interventions to fight it [52]. Social media platforms also
emphasize redirecting people to articles with accurate information by
consistently rejecting ads that include vaccine misinformation and
removing multiple posts containing harmful misinformation associated
with COVID-19 [53]. In particular, large social media platforms have
been using artificial technology in distributing reliable information [50,
54]. The WHO also launched a new platform from its risk management
team called WHO Information Network for Epidemics to utilize social
media amplifiers to disseminate tailored information about the virus
[5].

2.1.10. Tool for delivery of public education (SMR10)

Coleman et al. [55] highlighted the potential use of social media in
delivering education to the public amidst lockdown restrictions. Besides
enabling cross-course collaboration between student paramedics and
other degree programs, Perkins et al. [56] pointed out that social media
has also encouraged it to occur. For instance, medical students have
been seeking solicitation from the medical student body to create
COVID-19 educational materials and disseminate them via social media
for internal medicine residents, faculty, and the academic community
[55]. The public’s engagement and education are predominant in the
management of the pandemic. With these, social media plays a vital role
by ensuring its adherence with public health measures [23,55–57].

2.1.11. Expedite risk communication (SMR11)

Social media emerges as a powerful tool in influencing public
behavior [58]. Moreover, it has become an important entity for pro-
moting risk communication during a crisis to reach a broader public
health message [7,37,59–62]. The WHO defines risk communication as
an exchange of real-time information, advice, and opinions between
experts and individuals facing threats to their health, economic, or social
well-being [59]. Social media communication regarding the different
health issues impacts public response to emergencies, which can be
utilized to ease panic [63]. Social media platforms establish a commu-
nication channel for government organizations to respond to health risk
inquiries [37]. Thus, it plays a crucial role in communicating risks to the
public, especially during the COVID-19 pandemic.

2.1.12. Influences public behavior and response (SMR12)

The onset of the COVID-19 pandemic has caused billions of people
to take advantage of the effortless and immediate collection of information
about the virus from social media [64,65]. Furthermore, new items were
generated on social media platforms ensuring strong fluctuations in the
views of public opinion [66,67]. For instance, when a well-known expert
in infectious disease, Nanshan Zhong, confirmed that the transmission of
the virus is possible from human to human, outbreak-related topics
expanded exponentially in social media and PPE, such as masks and the
like, were instantly in urgent need by the public [67]. Analyzing and
understanding how these emerging topics spread in social media to alter
public behaviors and attitudes is crucial in designing effective commu-
nication and health promotion strategies, improving emergency re-
sponses, and enhancing sentiment awareness for rapid implementation
of public health interventions [64–67].

2.1.13. Facilitates telemedicine (SMR13)

The COVID-19 pandemic poses unprecedented difficulties to health
systems, particularly healthcare delivery [68]. The need to develop
virtual care has become an urgent demand from healthcare services to
facilitate continuity of patient-care management while minimizing risks
and exposures to the virus. Globally, there has been a massive adapta-
tion to telemedicine as it is considered a valuable tool to safely provide
medical consultations to patients, in which telephone or videoconfer-
cencing while utilizing remote communication technologies such as
Apple FaceTime, Facebook Messenger, Google Hangouts, Zoom, or
Skype [69]. With this telemedical innovation, physicians, nurses, and
other healthcare providers could virtually communicate with their pa-
tients without limiting COVID-19 patients, trauma patients, and those
with chronic diseases [69]. Social media is also widely utilized for
employing psychological first aid, which helps improve individuals’
mental health in isolation during lockdown [50,51].

2.1.14. Allows remote monitoring of COVID-19 patients (SMR14)

The Centers for Disease Control and Prevention (CDC) identified
people with underlying chronic diseases (e.g., diabetes, hypertension,
heart disease) to have increased risk for severe illness from COVID-19,
which led to the surge of patients in hospital intensive care units and
emergency rooms. Consequently, the recoveries of COVID-19 patients
with mild or no symptoms were advised to be in their homes, wherein
remote patient monitoring has been applied by physicians to connect
with their patients 24/7 without necessarily having in-person consul-
tations [70]. The success of this procedure was demonstrated by Xu et al.
[70], in which a smartphone application for instant messaging, specif-
cally WeChat, was utilized to establish two-way communication be-
tween the home-quarantined patients and a team of telemedicine
clinicians. Through this approach, there is a reduced risk of exposure for
both patients and the medical team while also mitigating the workload
of overwhelmed medical staff [32,71].

2.1.15. Real-time COVID-19 surveillance (SMR15)

News about the COVID-19 disease has spread more rapidly in social
media than it has afflicted people’s physical health. With the world
placed on lockdown, social media has contributed a significant role in
raising public concerns, broadcasting awareness, and sharing informa-
tion to control the transmission of the virus. This enabled the govern-
ments to speed up the tracking process of the spread of COVID-19 across
different areas as social media provides an excellent evaluation of real-
time data reporting [72]. With a thorough analysis of the data extracted
from social media posts, and other online forums and discussions, public
health officials could draw potential interventions to ensure public
health and safety [73]. Several works have recognized the utility of
social media in real-time COVID-19 surveillance (e.g., Refs. [3,43,66].

2.1.16. Facilitates digital contact tracing (SMR16)

The current dilemma of governments and healthcare facilities
worldwide is to efficiently trace symptomatic carriers of the virus and
identify people who have potentially contracted the disease without
showing any physical signs and symptoms [74]. Aside from the manual
contact tracing efforts, several digital technologies are being used to
facilitate digital contact tracing. These include mobile phone tracking,
bio-metric technologies, and data scraping, wherein the data mining is
done through a series of information extraction from social media posts
to understand the nature of the virus better and predict the pandemic’s
trend. Moreover, data scraping or collation allows early detection of a
potentially infected area to enable government units to perform appro-
priate quarantine measures to contain the virus and prevent its spread
[74]. Several other works have discussed the usefulness of social media
digital contact tracing (e.g., Refs. [47,75].

The summary of social media roles obtained from the current liter-
ature is presented in Table 1.

2.2. Some empirical evidence on the interdependencies of social media
roles

The current literature espouses some insights into the inter-
derendencies of social media roles [77], presents empirical evidence
on the positive effect of information dissemination (SMR8) on public
behavior and response (SMR12). Since social media platforms are
widely used as repositories for social health data (SMR7), a rich information source, it follows that SMR7 has a positive effect on SMR12. Also, several studies have utilized social health data for COVID-19 research (SMR6) (e.g., Refs. [76,77,79]). These studies suggest that SMR7 has a direct positive effect on SMR6. Research findings originating from social media data are also widely disseminated by scholars, scientists, and researchers in other social media platforms (e.g., ResearchGate and Academia). Some studies validate the utility of these social media platforms in developing public health policies (SMR4) [80,81]. Also, Keren et al. [82] reported empirical evidence on the positive influence of risk communication (SMR11) on public behavior and response (SMR12).

The work of Kuchler et al. [78] empirically showed how epidemiologists could use social networks to predict the spread of COVID-19, which is essential in disease surveillance (SMR15) efforts. Their research further suggests the importance of public participation (SMR1) in allowing more accurate social network data (e.g., location data), which is essential in developing a robust response against COVID-19 spread (SMR5). With these relationships, it follows that SMR15 has a positive influence on SMR5. Social media location data is also essential for contact tracing (SMR16). In the context of previous discussions, it is apparent that SMR1 has a positive influence on SMR16. Mandeville et al. [83] showed that for social media to become an effective tool for contact tracing, public participation and approval are required to prevent it from being considered a breach of privacy. Thus, their study suggests that SMR1 has a positive influence on SMR6. Carlsen et al. [84] empirically showed how public participation through Facebook groups aid the provision of a virtual alternative to physical activities (SMR3), e.g., virtual schooling, during the lockdown. They also reported that the most prevalent support provided by Facebook groups is public education (SMR10) on COVID-19 and the dissemination of critical information regarding it (SMR8). These few insights reported in the current literature on COVID-19 and the dissemination of critical information among social media roles is an important agenda for resource allocation, e.g., virtual schooling, during the lockdown. They also reported that the empirically showed how public participation through Facebook groups aid the provision of a virtual alternative to physical activities (SMR3), e.g., virtual schooling, during the lockdown. Thus, their study suggests tracing, public participation and approval are required to prevent it which is essential in developing a robust response against COVID-19 which is essential in disease surveillance (SMR15) efforts. Their research (SMR6) (e.g., Refs. [76,77,79]. These studies suggest that

### Table 1

| Code  | Description                                           | References       |
|-------|-------------------------------------------------------|------------------|
| SMR1  | Promotes public participation against COVID-19         | [3,21-23,61]     |
| SMR2  | Links multidisciplinary teams of experts worldwide     | [25,27]          |
| SMR3  | Provides virtual alternatives to physical activities  | [3,23,25,28-30]  |
| SMR4  | Facilitates the development of public health policies  | [31-37]          |
| SMR5  | Facilitates robust public health response              | [3,38,40]        |
| SMR6  | Facilitates COVID-19 research                         | [42-47]          |
| SMR7  | Repository for social health data                     | [24,35,43]       |
| SMR8  | Rapid information dissemination                       | [4,82,50,51]     |
| SMR9  | Facilitates the prevention of misinformation           | [3,50,52-54]     |
| SMR10 | Tool for delivery of public education                 | [23,55-57,76]    |
| SMR11 | Expedites risk communication                          | [7,37,59-63,76]  |
| SMR12 | Influences public behavior and response               | [64-67]          |
| SMR13 | Facilitates telemedicine                              | [50,51,69]       |
| SMR14 | Allows for remote monitoring of COVID-19 patients      | [32,70,71]       |
| SMR15 | Real-time disease surveillance                        | [3,43,66,72]     |
| SMR16 | Facilitates digital contact tracing                   | [47,74,75]       |

3. Preliminaries

3.1. Fuzzy set theory

Zadeh [10] introduced the fuzzy set theory in computing information that possesses vagueness and uncertainty. To ensure that this article is self-sustaining, we present the notion of the fuzzy sets, fuzzy numbers, and fuzzy matrix. Elaborate discussions on the background of fuzzy set theory have been presented in various works in the literature, including Zimmermann [85]. Kahraman et al. [86] reviewed its applications in various disciplines, highlighted its progress, and enumerated some extensions over the last 50 years.

**Definition 1.** [10]: Let X be a space of points or the universe of discourse, with a generic element of X denoted by x. A fuzzy set A in X is characterized by a membership function μ_A which associates with each x in X a real number in the closed interval [0,1], with the value of μ_A(x) at x representing the “grade of membership” of x in A. Succinctly, the set of 2-tuple A = {x, μ_A(x) : x ∈ X, μ_A(x) ∈ [0,1]} is a fuzzy set and the μ_A : X → [0,1] is the membership function of x in A.

**Definition 2.** [87]: A real fuzzy number ã is described as any fuzzy subset of the real number line whose membership function μ_ã is piece-wise continuous.

**Definition 3.** [88]: A fuzzy number ã is called non-negative, denoted by ã ≥ 0, if its membership μ_ã(x) satisfies μ_ã(x) = 0 for every x ≤ 0.

**Definition 4.** [87]: A fuzzy number ã is of LR-type if

\[
μ_ã(x) = \begin{cases} 
L \frac{m-x}{a} & x \leq m, a > 0 \\
R \frac{x-m}{β} & x \geq m, β > 0 
\end{cases}
\]

where m is the modal value of ã, and a and β are respectively called the left and right spreads of ã. L and R are reference functions, with L(.) = R(.) = max{1 - x, 0}, and L(0) = R(0) = 1. Symbolically, such LR-type fuzzy number is written as

\[
ã = (m; a, β)
\]

A special LR-type fuzzy number is a triangular fuzzy number. We represent a triangular fuzzy number ã = (l, m, u), l ≤ m ≤ u, l ≥ 0, where l = m - a and u = m + β.

**Definition 5.** For a triangular fuzzy number ã = (l, m, u), its membership function μ_ã(x) is defined as

\[
μ_ã(x) = \begin{cases} 
0 & x < l \\
l - x & l \leq x \leq m \\
\frac{m-x}{u-m} & m \leq x \leq u \\
0 & x > u 
\end{cases}
\]

**Definition 6.** [87]. Let ã1 = (l1, m1, u1), ã2 = (l2, m2, u2), and ã = (l, m, u) be triangular fuzzy numbers, and λ > 0. The following operations hold:

\[
ã1 ⊕ ã2 = (l1 + l2, m1 + m2, u1 + u2) \quad (4)
\]

\[
ã1 ⊖ ã2 = (l1 - l2, m1 - m2, u1 - u2) \quad (5)
\]

\[
ã1 ⊖ ã2 = (l1, m1, u1) \quad (6)
\]

\[
ã1 ⊗ ã2 = (l1/u2, m1/m2, u1/u2) \quad (7)
\]

\[
λã = (λl, λm, λu) \quad (8)
\]
Definition 7. [89]: \( \tilde{A} = (\tilde{a}_{ij})_{m \times n} \) is called a fuzzy matrix if \( \tilde{a}_{ij} (\forall i,j) \) are fuzzy numbers. \( \tilde{A} \) is non-negative, denoted by \( \tilde{A} \geq 0 \), if \( \tilde{a}_{ij} (\forall i,j) \) are non-negative.

3.2. DEMATEL

The DEMATEL is a problem structuring tool based on graph theory. It was developed in the 1970s by the Battelle Memorial Institute of Geneva for a Science and Human Affairs Program [90,91]. In the DEMATEL, the problem consists of homogeneous elements (e.g., factors) and treats these elements as vertices of a graph. The causal relationships of these elements, initially determined through expert opinions regarding the domain problem, constitute the edges of the graph. The computational structure of the DEMATEL intends to achieve two objectives: (1) to determine the total causal relationships and their corresponding degrees of direct and indirect (i.e., transitive) relations, and (2) to evaluate these elements either as the net cause or net effect. Resulting from the initial causal relationships introduced by the experts, each element takes on either a “cause” role or an “effect” role, or both on other elements. The notion of a net role identifies its final role in the problem. Following these objectives, the DEMATEL allows a better understanding of the problem under consideration, which is often convoluted [90,91]. The prominence-relations map, which is a directed graph, collectively provides a pictorial representation of the objectives of the DEMATEL. The use of the DEMATEL in structuring problems in various domains has been increasingly popular in the last decade, and Si et al. [92] provided a systematic literature review of these applications.

The computational steps of the DEMATEL are briefly described as follows.

Step 1 Identify the problem containing a finite number of \( n \) elements.

Step 2 Generate the direct-relation matrix.

An expert group of \( K \) decision-makers elicits judgments on the degree of the causal influence of \( i \) on element \( j \), \( i, j \in \{ 1, \ldots, n \} \). This generates a set of direct-relation matrices \( A^k = (a^k_{ij})_{n \times n}, k = 1, \ldots, K \). Here, \( a^k_{ij} \) represents such a causal influence of \( i \) on \( j \) as perceived by the \( k \)th member of the expert group, with an evaluation scale of 0, 1, 2, 3, and 4, representing ‘no influence’, ‘low influence’, ‘medium influence’, ‘high influence’, and ‘very high influence’, respectively. From the \( A^k \) matrices, the aggregate direct-relation matrix \( \bar{A} = (\bar{a}_{ij})_{n \times n} \) is obtained by any pre-defined aggregation method (e.g., arithmetic mean method). Note that when the expert group generates a single initial direct-relation matrix that reflects the group consensus, aggregation is not necessary. Nevertheless, this Step of the DEMATEL intends to generate a single initial direct-relation matrix that represents the domain problem.

Step 3 Obtain the normalized direct-relation matrix. Equation (9) is used to produce such a matrix.

\[
X = \left( \frac{1}{\max_{1 \leq j \leq n} \sum_{i=1}^{n} a^k_{ij}} \right) A
\]

(9)

Step 4 Calculate the total relation matrix \( T \), which represents all the degrees of direct and indirect (i.e., transitive) causal relationships among the elements of the problem. Equation (10) generates the total relation matrix \( \bar{T} = (\bar{t}_{ij})_{n \times n} \).

\[
T = X + X^2 + X^3 + \cdots = X(I - X)^{-1}
\]

(10)

Step 5 Compute for the prominence and relation vectors. Given Equation (10), vectors \( D \) and \( R \) are obtained using the following:

\[
D = \begin{pmatrix} \sum_{j=1}^{n} t_{ij} \end{pmatrix}_{n \times 1} = (t_i)_{1 \times n}
\]

(11)

\[
R = \begin{pmatrix} \sum_{i=1}^{n} t_{ij} \end{pmatrix}_{1 \times n} = (t_j)_{1 \times n}
\]

(12)

The values \( D \) vector can be thought of as the total causal influences given by the elements, while the \( R \) vector describes the total causal influences received by the elements. The prominence vector \( (D + R) \) represents the relative importance of each element in the problem. It signifies the strength of the relationships of the element with other elements, as reflected by the sum of all causal influences given and received by the element. The relation vector \( (D - R) \) denotes the net causal influences given and received by the element. Those having \( t_i - t_j > 0 \), \( i = j \) belong to the net cause group, while those elements with \( t_i - t_j < 0 \), \( i = j \) belong to the net effect group. Those in the net cause and effect groups are known as dispatchers and receivers, respectively.

Step 6 Construct the prominence-relation map. The map \((D + R), (D - R)\) represents the prominence-relation map where edges are derived from \( t_{ij} \). Given that some of \( t_{ij} \) values are insignificant (i.e., theoretically or practically), a threshold value \( \alpha \) is set in such a way that when \( t_{ij} \geq \alpha \), then a directed edge emanates from element \( i \) to element \( j \) in the prominence-relation map.

3.3. Analytic network process

The ANP is a generalization of the analytic hierarchy process (AHP) proposed by Saaty [93] as a priority measurement method used to handle a decision-making problem under multiple criteria, popularly known as an MCDM problem. While the AHP is confined to decision problems where components (e.g., goal, criteria, alternatives) are arranged in a hierarchy, the ANP extends this limitation by allowing feedback and dependence among decision components and elements represented by a decision network. This capability supports a wide array of MCDM problems that resemble in real-life. The details of the ANP, both from the theoretical and practical point of view, are extensively discussed in the literature, e.g., Saaty [94]. Recent insightful reviews of the AHP and the ANP are reported elsewhere, including Chen et al. [95] Kheybari et al. [96] and Khan and Ali [97]. The core component of both methods is the pairwise comparison matrix (PCM) derived from eliciting the estimated ratio of priorities between any two elements in the same decision component using the Saaty Fundamental Scale [93]. The priority weights of the elements in a PCM are determined by solving an eigenvalue problem in the form of

\[
A W = \lambda_{max} W
\]

(13)

where \( A \) is the positive reciprocal PCM, \( \lambda_{max} \) is the maximum eigenvalue, and \( W \) denotes the corresponding principal eigenvector associated with the \( \lambda_{max} \). Here, the \( W \) vector is considered the estimates of the priorities of the elements. For consistent judgment (i.e., associated with the transitive property of ratio scales), \( \lambda_{max} = n \); otherwise, \( \lambda_{max} > n \). The consistency of judgment is measured by the Consistency Ratio (CR), as shown in Equation (14).

\[
CR = \frac{CI}{RI}
\]

(14)

where \( RI \) represents a random consistency index for a given \( n \) and \( CI \) denotes the consistency index provided below

\[
CI = \frac{\lambda_{max} - n}{n - 1}
\]

(15)

Values of \( CR \geq 0.10 \) are considered acceptable. Otherwise, decision-
makers need to reconsider their judgments. In the ANP, the $w$ vectors obtained from Equation (13) signify the local priority vectors of the decision elements. Each $w$ vector is positioned appropriately in a super matrix – a partitioned matrix representing the decision network under consideration. The global priority vector of the decision elements is obtained by constructing a column stochastic super matrix and raising it to large powers. Conceptually,

$$\lim_{p \to \infty} \left( \frac{S}{\lambda} \right)^p = \lim_{p \to \infty} [S]^p = L \quad (16)$$

where $S$ denotes the initial super matrix and $L$ represents the limiting super matrix. Each column of $L$ is a unique positive column eigenvector that can be used to measure the overall priorities of the elements in the decision network.

4. Methodology

4.1. Case study: the Philippine scenario

The COVID-19 pandemic has been primarily associated with socioeconomic distress in the Philippines since the beginning of 2020 [2, 98]. The first two confirmed cases were reported in January, a Chinese-national couple from Wuhan City, China, where the outbreak began [99]. On 7 March, a 62-year-old male Filipino was confirmed by the Department of Health (DOH) to be the first localized transmission in the country [100]. This prompted DOH to raise the country’s COVID-19 alert system to Code Red, Sub-level 1, and appeal to the Office of the President to declare a state of national health emergency. With the country in a state of emergency, national and local government units and public and private healthcare providers were urged to implement response measures for the possible increase in suspected and confirmed cases.

Following the declaration of national emergency, the entire island of Luzon was placed under Enhanced Community Quarantine, wherein travel bans were implemented [101]. Strict physical distancing measures were also enforced, which led to the suspension of classes, holding work-from-home activities for employees, and the prohibition of social gatherings [102]. Additionally, the strategic installation of handwashing facilities in public areas was imposed to facilitate hand hygiene and sanitation. These control measures were similarly applied throughout the country as the number of community transmissions continued to surge. To alleviate the effects of the outbreak primarily on the country’s economy and public health, a national measure known as the Bayanihan to Heal as One Act was issued on the 24th day of March 2020, allowing the government to reallocate the funds from discontinued projects to COVID-19 expenses. According to the Department of Budget and Management report, the total budget allocated for COVID-19 response activities has already reached Php 376.57 billion (7.75 billion USD), of which Php 360.1 billion (7.41 billion USD) has been released as of August 10, 2020. Despite these mitigation efforts, there was still a continued upsurge in the number of COVID-19 cases bringing a total of 2,490,858 confirmed cases as of September 27, 2021 [103].

While the need to impose immediate and stringent control measures to combat the pandemic is crucial, the rapid dissemination of accurate information to the general public also plays a significant role because it dramatically influences people’s behavior in response to the COVID-19 outbreak. For decades, several broadcasting initiatives such as magazines, newspapers, and television have been deployed as mass communication tools. However, online platforms have undeniably advanced traditional media in which social media significantly played an integral part. In the Philippines, social media platforms (e.g., social networking sites) have been a massive source of information during the pandemic, considering many social network users comprise 81.53% of the country’s population [104]. Although the primary function of social media during a disease outbreak is information dissemination, its applications go beyond such a function. Thus, this study attempts to identify the roles of social media in emergency preparedness during COVID-19 in the Philippine setting. With the use of the FDANP approach, the crucial relationships of these roles, as well as their priorities, are established as inputs to policy- and decision-making for emergency management efforts during pandemics.

4.2. Proposed procedure: the application of FDANP

This work adopts the FDEMATEL to capture the complex inter-relationships between the different roles of social media. The fuzzy set theory, developed by Zadeh [10], combined with the DEMATEL method, is used to address vagueness and uncertainty while capturing the intertwined relationships of the roles. The FDEMATEL method has been widely used in understanding cause and effect relationships among criteria, factors, indicators under different domains in the presence of judgment vagueness and uncertainty [105,106]. Furthermore, the ANP measures the systemic impact of social media roles in emergency preparedness efforts during pandemics. It has been successfully used in synthesizing outcome of dependence and feedback within and between the clusters of elements, criteria, or alternatives to create a framework dealing with decisions without the assumptions on the independence of elements as in a hierarchy [94,107,108]. Such an integration of the FDEMATEL and ANP is hereby known as the FDANP approach.

FDANP is one of the most successful integrations of MCDM approaches recently adopted by Hsu and Liou [109]. The non-fuzzy predecessor of the FDANP is known as the DANP [110]. The concept assumes that a given set of criteria may display inherent interrelationshions among one another and that such can serve as a foundation in arriving at an influential global weight of each criterion. While FDE- MATEL on its own can map out complex constructs and analyze a structural model involving cause and effect interrelationships [111], the integration of ANP provides an even more comprehensive measurement of ratio scale priorities for the distribution of influence among criteria and group of criteria in the decision problem [112]. FDANP, along with other MCDM methodologies, has been applied in various research areas, such as prioritizing criteria for national hospital accreditation [113], quality assessment of higher education institutions [114], and ranking lean production factors [115]. However, the FDANP has never been applied in the context of crisis management. Thus, in addition to the previously discussed contributions of this work, it also pioneers the illustration of the applicability of the FDANP in said context. Fig. 1 shows the overall flow of the FDANP approach adopted in this work.

The computational steps of the FDEMATEL, as described by Lin and Wu [9], are shown as follows:

Step 1 Form the expert group of decision-makers.

The domain experts were identified based on two criteria: (1) extent of involvement in emergency response activities (e.g., research, planning, implementation) against COVID-19, and (2) relevance of social media in their involvement. In this work, frontline, academic, and managerial experts were considered. Frontline experts are those directly involved in the implementation of COVID-19 emergency response activities. Academic experts are those specializing in social media research or have engaged in social media research on COVID-19. On the other hand, managerial experts possess positions of authority in organizations related to public health or COVID-19 emergency response. Following the guidelines of Anderson et al. and Gumus [116,117] about the size of the expert group, 15 experts were consulted in this study. The following experts are detailed in Table 2.

The expert decision-makers were asked to elicit judgments on the influence of social media role $i$ on social media role $j$ using a linguistic scale (i.e., shown in Table 3), where $i,j \epsilon \{1,2, ..., n\}$ and $n$ is the number of social media roles. The corresponding triangular fuzzy numbers (TFNs) used for the baseline analysis of this work follow those
Fig. 1. The overall flow of the FDANP approach.

### Table 2
Relevant demographics of the domain experts.

| Experts | Category          | Position                  | Educational qualification |
|---------|-------------------|---------------------------|---------------------------|
| Expert 1 | Frontline         | COVID-19 taskforce member | Master’s degree           |
| Expert 2 | Frontline         | COVID-19 taskforce member | Bachelor’s degree         |
| Expert 3 | Frontline         | COVID-19 taskforce member | Bachelor’s degree         |
| Expert 4 | Frontline         | COVID-19 response nurse   | Bachelor’s degree         |
| Expert 5 | Frontline         | Medical technologist      | Master’s degree           |
| Expert 6 | Academic          | Social media researcher   | Bachelor’s degree         |
| Expert 7 | Academic          | Social media researcher   | Bachelor’s degree         |
| Expert 8 | Academic          | Social media researcher   | Bachelor’s degree         |
| Expert 9 | Academic          | Social media researcher   | Master’s degree           |
| Expert 10 | Managerial       | Special group against COVID-19 | Master’s degree   |
| Expert 11 | Managerial       | Clinical Director         | Doctorate                 |
| Expert 12 | Managerial       | COVID-19 emergency task force | Doctorate             |
| Expert 13 | Managerial       | COVID-19 contact tracer team lead | Doctorate |
| Expert 14 | Managerial       | Social media manager      | Doctorate                 |
| Expert 15 | Managerial       | Social media manager      | Bachelor’s degree         |

### Table 3
The linguistic scale and the corresponding triangular fuzzy numbers.

| Linguistic variables      | Code | Equivalent triangular fuzzy numbers (TFNs) |
|---------------------------|------|--------------------------------------------|
| No influence              | 0    | (0.0, 0.1, 0.3) (0.0, 0.25) (0.0, 0.1, 0.2) |
| Weak influence            | 1    | (0.1, 0.3, 0.5) (0.0, 0.25, 0.5) (0.2, 0.3, 0.4) |
| Medium influence          | 2    | (0.3, 0.5, 0.7) (0.25, 0.5, 0.75) (0.4, 0.5, 0.6) |
| High influence            | 3    | (0.5, 0.7, 0.9) (0.5, 0.75, 1) (0.6, 0.7, 0.8) |
| Very high influence       | 4    | (0.7, 0.9, 1.0) (0.75, 1, 1) (0.8, 0.9, 1) |

The linguistic responses of the experts were converted into their corresponding triangular fuzzy numbers to construct the fuzzy direct-relation matrices $Z_k = (z_{ik})_{n \times n} = ([l_{ik}^k, m_{ik}^k, u_{ik}^k])_{n \times n}$ where $z_{ik}^k$ represents the equivalent TFN of the judgment of the $k$th expert ($k = 1, 2, \ldots, p$) on the degree of influence of social media role $i$ on $j$, for $i, j \in \{1, 2, \ldots, n\}$, $i \neq j$. $Z_k$ is illustrated in Equation (17).

$$
Z_k = (z_{ik})_{n \times n} = 
\begin{pmatrix}
0 & z_{12k} & \cdots & z_{1nk} \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & z_{nk} & \\
\end{pmatrix}
$$

Step 4 Aggregate the fuzzy initial direct relation matrices.
Table 4
Sample initial direct-relation matrix with linguistic variables (Expert 1).

| Social media roles | SMR1 | SMR2 | SMR3 | SMR4 | SMR5 | SMR6 | SMR7 | SMR8 | SMR9 | SMR10 | SMR11 | SMR12 | SMR13 | SMR14 | SMR15 | SMR16 |
|--------------------|------|------|------|------|------|------|------|------|------|-------|-------|-------|-------|-------|-------|-------|
| SMR1               | 1    | 2    | 3    | 2    | 2    | 4    | 4*   | 3    | 2    | 2     | 3     | 2     | 2     | 3     | 2     | 2     |
| SMR2               | 3    | 4    | 4    | 3    | 3    | 2    | 1    | 2    | 3    | 3     | 4     | 3     | 2     | 2     | 2     | 2     |
| SMR3               | 3    | 4    | 4    | 3    | 2    | 2    | 1    | 2    | 3    | 2     | 2     | 3     | 2     | 2     | 2     | 2     |
| SMR4               | 3    | 4    | 4    | 3    | 2    | 1    | 1    | 2    | 3    | 3     | 4     | 3     | 3     | 3     | 3     | 3     |
| SMR5               | 3    | 4    | 3    | 4    | 2    | 3    | 3    | 4    | 4    | 4     | 2     | 3     | 3     | 3     | 3     | 3     |
| SMR6               | 4    | 3    | 3    | 4    | 2    | 3    | 2    | 1    | 2    | 3     | 3     | 4     | 3     | 2     | 2     | 2     |
| SMR7               | 2    | 3    | 4    | 3    | 2    | 2    | 1    | 1    | 2    | 3     | 3     | 3     | 2     | 2     | 2     | 2     |
| SMR8               | 4    | 3    | 4    | 3    | 3    | 2    | 2    | 2    | 3    | 3     | 3     | 4     | 3     | 3     | 3     | 3     |
| SMR9               | 1    | 2    | 3    | 2    | 3    | 2    | 2    | 3    | 3    | 3     | 4     | 3     | 3     | 3     | 3     | 3     |
| SMR10              | 2    | 3    | 3    | 4    | 3    | 3    | 2    | 3    | 3    | 3     | 4     | 2     | 3     | 2     | 1     | 1     |
| SMR11              | 2    | 3    | 3    | 4    | 2    | 2    | 2    | 1    | 2    | 3     | 1     | 0     | 0     | 2     | 2     | 2     |
| SMR12              | 2    | 3    | 3    | 4    | 2    | 2    | 2    | 3    | 3    | 2     | 2     | 3     | 2     | 2     | 2     | 2     |
| SMR13              | 3    | 4    | 3    | 2    | 2    | 2    | 2    | 2    | 3    | 2     | 1     | 2     | 2     | 3     | 2     | 2     |
| SMR14              | 1    | 2    | 3    | 2    | 2    | 1    | 1    | 2    | 3    | 2     | 1     | 1     | 2     | 1     | 2     | 1     |
| SMR15              | 1    | 2    | 3    | 2    | 2    | 2    | 2    | 1    | 2    | 3     | 2     | 3     | 2     | 2     | 2     | 2     |
| SMR16              | 2    | 3    | 3    | 2    | 2    | 4    | 1    | 1    | 2    | 3     | 3     | 4     | 4     | 2     | 2     | 2     |

The matrix $Z_k$ is used to obtain the aggregate fuzzy direct-relation matrix $Z$, which aggregates the judgments of $p$ experts. $Z$ is obtained using Equation (18), following Equation (4) on the addition operation of TFNs. The resulting $Z$ is shown in Equation (19).

$$Z = \left(\tilde{z}_{ij}\right)_{n \times n} = \left(\frac{\tilde{z}_{1i} \oplus \tilde{z}_{2j} \oplus \ldots \oplus \tilde{z}_{kp}}{p}\right)_{n \times n} \quad \text{for } i, j = (1, 2, \ldots, n) \quad (18)$$

Here, $\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

Using Equation (20). Equation (21) presents the resulting $W$.

$$W = \left(\tilde{w}_{ij}\right)_{n \times n} = \left(\tilde{w}_{11}, \ldots, \tilde{w}_{1n}, \ldots, \tilde{w}_{n1}, \ldots, \tilde{w}_{nn}\right) \quad (20)$$

where $\tilde{w}_{ij} = \left(\tilde{w}_{ij}^f, \tilde{w}_{ij}^m, \tilde{w}_{ij}^u\right)$, and $s = \max_{i, j} \left(\sum_{k=1}^{n} \tilde{w}_{ik}^f\right)$, for $i, j = (1, 2, \ldots, n)$. The operation $\frac{s}{2}$ follows Equation (8).

| SMR1  | 0 | (0.023, 0.039, 0.055) | (0.046, 0.062, 0.074) |
|-------|---|-----------------------|-----------------------|
| SMR2  | (0.037, 0.054, 0.07) | 0                     | (0.041, 0.057, 0.07)  |
| SMR16 | (0.019, 0.033, 0.049) | (0.022, 0.037, 0.053) | 0                     |

$$Z = \left(\tilde{z}_{ij}\right)_{n \times n} = \left(\begin{array}{cccc}
0 & (0.28, 0.473, 0.667) & \cdots & (0.553, 0.753, 0.893) \\
(0.477, 0.647, 0.847) & 0 & \cdots & (0.493, 0.687, 0.84) \\
(0.227, 0.393, 0.593) & (0.267, 0.447, 0.64) & \cdots & 0 \\
\end{array}\right) \quad (19)$$

Step 5 Obtain the normalized fuzzy direct-relation matrix.

The normalized fuzzy direct-relation matrix, $W$, which is calculated using Equation (22) obtained through the following process. The computational procedure to obtain $V$ is detailed in the following. Let $W = (l_{ij})_{n \times n}$, $M_w = (m_{ij})_{n \times n}$, and define $W_l = (l_{ij})_{n \times n}$, $W_m = (m_{ij})_{n \times n}$, and $W_u = (u_{ij})_{n \times n}$. These matrices are extracted from $W$, as presented in Equation (22). On that basis, $V$ is obtained using Equation (23) and Equation (24).

$$W = \left(\begin{array}{cccc}
l_{12} & \cdots & l_{1n} \\
l_{21} & 0 & \cdots & l_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
l_{1n} & l_{2n} & \cdots & 0 \\
\end{array}\right), W_m = \left(\begin{array}{cccc}
m_{12} & \cdots & m_{1n} \\
m_{21} & 0 & \cdots & m_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
m_{1n} & m_{2n} & \cdots & 0 \\
\end{array}\right), W_u = \left(\begin{array}{cccc}
u_{12} & \cdots & v_{1n} \\
v_{21} & 0 & \cdots & v_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
v_{1n} & v_{2n} & \cdots & 0 \\
\end{array}\right) \quad (22)$$
\[ V = \lim_{k \to \infty} (\bar{W} + \bar{W}^2 + \cdots + \bar{W}^k) \]  
(23)

\[ \bar{V} = \left( \bar{V}_{ij} \right)_{n \times n} = \left( \bar{v}_{11}, \bar{v}_{12}, \cdots, \bar{v}_{1n} \bar{v}_{21}, \bar{v}_{22}, \cdots, \bar{v}_{2n} \bar{v}_{31}, \bar{v}_{32}, \cdots, \bar{v}_{3n} \bar{v}_{41}, \bar{v}_{42}, \cdots, \bar{v}_{4n} \bar{v}_{51}, \bar{v}_{52}, \cdots, \bar{v}_{5n} \bar{v}_{61}, \bar{v}_{62} \cdots, \bar{v}_{6n} \right) \]  
(24)

where \( \bar{V} = (\bar{v}_{ij}, \bar{m}_{ij}, \bar{u}_{ij}) \), \( \bar{I}_{ij} = W_i \times (I - W_i)^{-1} \); \( \bar{u}_{ij} = W_n \times (I - W_n)^{-1} \); \( \bar{u}_{ij} \) for \( i, j = 1, 2, \ldots, n \).

To obtain the crisp (non-fuzzy) values of the crisp total-relation matrix \( V = (\bar{v}_{ij})_{n \times n} \), the graded mean integration representation shown in Equation (25) is used.

\[ \bar{v}_{ij} = \left( \frac{0.033, 0.121, 0.705}{0.050, 0.143, 0.701} \right) \cdots \left( \frac{0.078, 0.182, 0.782}{0.069, 0.172, 0.771} \right) \cdots \left( \frac{0.039, 0.113, 0.584}{0.039, 0.112, 0.627} \right) \cdots \left( \frac{0.022, 0.091, 0.586}{0.022, 0.091, 0.586} \right) \]  
(25)

The elements in \( V \) demonstrate the strength of influence of the row elements on column elements (i.e., a high rating corresponds to high influence while a low rating is to low influence).

Step 7 Obtain the \((D + R)\) and \((D - R)\) vectors.

From \( V \), the vectors \((D + R)\) and \((D - R)\) are obtained, where \( D \) and \( R \) are associated with columns and row sums, respectively. \( D \) pertains to the levels of influence social media role \( i \) on others while \( R \) pertains to the levels of relationships of social media role \( i \) with others. \( D \) and \( R \) are defined in Equation (28) and Equation (29). They illustrate the importance of social media roles and classify them into causal or effect clusters. In identifying the importance of each social media role, the horizontal axis vector \((D + R)\) is used while the vertical axis vector \((D - R)\) is used to classify them. As previously defined, \( D \) pertains to the levels of influence on others, and \( R \) pertains to the levels of influence from others. If the result when subtracting \( D \) with \( R \) is positive, this essentially means that a role has a greater value of influencing other roles than being influenced by other roles; thus, roles with positive values of \((D - R)\) significantly influence other roles. These elements are called dispatchers and are classified under the causal cluster. Subsequently, roles with negative values of \((D - R)\) mean that roles have greater values on being influenced by others. These are called receivers and are classified under the effect cluster. The value of \((D + R)\) indicates the degree of relationship between a social media role with others. Social media roles having higher values of \((D + R)\) have stronger relationships with others, while those having smaller values of \((D + R)\) have less of a relationship with others. Table 5 shows the \((D + R)\) and \((D - R)\) vectors, as well as the classification of social media roles.

### Table 5

| Codes  | Social media roles                                      | \( D \)   | \( R \)   | \( D + R \) | \( D - R \) | Cluster |
|--------|--------------------------------------------------------|-----------|-----------|-------------|-------------|---------|
| SMR1   | Promotes public participation against COVID-19         | 4.074     | 3.401     | 7.475       | 0.673       | Cause   |
| SMR2   | Links multidisciplinary teams of experts worldwide    | 4.089     | 3.055     | 7.143       | 1.034       | Cause   |
| SMR3   | Provides virtual alternatives to physical activities  | 3.715     | 3.178     | 6.893       | 0.537       | Cause   |
| SMR4   | Facilitates the development of public health policies  | 4.125     | 3.789     | 7.914       | 0.336       | Cause   |
| SMR5   | Facilitates robust public health response             | 3.221     | 3.616     | 6.838       | -0.395      | Effect   |
| SMR6   | Facilitates COVID-19 research                         | 3.793     | 3.429     | 7.222       | 0.364       | Cause   |
| SMR7   | Repository for social health data                     | 3.216     | 2.618     | 5.834       | 0.597       | Cause   |
| SMR8   | Rapid information dissemination                       | 3.960     | 3.515     | 7.476       | 0.445       | Cause   |
| SMR9   | Facilitates the prevention of misinformation          | 2.934     | 3.770     | 6.704       | -0.836      | Effect   |
| SMR10  | Tool for delivery of public education                 | 3.201     | 3.571     | 6.771       | -0.370      | Effect   |
| SMR11  | Expedite risk communication                           | 3.093     | 3.664     | 6.757       | -0.570      | Effect   |
| SMR12  | Influences public behavior and response              | 3.199     | 3.706     | 6.905       | -0.508      | Effect   |
| SMR13  | Facilitates telemedicine                              | 2.966     | 3.331     | 6.297       | -0.365      | Effect   |
| SMR14  | Allows for remote monitoring of COVID-19 patients      | 2.728     | 3.247     | 5.975       | -0.520      | Effect   |
| SMR15  | Real-time disease surveillance                        | 3.296     | 3.427     | 6.723       | -0.131      | Effect   |
| SMR16  | Facilitates digital contact tracing                   | 3.169     | 3.461     | 6.629       | -0.292      | Effect   |

\[ \bar{V} = \left( \begin{array}{cccc} 0.203 & 0.221 & \cdots & 0.264 \\ 0.255 & 0.184 & \cdots & 0.261 \\ 0.191 & 0.180 & \cdots & 0.162 \end{array} \right) \]  
(27)

Step 8 Construct the cause-effect network map.

Represented as a directed graph, the cause-effect network map can be generated on the basis of \((D + R)\) and \((D - R)\) vectors. The selection of relevant relationships makes the analysis of the cause-effect network map feasible, especially when a plethora of interrelationships occurs in the system. To determine the relevant relationships, the experts must set up a threshold value \( \alpha \) (e.g., arithmetic mean of \( \bar{v}_{ij} \)) to screen out some negligible interrelationships. In developing the matrix of significant relationships \( A \), which can be used as the weights of the edges for the relationship digraph, Equation (30) is employed. If \( a_i \neq 0 \), then an arrow emanates from social media role \( i \) to social media role \( j \) in the cause-effect network map. Fig. 2 illustrates this map.

\[ A = (a_{ij})_{n \times n} = \begin{cases} \bar{v}_{ij}, & \bar{v}_{ij} \geq \alpha \\ 0, & \bar{v}_{ij} < \alpha \end{cases} \quad \text{for } i, j = 1, 2, \ldots, n \]  
(30)

In applying the ANP in conjunction with the FDEMATEL, the normalized total-relation matrix \( V^{nor} \), computed using Equation (31), is deemed the column stochastic supermatrix. The resulting \( V^{nor} \) is presented in Equation (32).

\[ V^{nor} = \left( \bar{v}_{ij}^{nor} \right)_{n \times n} \]  
(31)

where \( \bar{v}_{ij}^{nor} = \frac{\bar{v}_{ij}}{\sum_{j=1}^{n} v_{ij}} \).
The elements of $V_{\text{nor}}$ translate the impact of one social media role to another and the impact it receives from another. For instance, the element highlighted by a single asterisk (*) shows a value of 0.054 (i.e., total influential relations of SMR1 to SMR2) while the element highlighted by a double asterisk (**) displays a value of 0.065 (i.e., total influential relations of SMR1 to SMR16). This denotes that the influence of SMR1 on SMR16 is higher than its influence on SMR2. Thus, when a value in any element is high, it implies a high influence; when the value is low, it indicates less influence on another. The FDANP supermatrix is obtained by raising $V_{\text{nor}}$ to a sufficiently large power $p$ until it converges and becomes a long-term stable supermatrix, as shown in Equation (16). As a result, a global priority vector defining the ratio scale priority weights $w = (w_1, ..., w_j, ..., w_n)$ from $\lim_{p \to \infty} (V_{\text{nor}})^p$ (i.e., see Equation (33)) for each social media role can be estimated.

$$\lim_{p \to \infty} (V_{\text{nor}})^p = L = \begin{pmatrix}
0.062 & 0.056 & \cdots & 0.063 \\
0.062 & 0.056 & \cdots & 0.063 \\
\vdots & \vdots & \ddots & \vdots \\
0.062 & 0.056 & \cdots & 0.063
\end{pmatrix} (33)$$

The weights of social media roles presented in Table 6 obtained from the limiting process of FDANP supermatrix represent a measure of social media roles’ impact on emergency preparedness during the COVID-19 pandemic.

5. Results and discussion

5.1. Baseline results

This section highlights the results of applying the FDANP approach in the causal analysis of social media roles in emergency preparedness during COVID-19. A sample survey questionnaire accomplished by one of the experts is shown in Table 4. The experts elicited judgments on the relationship between social media roles using a linguistic scale (see Table 3). For instance, in Table 4, SMR1 (Promotes public participation against COVID-19) is believed to have a very high influence on SMR8 (Rapid information dissemination) as represented by a rating of 4 in the cell highlighted with an asterisk (*). For brevity, this paper presents the rest of the matrices obtained using the FDANP in their short form. For computational tractability, the experts’ detailed responses along with the matrices of the FDANP can be accessed as datasets in Selerio et al. [120]. Following the procedure of FDANP, the ratings given by each expert in evaluating the relational impact among social media roles are converted into their fuzzy equivalents. The conversion of the ratings into their corresponding TFNs was performed to develop the matrix $\tilde{Z}_k$ using Equation (17). The diagonals of such matrix $\tilde{Z}_k$ are zero indicating that there is no influence between the same social media role. The individual

![Fig. 2. The cause-effect network map of social media roles.](image-url)

Step 9 Determine the priority weights of social media roles using the ANP supermatrix approach.
ratings of the experts were then aggregated using Equation (18) to construct the aggregate matrix $Z$.

Following the classification of social media roles under DEMATEL, the following are classified under the causal cluster (dispatchers): SMR1 (Promotes public participation against COVID-19), SMR2 (Links multidisciplinary teams of experts worldwide), SMR3 (Provides virtual alternatives to physical activities), SMR4 (Facilitates the development of public health policies), SMR6 (Facilitates COVID-19 research), SMR7 (Repository for social health data), and SMR8 (Rapid information dissemination). On the other hand, the following social media roles are classified under the effect cluster (receivers): SMR5 (Facilitates robust public health response), SMR9 (Facilitates the prevention of misinformation), SMR10 (Tool for delivery of public education), SMR11 (Expedites risk communication), SMR12 (Influences public behavior and response), SMR13 (Facilitates telemedicine), SMR14 (Allows for remote monitoring of COVID-19 patients), SMR15 (Real-time disease surveillance), and SMR16 (Facilitates digital contact tracing).

The influential relations among social media roles can be visually depicted in Fig. 2. This map is generated by plotting the data set of $(D + R, D − R)$. An arrow pointing from one vertex to another denotes a significant causal relation or influence. For instance, SMR4 (Facilitates the development of public health policies) can prompt the development of social media technologies for storing social health data (SMR7) and real-time communication of risk (SMR11), the establishment of committees for the utilization of social media in disseminating information about the pandemic (SMR8), development of procedures for safer contact tracing using SM (SMR16), among others; making the four social media roles among the receivers of the influence of SMR4 (Facilitates the development of public health policies). Although SMR4 (Facilitates development of public health policies), SMR7 (Repository for social health data), and SMR8 (Rapid information dissemination) are classified as dispatchers, they can also influence each other which, in part, contributes to the complexity of interrelationships in the system. A clear demonstration of these relationships is observed in the Philippines. For example, the massive flow of data in social media platforms during lockdown prompted the local government of Cebu – one of the major provinces in the country – to develop a software application that employs social media functionalities (e.g., messaging, posting, location tracking) for digital tracing and real-time risk communication on COVID-19. The application is called WeTrace [121]. WeTrace is a locally developed social media platform for COVID-19 emergency response, which was then used in employing travel restriction policies (e.g., work travel pass). Data obtained from WeTrace allows for targeted lockdown policies, which made an emergency response in the province more efficient. In the same way, the WeTrace application has been essential in preventing misinformation (SMR9) because it only allows information from reliable sources (e.g., Department of Health).

Based on the $(D + R)$ values, the following SMRs are ordered in descending importance: SMR4 (Facilitates development of public health policies) > SMR8 (Rapid information dissemination) > SMR1 (Promotes public participation against COVID-19) > SMR6 (Facilitates COVID-19 research) > SMR2 (Links multidisciplinary teams of experts worldwide) > SMR12 (Influences public behavior and response) > SMR3 (Provides virtual alternatives to physical activities) > SMR5 (Facilitates robust public health response) > SMR10 (Tool for delivery of public education) > SMR11 (Expedites risk communication) > SMR15 (Real-time disease surveillance) > SMR9 (Facilitates the prevention of misinformation) > SMR16 (Facilitates digital contact tracing) > SMR13 (Facilitates telemedicine) > SMR14 (Allows for remote monitoring of COVID-19 patients) > SMR7 (Repository for social health data).

SMR4 (Facilitates development of public health policies), having the highest importance, has been justified in previous discussions. On the other hand, SMR8 (Rapid information dissemination), having the second-highest importance, can be clearly observed in the Philippines. For example, the Department of Health used several social media platforms (e.g., Facebook, Twitter, and Youtube) for strategic health emergency communication. These platforms play a vital role to timely inform and effectively manage the information needs of the people. Social media has a useful feature for spreading information. Public health authorities widely employ this feature in the Philippines in utilizing social media to properly communicate risk (SMR11) to the public. It also helps alleviate the composure of people (SMR12) by gaining more knowledge regarding COVID-19 (i.e., SMR10). Furthermore, SMR1 (Promotes public participation against COVID-19), having the third-highest importance, has been instrumental in adopting government policies. For instance, in implementing online learning protocols by the Department of Education, advertisements are proliferated in social media (e.g., Facebook) to promote online learning to increase the adoption of such policy (SMR12). Social media also engages individuals (SMR1) and serves as a platform for discussions on the measures implemented by the government in response to COVID-19. For instance, the mandatory implementation of back-riding shields by the Inter-Agency Task Force for the Management of Emerging Infectious Diseases (IATF-EID) received criticisms on various social media platforms prompting the agency to revise the policy (SMR4). Finally, the findings of the FDANP supermatrix are presented as grounds for policy insights.

Although social media poses an important role in spreading awareness regarding COVID-19 to the general public, there is also a need for caution on the drawbacks of its usage that might ruin its effectiveness. For example, SMR4 (Facilitates development of public health policies) emphasizes the timeliness of delivering health policies across the public. Health policies issued to the public might only be taken lightly because the general public perceived it as unimportant, or the person imposing the policies is someone the people do not view as an authoritative figure. Furthermore, SMR8 (Rapid information dissemination) pertains to the massive flow of information across the country. There are cases that the quality of information disseminated is not validated. Accounts with high influence counts might be treated as a more reliable source of information by the public instead of those accounts owned by the government or those people credible to hold reliable information. Threats of spreading erroneous information might arise since anyone can access social media. Despite the aforementioned issues acknowledged, it has been highlighted within the study how social media can be an effective medium to spread awareness regarding COVID-19. There is just a need to be cautious about what can be found and spread within social media while focusing on the numerous quality information easily accessed.

5.2. Sensitivity analysis

In the current fuzzy MCDM literature, where judgments are expressed in TFNs, there is no consensus on the choice of linguistic variables and their corresponding TFNs. To test the robustness of the results of this work, the FDANP methodology is solved for all equivalent TFNs in Table 3. Three highly cited studies that employ different equivalent TFNs for a TFN-based FDEMATEL are selected for this analysis. The priority weights for each SMR given the three different scales are summarized in Fig. 3. The baseline results of this work (i.e., the Tables and Figures presented previously) employ the equivalent TFNs adopted by Tseng [111]. From the sensitivity analysis, it is apparent that the results of this work are robust with the choice of the equivalent TFNs, as evidenced by the minor changes in the priority weights of social media roles.

6. Policy insights

While the utility of social media has been collectively recognized in previous literature, it may vary depending on the conditions that social media is being applied. For instance, YouTube may be an outstanding platform in terms of its utility for streaming videos, which can be exploited for educational purposes, but it is not as efficient in propagating news as other social media platforms such as Twitter and Facebook. Thus, the utility of social media platforms varies with the need of
the event that they can be utilized. In disasters like the COVID-19 pandemic, optimizing that utility is critical in the strategies employed to mitigate, contain, and suppress the virus spread. The findings of this study may be used to address such a goal. The priority weights of the social media roles can be employed to select appropriate social media platforms that maximize the deployment of priority roles during pandemics.

It is apparent that different social media platforms have varying capabilities to support the roles identified in this study. Thus, it follows that there are social media platforms that are best fit for use to maximize the deployment of priority roles. For instance, the top role (first priority) determined in this study is SMR4 (Facilitates the development of public health policies). It is apparent that expert views are essential in public health policy development. However, limited resources and various complexities arising from political and financial instabilities limit the capabilities of epidemiologists and public health experts in developing countries to participate in science-driven policy development effectively. Mainstream social media platforms like Facebook and Twitter offer limited help in deploying this role. However, ResearchGate – a social media predominantly used by scholars, scientists, and researchers – can be used to this end. In fact, several results support the utility of ResearchGate in obtaining high-quality COVID-19-related public policy insights from experts worldwide [80, 81]. Specifically, Sanusi et al. [80] obtained several success factors of online teaching during the COVID-19 semester and the best assessment strategies used during the pandemic through discussions and responses from questions posted on ResearchGate.

Furthermore, the second priority role determined in this study is SMR9 (Facilitates the prevention of misinformation). It is widely known that several social media platforms like Twitter are notorious for spreading fake news [122]. Such platforms would thus have minimal utility in preventing misinformation because they are easily saturated with false information, which, on the users’ end, makes it difficult to distinguish accurate from inaccurate information. This difficulty is facilitated by the design of these platforms, which allow the effortless capability of users to share inaccurate information (e.g., via “retweet”). On the other hand, several studies have empirically shown that YouTube videos, unlike content on other mainstream platforms, present more credible information [123]. Doganer and Zhang [123] emphasized that YouTube videos presenting symptoms, diagnosis, and treatment of COVID-19 and those with scientific content “have the most reliable source of information on Coronavirus” [123]. Moreover, YouTube.com is the most visited social media website worldwide [124]. Thus, the deployment of SMR9 can be best facilitated using YouTube compared to other social media platforms.

These insights are of great significance to developing countries like the Philippines. With limited financial resources to address the needs of people during a pandemic, the optimal utilization of social media may be leveraged by the government for efficient resource use. The interrelationships of social media roles identified in this work can inform the design of a more detailed strategy that employs social media platforms in emergency preparedness during pandemics. As a preliminary proposal based on these findings, this study suggests the utilization of ResearchGate and similar social media platforms (e.g., Academia) to buffer the need for expert insights in developing public health policies if the population of endogenous experts is lacking in a particular region. This can be employed in the Philippines by creating social media research teams devoted to this purpose. Furthermore, this study suggests using YouTube and similar social media platforms (e.g., TikTok) to spread video infomercials and other multimedia paraphernalia to fight misinformation about the pandemic. This can be employed in the Philippines by institutionalizing tax discounts to YouTube “influencers” who post effective content to help fight pandemic misinformation. These suggestions are targeted at first- and second-ranked SMRs, i.e., SMR4 and SMR9.

7. Conclusion and future works

Very few attempts have been made in recent literature to exhaustively identify the roles of social media in emergency preparedness during extreme disruptive events such as the COVID-19 pandemic, as well as an in-depth analysis of their interdependencies and priority measures. With a comprehensive literature search on these social media roles and the application of the FDANP approach, this work offers insights on the crucial relationships of these roles and identifies their priorities that policy- and decision-makers must consider in leveraging social media platforms towards emergency preparedness efforts during public health disruptions, such as epidemics and pandemics. A case study in the Philippines was carried out to demonstrate such a methodological approach and provide policy and managerial insights on social media roles. First, a total of 16 social media roles were identified from the literature search. Second, the application of the FDEMATEL revealed that the majority of the social media roles are identified as receivers. In fact, most of them are consequent to SMR1 (Promotes public participation against COVID-19), SMR2 (Links multidisciplinary teams of experts worldwide), SMR3 (Provides virtual alternatives to physical activities), SMR4 (Facilitates the development of public health policies), SMR6 (Facilitates COVID-19 research), SMR7 (Repository for social health data), and SMR8 (Rapid information dissemination), which are classified as dispatchers. Further analysis with the ANP allows the measurement of the systemic impact of social media roles on emergency preparedness actions. The priority weights reveal that the top two roles are SMR4 (facilitates the development of public health policies) and SMR9 (facilitates the prevention of misinformation). The findings of this work contribute to
the literature in providing insights that would advance the current understanding of social media roles in emergency preparedness during the COVID-19 pandemic.

This work contains limitations that could be grounds for future work. The findings of this work are dependent on expert judgments, which require some empirical validation. Thus, as a follow-up study, the post-evaluation of strategies derived from the findings of this work could be a departure point of inquiry. Furthermore, due to the study being performed in a specific case, the findings, to some extent, would be subject to its conditions (e.g., cultural, social, and bureaucratic factors). For future works, empirical approaches such as statistical modeling to confirm the structural relationships found in this paper may be conducted as future work. Moreover, while the FDANP accounts for both direct and indirect influences of SMRs to one another in assigning priorities, it is incapable of providing useful insights as to the rationale behind the priority assignments. However, this concern may be addressed by decomposing the DEMATEL graph into subgraphs where a critical ‘node’ can be determined for each subgraph along with its input-output influence flows. These flows can then be used to map the relationships leading to the priority assignment for each node. This process can potentially increase the interpretability of the FDANP results by determining the contribution of specific nodes on the priority assignment of the nodes of concern. Future works may investigate how such a graph decomposition method may be implemented in the context of the FDANP.

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Supplementary Material

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