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Toward More Effective Public Health Interventions during the COVID-19 Pandemic: Suggesting Audience Segmentation Based on Social and Media Resources

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ABSTRACT

In response to the COVID-19 pandemic, public health communication campaigns have been targeted at reducing viral transmission, specifically among populations most vulnerable to infection and death from the virus (e.g. older adults). However, other individuals who have not been defined as vulnerable populations may also suffer from a decrease in health because of the measures aimed at reducing viral transmission, such as social distancing. To illuminate this issue, we investigate the role of social and media resources in complementing limited offline communication and supporting mental and physical health during this pandemic. We then suggest an alternative audience segmentation strategy based on social and media resources for public health interventions. Based on online survey data from 723 adults in South Korea, the regression analysis results indicated that individuals with lower levels of social resources suffered more during the pandemic. The cluster analysis results revealed that, contrary to the traditional definition of vulnerable populations, a cluster of younger people were unhealthier than a cluster of older people because of a lack of social resources. Clusters with different levels of ICT skills and uses for health-related activities also experienced the pandemic differently. These findings imply public health interventions should focus on social resources beyond the demographic factors to determine target audiences, and that they should take advantage of the target audiences' media resources to encourage them to forge intimate connections with others and to engage in health-related activities.

In response to the global COVID-19 pandemic, public health communication campaigns have been targeted at reducing viral transmission by social distancing, handwashing, mask-wearing, and disinfecting. This public health intervention has generally identified older adults and racial/ethnic minorities as populations more vulnerable to infection and death from the virus (Centers for Disease Control and Prevention, 2020).

However, as the pandemic continues longer than expected, other individuals who have not been defined as "vulnerable populations" suffer from a decrease in physical and mental health because of the measures aimed at reducing viral transmission. The loss of health care, exercise opportunities, social connection, and cultural experiences take a toll. Thus, the most effective public health intervention requires a more comprehensive understanding of who the pandemic affects deeply and what factors – beyond the demographic factors, previous interventions have identified – cause them physical and mental suffering.

Communication scholarship has a long tradition of investigating the role of social resources in enhancing individual health and the role of media resources in complementing offline communication (Rainie & Wellman, 2012). Following this tradition, we examine whether and how differences in social and media resource transfer to inequalities in mental and physical health during a pandemic and how audiences of the public health intervention are segmented based on such differences.

Differences in social networks, social support, and health

Previous research described social networks and social support as two important aspects of social resources (Smith & Christakis, 2008). Social networks represent the structural aspects of social resources; network properties of individuals' social networks (e.g., the size and density) structure individuals' relational positions and determine the available social resources they can access from those positions (Borgatti et al., 1998). Social support represents individuals' functional and qualitative aspects of social resources (Cohen, 2004). Individuals may receive or exchange different types of social resources such as informational or emotional support.

Most studies of the effects of social resources on health have addressed the close link between social networks and social support (Smith & Christakis, 2008). They explained that the ego's social networks construct the accessibility to different types of social support for individual health, suggesting the indirect link from social networks (e.g. ego's density and homophily, Lee et al., 2018; size and the strength of their ties, Zhu et al., 2013) to individual health via social support.

Social networks may also play direct, important roles in individual health. Network structures create the basis of social interaction and social integration, and directly affect the feeling of belonging and stability (Lin, 1999). Individuals also gain a sense of social identity through their networks and increase their ability to cope with health problems (Cohen, 2004). These

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studies suggest that both social networks and social support have different and profound influences on individual health during a pandemic. Specifically, the pandemic has changed both aspects of social resources (e.g. the strength of offline networks or necessary support when quarantined). Therefore, we examine how both aspects of social resources are related to individuals' mental and physical health, leading to individual segmentation based on social resources during the pandemic.

Structural factors of social networks and individual health

Previous research has revealed varied structural factors of social networks that may affect individual health. First, *density* has been an important attribute of social networks for individual health. Density refers to "the extensiveness or completeness" of the relationships among actors in the network (Monge & Contractor, 2003, p. 44). Denser networks have higher connectedness and a greater number of shared resources among actors (Lin, 1999), which may contribute to the flow of information (e.g. nearest hospital or the symptoms of COVID-19) and supplies (e.g. masks and food) necessary to stay healthy and safe during the pandemic. Participants in dense networks are also more likely to feel trust, group cohesion, or community belonging (Borgatti et al., 1998), which increases mental health (Lee et al., 2018). Therefore, we hypothesize:

H1: Network density is positively related to the ego's a) cognitive well-being, b) affective well-being, and c) physical health during a pandemic.

Second, *the strength of ties* between the ego and alters may influence the ego's health. Previous research suggests that strong ties are more motivated and easily available to help the ego than weak ties (Granovetter, 1983), specifically in an emotional way, because they "constitute a base of trust" and "provide comfort in the face of uncertainty" (Krackhardt, 1992, p. 218). Previous studies correspondingly have found that strong ties provide emotional support to the ego, which increased their use of more positive language (Chen et al., 2020) and their psychological well-being (Burke, 2011). Specifically, during a pandemic, individuals may depend more on strong ties with the emotional intensity to receive emotional support (e.g. trust and comfort, Granovetter, 1983), because individuals generally choose to interact with strong ties based on emotional intensity when they want to share personal thoughts and emotions (Ihm & Kim, 2018). Therefore, we focus on the feeling of closeness in tie strength and hypothesize:

H2: The strength of ties (i.e. feeling of closeness) is positively related to the ego's a) cognitive well-being, b) affective well-being, and c) physical health during a pandemic.

Additionally, change in the strength of ties in individuals' networks during a pandemic may influence individual health. Individuals change the number and the strength of ties as an evolutionary strategy to adapt to different situations (Monge & Contractor, 2003). Such changes in ties may become more evident during a crisis. For instance, Doerfel et al. (2010) explained that after Hurricane Katrina, individuals connected to new ties or took advantage of preexisting ties to seek resources and comfort. The change in the number and strength of ties plays important roles in facilitating the recovery and stabilizing of their situations. In the same way, during a pandemic, if a greater number of an ego's ties become stronger, the ego benefits more from those strong ties. Therefore, we hypothesize:

H2-1: The number of ties that become stronger during a pandemic is positively related to the ego's a) cognitive well-being, b) affective well-being, and c) physical health.

Communication multiplexity may also affect individual health during a pandemic. In this paper, multiplexity refers to the extent to which the ego is linked to the alter by communicating with multiple channels (Monge & Contractor, 2003). Previous research has found that communication multiplexity increases intimacy between actors and enhances individual health by diversifying access to necessary resources (Lee et al., 2018). On the other hand, a low level of communication multiplexity may restrict alternative channels for relationship maintenance and emotional stability, which is especially important during a pandemic as it prevents face-to-face interactions. Therefore, we hypothesize:

H3: Communication multiplexity is positively related to the ego's (a) cognitive well-being, (b) affective well-being, and (c) physical health during a pandemic.

Different functions and content of social support in individual health

Social support refers to the provision or exchange of emotional, or informational resources from social relationships to promote mental and physical health (Cohen, 2004). Previous studies have suggested that different functions of social support have mixed roles in individual health. For instance, Cheng et al. (2018) revealed that emotional support increased international students' sociocultural adjustment to their new environment, while informational support contributed to their psychological adjustment. On the contrary, Meng et al. (2019) found that the emotional support provided by communicating sympathy to cancer patients led to better psychological well-being, whereas informational support such as providing information about how to appraise and cope with the problem negatively influenced their psychological well-being; receiving unwanted advice and overwhelming information threatened patients' sense of autonomy and increased their anxiety. The mixed roles of emotional and informational support addressed in the previous research suggest the need for more investigation on how each function may influence individual health during a pandemic.

Further, these studies on functions of social support have focused primarily on the social support that individuals *receive* from others, but the concept of social support includes the "exchange of" resources (Cohen, 2004). Prior research has suggested that *providing* support to others positively influences life satisfaction and decreases depression and mortality, because the activity induces feelings of self-efficacy, autonomy in life, and a sense of belonging to society (Kwok et al., 2013). Together, previous research suggests that those who are embedded in (receiving and providing) support networks may take advantage of the different functions of social resources, while those who lack such networks may suffer more. Therefore, we investigate how different types of social support influence individual health during a pandemic:

RQ1: How are receiving and providing informational and emotional support related to individual health during a pandemic?

In addition to the functions of social support, we classify social support into two types based on previous studies. First, we focus on the distinction between online and offline support. Online and offline environments are deeply connected to each other (Rainie & Wellman, 2012), but more research is necessary to examine the different roles of offline and online support when offline communication is limited during a pandemic (e.g. whether online support becomes more important during a pandemic as it substitutes offline support). Indeed, previous research has suggested different, yet inconsistent roles of online and offline networks in individual health (Cohen, 2004). For instance, Lee et al. (2018) found that offline social networks were more influential than online networks on life satisfaction, because online interactions do not transfer to offline worlds. Meng et al. (2019), on the other hand, explained that offline support consisting of "reassurance ('everything will be fine') and empathy ('I know how you feel')" (p. 7) may backfire and negatively affect cancer patients' emotional health; online support provided by other patients may be perceived as genuine and positively influence the emotional health. Considering the mixed findings, we ask:

RQ2: How are offline and online support related to individual health during a pandemic?

Second, we focus on the distinction between family ties and nonfamily ties. Previous research has shown mixed findings on the role of family support in individual health. For instance, family-focused ties may decrease the quality and diversity of support (Fiori et al., 2006). However, family ties also represent strong ties, which provide emotional support to survive a time of crisis (Krackhardt, 1992). The role of family ties may transform during a pandemic, because individuals are limited in their face-to-face communication with colleagues or classmates, while they may communicate more with their families (e.g. grandparents) to ask about their health and exchange necessary help with them. Considering the mixed findings in previous studies and the possibility of a changed role of family ties in a pandemic, we ask:

RQ3: How are family ties related to individual health during a pandemic?

Differences in media resources and individual health

The recent pandemic has led us to rethink how media resources influence individual health differently than at other times and whether and how they complement the social support from personal networks and limited offline interactions in this period. Research on the digital divide suggests that media resources are not only the available ICTs individuals have (access to), but also the fluency and diversity in using ICTs (Hargittai, 2002). Researchers explained that the disparities in how they use ICTs are more critical than their access to ICTs in determining what individuals can do and how they can enjoy their lives, referred to as the "second-level digital divide" (Hargittai, 2002).

Developing the theoretical discussion on the second-level digital divide, researchers identified a "third-level digital divide" among individuals and demonstrated that individuals' different skills in using ICTs extend to differences in outcomes and benefits from using ICTs (Selwyn, 2004; Van Deursen & Helsper, 2015). For instance, Selwyn (2004) paid attention to five types of activities (i.e. production, political, social, consumption, savings) for which individuals use ICTs in their own ways for social inclusion. He explained that these activities reflect how ICTs may "enable individuals to participate and be part of society" (p. 351) and how there is an inequality in which individuals can benefit from ICTs to become embedded in their society and enrich their lives. Van Deursen and Helsper (2015) also emphasized that ICT skills are closely connected to how individuals use ICTs for economic, social, political, educational, and health outcomes.

In line with these studies, many studies found that those who were more skilled with using ICTs used them more to perform health-related behaviors (e.g. seeking health information and participating in wellness programs online) and had better health literacy (Dobransky & Hargittai, 2012; Levy et al., 2015). These studies suggest that individuals with high ICT skills may take advantage of media resources for health purposes and stay healthy during a pandemic. Thus, we hypothesize:

H4: Individuals' ICT skills are positively related to their (a) cognitive well-being, (b) affective well-being, and (c) physical health during a pandemic.

Prior research has suggested the importance of ICT skills in performing diverse online activities, but less is known about how each activity (e.g. production, political, and social) affects individual health. How individuals take advantage of ICTs for varied purposes other than health-related ones may determine whether they enjoy their lives to a similar extent as they did before the pandemic or whether they become mentally and physically ill. Thus, we ask:

RQ4: How are different types of online activities related to individual health during a pandemic?

So far, this paper explained factors that may be related to disparities in individual health during a pandemic. These factors provide new insights to public health interventions in terms of audience segmentation. Prior research in public health interventions has focused on demographic factors in audience segmentation, because audience segmentation has been regarded as an effective and politically legitimate way to redress health inequalities which are typically between different races, ethnicities, or genders (Hornik & Ramirez, 2006). However, the current study suggests that individuals with different levels of social and media resources, instead of demographic factors, may experience the pandemic in different ways. Therefore, we ask:

RQ5: How are individuals with different levels of social and media resources segmented into different groups during a pandemic?

Methods

Sample and procedure

The sample for this study was obtained from general online panel data available from Embrain, an online survey company in South Korea (www.embrain.com, see Appendix A for details). The country's social distancing policy (i.e. no gatherings or events allowed) was active from March 22 to May 5, 2020, during the most severe period of the spread of COVID-19 in the country. Right after the Korean government eased the policy to a daily distancing policy (i.e. allowing gatherings and events so long as they followed disinfection, distancing of at least 6 feet, and frequent handwashing guidelines) on May 6th, we asked 723 Korean adults (see Appendix B for demographics) about their health status, and social and media resources "over the last month when the social distancing policy was active."

Measures

Social resources

To measure each participant's social networks (see Appendix E for descriptives and correlations of main variables), we adjusted the standard name generator question and name interpreter items from previous research to apply to the context of COVID-19 (Marsden & Campbell, 1984): "From time to time, most people discuss important personal matters with other people. Who are the people with whom you discussed important personal matters *over the last month since the COVID-19 outbreak*? Just tell us the first names or initials of up to six people." We then asked name interpreter items to measure the attributes of their networks.

We measured the strength of ties by measuring *the feeling of closeness* between the ego and the alter. We used five previous measures of 5-point Likert scales (e.g. "we have a close relationship" and "I feel close to this person," α = .90; Ihm & Kim, 2018) and summed the values of every alter. For *communication multiplexity*, we first asked participants the number of times they communicated with each alter over the last month by using four types of channels (i.e., face-to-face, cell/phone, e-mail, and social media, Lee et al., 2018). We summed the number of channels used at least once a month for all alters.

Network density was measured by a question adapted from previous research (Lee et al., 2018): "Think about the relationship between (Person 1) and (Person 2). Would you say that they are strangers (1), just friends (2), or especially close (3)? Please choose the number that best describes the relationship between the pairs." We calculated the proportion of existing ties who are "especially close" out of all possible connections among pairs of alters.

For *a change in the strength of ties*, we created four categories of change in relationships during crisis based on previous research (Doerfel et al., 2010) and asked participants to choose among four categories that best described the relationship change for each person they named in the previous name generator question (1: formed a new relationship over the last month, 2: communicated more often or became closer, 3: communicated less often or became less close, 4: no change). We calculated the number of people for the first three categories out of total alters.

For *social support*, participants chose every type of social support (i.e. informational and emotional; Meng et al., 2019) they *received* and *gave over the last month* for each person in participants' networks. We counted the number of people participants indicated for the two types of social support they received and gave, respectively. We measured the *family support* by counting the number of family or relatives that participants indicated out of their total ties. We also measured the *offline support* by counting the number of alters they communicated with face-to-face at least once a month out of total alters.

Media resources

For *ICT skills*, we used the averaged values of 5-point Likert scales consisting of 23 items from previous research (1: not at all true of me, 5: very true of me; Van Deursen et al., 2016, α = .90) which measured operational, information navigation, social, and mobile skills. For *online activity*, we asked participants' degree of engagement (1: not at all, 5: always) in six activities addressed in previous research (i.e. production, political, social, consumption, savings, health; Selwyn, 2004; Yu et al., 2016).

Mental and physical health during the pandemic

We examined both mental and physical health during a pandemic. For mental health, we used previous measures on affective and cognitive dimensions of subjective well-being (Diener, 2009). For the affective dimension, we measured and averaged the 12 items from the 5-point Likert scales about participants' experience of positive and negative feelings over the past month (1: not at all, 5: always, α = .91). For the cognitive dimension, we measured and averaged the five items from the 7-point Likert scales about participants' satisfaction with their lives (1: not at all true, 7: very true, α = .92). For physical health, we used the measure of self-rated health based on a 5-point Likert scale (1: not at all healthy, 5: very healthy).

Analysis

First, we conducted three Ordinary Least Squares regression analyses to examine how social and media resources, in addition to demographic variables, are related to individual health during a pandemic. Each regression model examined the influence of social and media resources on mental and physical health when demographic variables were controlled.

Second, based on the regression results, we conducted a cluster analysis on social and media resource variables that showed significant correlations to individual health and investigated how individuals are segmented into different groups during a pandemic. We applied a Ward clustering approach with the squared Euclidean distance measure using the hclust package in R (R Core Team, 2018) and identified three clusters of individuals based on their social and media resources (see Appendix C for full procedures). We additionally conducted a one-way analysis of variance (ANOVA) and the Tukey post-hoc test to examine whether demographic factors differed among clusters.

Results

Regression on Social Resources and Differences in Individual Health (see Table 1)

The results suggest how individuals' social networks are related to individual health. Network density (H1) was positively related to cognitive well-being ($\beta = .09$, $p < .05$), but not to effective well-being or physical health. Thus, H1 was partially supported. Regarding the strength of ties (H2), feeling of closeness was *positively* related to all health variables (affective: $\beta = .25$, $p < .001$; cognitive: $\beta = .25$, $p < .001$; physical: $\beta = .15$, $p < .05$). Therefore, H2 was supported. In terms of the change in relationships (H2-1), ties that became weaker were negatively related to affective well-being ($\beta = -.08$, $p < .05$); ties that became stronger were positively related to cognitive well-being ($\beta = .18$, $p < .01$). Therefore, H2-1 was partially supported. Communication multiplexity (H3) was positively related to cognitive well-being ($\beta = .11$, $p < .05$).

The results also suggest how individuals' social support is related to individual health. Regarding the functional type of social support (RQ1), receiving informational support was positively related to affective well-being ($\beta = .12$, $p < .05$). Offline (RQ2: $\beta = -.12$, $p < .05$) and family support (RQ3: $\beta = -.08$, $p < .05$) were *negatively* related to physical health.

Regression on media resources and differences in individual health

The results suggest the role of ICT skills and activities in individual health. ICT skills were positively related to affective well-being ($\beta = .16$, $p < .001$) and physical health ($\beta = .15$, $p < .01$), but not to cognitive well-being. Therefore, H4 was partially supported. Regarding different types of online activities (RQ4), doing consumption activities online was *negatively* related to cognitive well-being ($\beta = -.11$, $p < .05$) and physical health ($\beta = -.11$, $p < .05$). Doing health activities online was positively related to cognitive well-being ($\beta = .13$, $p < .01$) and physical health ($\beta = .10$, $p < .05$).

Clusters of Individuals During the Pandemic (see Table 2 for details)

Cluster 1: Unhealthy, unhappy individuals with poor networks and good ICT skills

The cluster analysis results suggest three types of individuals who experience the pandemic in different ways because of their social and media resources. Cluster 1 consists of individuals whose levels of mental and physical health were the lowest ($n = 166$, 23%). Their level of social resources was the lowest in every aspect, while their ICT skills were higher than Cluster 3. They used ICTs for consumption more and for health-related activities less than Clusters 2 and 3.

Cluster 2: Individuals with mid-level resources and health

Cluster 2 consists of individuals whose characteristics are at the middle level in many aspects ($n = 305$, 42%). Their mental health was at the middle level. Their physical health was lower than Cluster 3. Their social resources were mostly at the middle level as well. Their ICT skills were higher than Cluster 3 and their ICT uses for health-related activities were at the middle level.

Table 1. Relationships of social and media resources with mental and physical health.

		Mental Health					
		Affective Well-Being		Cognitive Well-Being		Physical Health	
		β	*(SE)*	β	*(SE)*	β	*(SE)*
Gender		.01	(.59)	.02	(.09)	.05	(.06)
Age		.28**	(.27)	.08	(.04)	.10*	(.03)
Education		.05	(.30)	.11**	(.05)	.02	(.03)
Income		.11**	(.16)	.19**	(.02)	.09*	(.02)
Employment		−.11*	(.66)	−.11**	(.10)	−.05	(.07)
Marital		−.01	(.76)	.10*	(.12)	.003	(.08)
Density		.01	(.87)	.09*	(.14)	.04	(.09)
Tie Strength	(Closeness)	.25***	(.02)	.25***	(.00)	.15*	(.00)
Tie Change	(New)	.04	(.73)	−.01	(.29)	.03	(.20)
	(Stronger)	.09	(.56)	.18**	(.15)	.01	(.10)
	(Weaker)	−.08*	(.81)	−.06	(.15)	.01	(.10)
Multiplexity		−.02	(.09)	.11*	(.01)	−.06	(.01)
Receiving Info. Support		.12*	(.86)	.02	(.13)	.04	(.09)
Receiving Emotion. Support		−.05	(.95)	−.01	(.15)	.03	(.10)
Giving Info. Support		−.05	(.84)	−.05	(.13)	−.04	(.09)
Giving Emotion. Support		−.06	(.85)	−.01	(.13)	.02	(.09)
Offline Support		−.05	(.53)	−.002	(.19)	−.12*	(.13)
Family Support		−.03	(.98)	−.08	(.15)	−.08*	(.10)
ICT Skills		.16***	(.53)	.07	(.08)	.15**	(.06)
ICT Uses	(Production)	.02	(.25)	.05	(.04)	.00	(.03)
	(Political)	.04	(.32)	.05	(.05)	.09	(.03)
	(Social)	.07	(.32)	.05	(.05)	.04	(.03)
	(Consumption)	−.05	(.35)	−.11*	(.05)	−.11*	(.04)
	(Savings)	−.03	(.31)	.01	(.05)	−.06	(.03)
	(Health)	.02	(.31)	.13**	(.05)	.10*	(.03)
N		723		723		723	
R^2		.17		.18		.13	
F		5.69**		6.03**		4.10**	

*p <.05, **p <.01, ***p <.001.

Table 2. Descriptive statistics of three clusters.

Cluster Type		1		2		3		*F-value*
Mental Health	(Affective)	3.00	(2, 3)	3.23	(1, 3)	3.52	(1, 2)	34.63***
	(Cognitive)	3.12	(2, 3)	3.41	(1, 3)	3.92	(1, 2)	23.12***
Physical Health		3.02	(3)	3.13	(3)	3.31	(1, 2)	6.53**
Gender		1.56		1.50		1.49		1.09
Age		45.42	(3)	45.28	(3)	47.15	(1, 2)	3.07*
Education		5.50		5.51		5.68		2.38
Income		4.60	(3)	4.61	(3)	5.40	(1, 2)	15.25**
Employment		0.64		0.71		0.68		1.46
Marital		0.63		0.64		0.67		0.57
Density		0.40	(3)	0.37	(3)	0.48	(1, 2)	6.60**
Tie Strength	(Closeness)	25.78	(2, 3)	52.37	(1, 3)	72.98	(1, 2)	1910.45***
Tie Change	(New)	0.03		0.08		0.03		1.62
	(Stronger)	0.07	(3)	0.14	(3)	0.15	(1, 2)	3.62*
	(Weaker)	0.06	(1)	0.03	(2)	0.06		3.48*
Multiplexity		5.70	(2, 3)	11.29	(1, 3)	15.26	(1, 2)	321.68***
Receiving Info. Support		1.02	(2, 3)	2.37	(1, 3)	3.34	(1, 2)	80.02***
Offline Support		0.49	(3)	0.51	(3)	0.42	(1, 2)	8.14***
Family Support		0.45		0.39		0.42		1.84
ICT Skills		3.98	(3)	3.95	(3)	3.65	(1, 2)	6.47**
ICT Uses	(Consumption)	3.54	(2, 3)	3.28	(1)	3.21	(1)	9.04***
	(Health)	2.32	(2, 3)	2.66	(1, 3)	2.92	(1, 2)	15.99***
N		166		305		252		

The numbers in parentheses show the cluster number from which this cluster was significantly different at the 0.05 level, based on Tukey post-hoc test.
* *p* <.05; ** *p* <.01; *** *p* <.001.

Cluster 3: Healthy, digitally less savvy individuals with rich networks

Cluster 3 consists of individuals who were mentally and physically healthier than other clusters (n = 252, 35%). Their level of social resources was the highest in many aspects. Their levels of ICT skills and ICT uses for consumption were low, but their level of ICT use for health was the highest.

Regarding demographic variables, the additional ANOVA results suggest that there were significant age and income differences between Cluster 3 with Cluster 1 and Cluster 2.

Discussion and conclusion

We examined how social and media resources are related to individual health during the COVID-19 pandemic. Although public health interventions usually use demographic factors to determine target audiences, the results suggest social and media resources are defining variables for audience segmentation.

Regression on disparities in individual health

The regression results suggest that structural aspects of social resources are related to how individuals experience the pandemic. Those who had denser networks and communicated with more diverse channels were mentally healthier (H1, H3). Corresponding with previous studies (Borgatti et al., 1998; Lee et al., 2018; Lin, 1999), well-connected networks and varied channels to connect to them seem to enrich the ego's life and provide feelings of satisfaction and belonging, specifically during a pandemic. The shared resources and information in the networks seem to contribute more to the ego's mental health than physical health, because such resources and information cannot directly substitute the exercise opportunities in fitness clubs or health services from hospitals.

Regarding the strength of ties, the feeling of closeness was positively related to individual health (H2). Strong ties based on the feeling of closeness seem to provide urgent support and psychological stability during a pandemic (Burke, 2011; Chen et al., 2020) and enhance every aspect of individual health. Change in the strength of ties also influenced mental health (H2-1). Those who had a greater number of ties that became stronger were mentally healthier. The pandemic changed how people interact with their networks, so they (must) adjust to this situation by activating and changing the strength of ties (Doerfel et al., 2010). Individuals who experience the decrease in the strength or the number of ties may represent no active adjustment to the situation or being overwhelmed by the situation, consequently decreasing health status. However, these individuals may have already lacked social resources that they could activate at the time of crisis. A greater number of stronger ties may denote autonomous adjustment to the situation as well as the prepared social resources that can be activated whenever necessary. The results reemphasize that different levels of prepared social resources may segment individuals during a crisis by differentiating their tie adjustment level and consequently their mental health.

Second, social support was closely related to individual health during the pandemic, but its role was not as influential as social networks (RQ1). This result differs from many previous studies (Cheng et al., 2018; Meng et al., 2019). While informational and emotional support are salient dimensions of social support discussed in the previous research, other types of support (i.e. network or esteem support, Meng et al., 2019) may have more interesting associations with individual health during the pandemic.

Additionally, the proportion of offline support and family support were negatively related to physical health (RQ2, RQ3). This result suggests that individuals with less online support may lack opportunities to connect with others during quarantine and thereby suffer more from the pandemic. Family ties have been defined as a type of strong ties (Krackhardt, 1992), but too much dependency on family ties may represent less diverse networks and less provision of resources (Fiori et al., 2006), which may lead to a negative association with physical health.

Third, differences in media resources affected individual health during a pandemic, but they did not translate to differences in health in a simple, consistent way (H4, RQ4). Those with better ICT skills and those who used ICTs more for health-related activities were healthier during the pandemic, consistent with previous research (Dobransky & Hargittai, 2012; Levy et al., 2015). However, those who used ICTs for consumption activities were mentally and physically less healthy. These results suggest *how* individuals use media resources may play a great role in individual health.

In addition to social and media resources, some demographic factors were significantly related to individual health. However, apart from education and income, their associations differed from those found in the previous research (Silk et al., 2011). Such contradiction redirects attention to the traditional definition of vulnerable population and the strategies of targeting such population in public health campaigns. The results from cluster analysis in the next section more clearly identifies the target audience, preferable channels, and strategies.

Clusters of individuals during the pandemic

The cluster analysis results identified three groups of individuals who were affected by the pandemic in different ways (RQ5). Social and media resources played a critical role in classifying each group and differentiating each group's individual health. Cluster 1 was the group with the lowest social resources who suffered the most from the pandemic; it also had a high level of ICT skills and used ICTs actively for consumption, but not actively for health-related activities. Cluster 3 was the group with the highest social resources who were mentally and physically healthy; it had a low level of ICT skills and ICT use for consumption, but they used ICTs for health most actively.

We can compare these results to previous public health interventions that have focused on demographic variables. First, social resources in this study help determine the right audience in ways that demographic variables cannot identify. While older adults may suffer disproportionately from high infection and mortality rates (Centers for Disease Control and Prevention, 2020), this study indicates that older adults may be healthier than younger ones because of their social resources. Considering social resources may provide more useful information for audience targeting than demographic variables.

Second, taking account of social resources may lead to more sophisticated audience segmentation and more effective health campaigns than taking account of demographic variables. Whereas demographic variables could not explain the differences between every cluster, most social resource variables differentiated all three clusters and captured small distinctions between audience groups who experienced the pandemic differently.

Together, our findings provide the following three key insights for public health interventions during a pandemic. First, instead of focusing only on the traditional definition of vulnerable populations based on demographics, public health campaigns should target those with the lowest level of social resources who are the least healthy (Cluster 1). Health campaigns may use preexisting nationally representative large-scale survey data such as data from the General Social Survey, which includes questions on social resources (The General Social Survey, 2020). Second, these groups have high ICT skills (Cluster 1), so using campaign channels based on advanced technologies may be effective to target this audience. Specifically, we conducted additional t-tests (See Appendix D for details) and found that individuals in Cluster 1 acquired health information most frequently from (1) online news channels, followed by (2) television, and (3) social media. Considering the high cost of traditional campaigns based on mass media (e.g. television), practitioners may take advantage of online news channels or social media to target the online savvy audience represented by Cluster 1 (e.g. one-to-one tailored strategies). Third, public health campaigns should have different message strategies. In addition to promoting behaviors aimed to reduce virus infection (e.g. social distancing and mask-wearing), campaigns should encourage connections with others in intimate ways and direct the use of ICT skills to engage in health-related activities.

This study has several limitations. First, this study is a cross-sectional study. Longitudinal studies may provide a more accurate understanding of the associations between individual resources and health found in this study (e.g. between online consumption activity and a low level of health). Second, the change in the strength of ties comprised both their quantity and their quality (i.e. communication frequency and feeling of closeness). Future studies may reveal how each is related to individual health.

This study captures the role of social and media resources in individual health and suggests unique strategies for audience segmentation, channels, and messages during a pandemic that the traditional health intervention did not capture. In this way, we provide practical ways to understand audience segmentation for effective public health interventions. We also offer new theoretical directions to investigate vulnerable populations and target audiences.

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Appendix A. Details of Sample and Procedure

The power analysis suggested a minimum of 588 participants as a recommended sample size in order to detect an effect size at the level of.05 and have statistical power at the level of.09 with 25 independent variables. Therefore, we initially set 700 as our target sample size to take account of the potential missing or invalid data. the survey company randomly chose and sent invitation e-mails to 7,207 Koreans among the company's 1,148,766 opt-in online panels. The chosen individuals participated in the anonymous survey by voluntarily clicking the link in the e-mail. Among those who received the link, 1,055 clicked on the survey, and 742 of them completed the survey. Based on the formula for opt-in online panels (Callegaro & DiSogra, 2008), the completion rate was 10.3%, which is within the range of the response rate of detailed online surveys (Sauermann & Roach, 2013): 10–25%. Nineteen of the completed responses were excluded from the analysis because of invalid data.

Appendix B. Measurement and Descriptives of Demographics

	Measure	*M (SD)* or %
Age	Age	45.76 (13.56)
Gender	1: Male	52%
	0: Female	48%
Highest educational attainment	1: No education	0.14%
	2: Elementary school graduate	0.14%
	3: Middle school graduate	0.28%
	4: High school graduate	19.78%
	5: Associate's degree	15.08%
	(degree from a 2 year college program)	53.53%
	6: Undergraduate degree	8.71%
	7: Master's degree	2.35%
	8: Doctoral degree	
Monthly household income (converted from KRW to USD)	1: Less than $850	3.46%
	2: $850- $1,700	8.02%
	3: $1,700-$2,550	14.80%
	4: $2,550-$3,400	17.57%
	5: $3,400-$4,250	16.18%
	6: $4,250-$5,100	16.18%
	7: $5,100-$5,950	8.71%
	8: More than $5,950	15.08%
Employment status	0: unemployed, retired, homemaker, student	67%
	1: employed	
employed		
Marital status	0: single, separated, divorced, widowed, cohabiting	64% married
	1: married	

Their education (*Mdn* = completed an undergraduate degree) and monthly household income (*Mdn* = $3,400–$4,250) were similar to those of the Korean national population: 47% of Koreans have an undergraduate degree (Organization for Economic Co-operation and Development, 2016) and an average monthly household income of $4,100 (Korean Statistical Information Service, 2020). Variables of employment status and marital status were dummy coded after participants chose among five and six categories, respectively.

Appendix C. Cluster Analysis Procedure

This study conducted a cluster analysis on variables that showed significant correlations to individual health and investigated how individuals are segmented into different groups during a pandemic. The variables are: affective well-being, cognitive well-being, physical health, density, the strength of ties (feeling of closeness), change in the strength of ties (new, stronger, weaker), multiplexity, receiving informational support, offline support, family support, ICT skills, ICT uses (consumption, health).

In the cluster analysis, we applied a Ward's method with the squared Euclidean distance measure using the hclust package in R (R Core Team, 2018). The validity of cluster analysis results depends on the selection of the most appropriate number of clusters and the balance between parsimony and explanatory power. This study used guides for determining the appropriate number of clusters used in previous studies (Kodinariya & Makwana, 2013; Miller & Roth, 1994).

First, this study used a hierarchical clustering model to generate a dendrogram, which graphically illustrated how individuals grouped into three main clusters (Hothorn & Everitt, 2014). Our initial cluster analysis results suggested a three-cluster solution (see Figure A1)

Second, to check the stability of membership in the three clusters, we performed three iterations of Ward's method with the number of clusters set at two, three, and four. A comparison of the three solutions indicated that the cluster membership was stable across solutions, and new clusters were formed only by splitting large clusters. For instance, when the number of clusters increased from 2 to 3, Clusters 2 and 3 were divided from one cluster ($n = 557$). When the number changed from 3 to 4, Cluster 2 was divided into two clusters (n = 118, n = 187). The resulting clusters suggested three distinct types of individual groups as characterized by social and media resources, which we termed as Cluster 1, Cluster 2, and Cluster 3.

Finally, we performed a series of tests to further interpret the three-cluster solution (Kathuria, 2000). In the first step, we used a one-way analysis of variance (ANOVA) to test for differences in the defining variables among the three clusters. The null hypothesis that the three clusters are equal was rejected for 13 variables out of 15 variables. In the second step, we performed the Tukey post-hoc test to determine which pairs were significantly different. The Tukey post-hoc test, at the 0.05 level or less, indicated that cluster means were significantly different from each other for all three pairs (i.e., Type 1 vs. Type 2, Type 1 vs. Type 3, and Type 2 vs. Type 3) in 6 out of the 15 defining variables. In the other six variables, cluster means were significantly different from each other for two pairs out of all three pairs. Cluster means were significantly different from each other for one pair out of all three pairs for one variable. Therefore, the three-cluster model best met the above criteria.

In order to examine whether demographic factors (i.e. gender, age, education, income, employment status, and marital status) also differed among clusters, we additionally conducted ANOVA and the Tukey post-hoc test. Age had significant differences among three clusters (F(2,

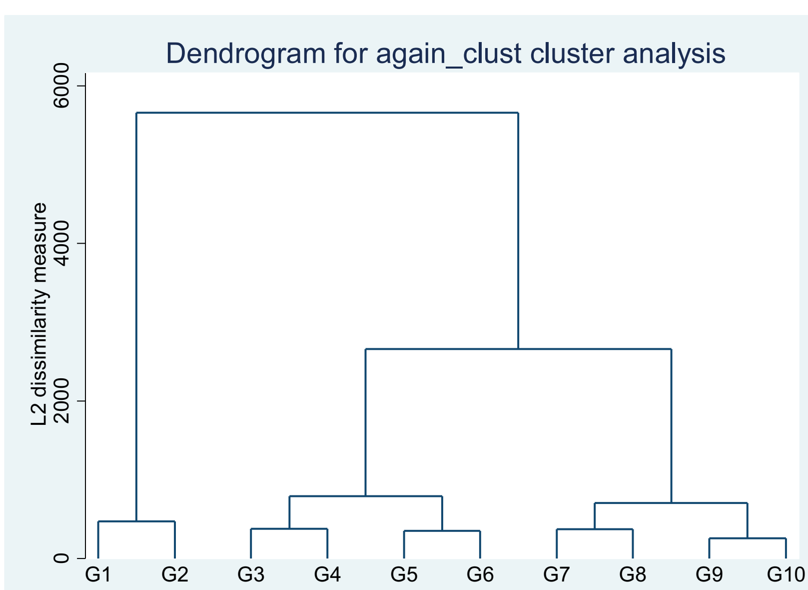

Figure A1. Dendrogram of cluster analysis.

720) = 3.07, p <.01). A Tukey post-hoc test showed that Cluster 3 (M = 47.15, SD = 12.63) was older than Cluster 1 (M = 45.42, SD = 14.32) and 2 (M = 45.28, SD = 13.39). Income also showed significant differences among 3 clusters (F(2, 720) = 15.25, p <.01). A Tukey post-hoc Cluster 3 (M = 5.40, SD = 1.94) had a higher level of income than Cluster 1 (M = 4.60, SD = 1.97) and 2 (M = 4.61, SD = 1.93).

Appendix D. T-test Results

Participants in Cluster 1 indicated the degree of frequency (i.e. 1: never, 4: very frequent) for seven sources from which they acquired health-related information over the last month during a pandemic. We conducted t-tests to compare means among the seven sources.

	Source	*M*	*(SD)*
1	Daily newspaper or magazine	1.95	(.86)
2	Television	3.22	(.75)
3	Online news channels (e.g. online news portal site or service, online and online news application)	3.28	(.77)
4	Social media	2.80	(.90)
5	Health-related websites (e.g. Ministry of Health and Welfare, and Center for Disease Control)	2.37	(.86)
6	Other individuals (e.g. family, friend, and colleague)	2.59	(.71)
7	Doctors or other medical professionals	2.18	(.85)

T-values of the mean comparisons between two pairs of sources.

	1	2	3	4	5	6	7
1	-						
2	15.13***	-					
3	14.45***	4.58*	-				
4	9.10***	5.23**	4.65***	-			
5	4.79***	10.13***	9.49***	4.43***	-		
6	9.68***	6.11***	5.45***	5.27*	7.57***	-	
7	4.43**	12.70***	12.03***	6.78***	4.39**	7.16***	-

Note. *p <.05, **p <.01, ***p <.001.

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Appendix E. Descriptives and Pairwise Correlations of Main variables

(1) Affective Subjective Well-Being, (2) Cognitive Subjective Well-Being, (3) Physical Health, (4) Density, (5) Tie Strength (Closeness), (6) Tie Change (New), (7) Tie Change (Stronger), (8) Tie Change (Weaker), (9) Multiplexity, (10) Receiving Info. Support, (11) Receiving Emotion. Support, (12) Giving Info. Support, (13) Giving Emotion. Support, (14) Offline Support, (15) Family Support, (16) ICT Skills, (17) ICT Uses (Production), (18) ICT Uses (Political), (19) ICT Uses (Social), (20) ICT Uses (Consumption), (21) ICT Uses (Savings), (22) ICT Uses (Health).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	-										
(2)	.67*	-									
(3)	.43*	.40*	-								
(4)	.08*	.07*	−.03	-							
(5)	.21*	.22*	.16*	.06*	-						
(6)	.06*	.07*	.04	−.07*	.03	-					
(7)	−.01	.09*	.05*	−.08*	.07*	.08*	-				
(8)	−.07*	.03	.05	−.11*	.05*	.01	.13*	-			
(9)	.17*	.19*	.11*	−.06*	.67*	.04	.14*	.15*	-		
(10)	.10*	.06*	.07*	−.02	.43*	−.05*	.08*	.05*	.37*	-	
(11)	.07*	.09*	.08*	.07*	.51*	−.03	−.01	−.01	.33*	.32*	-
(12)	.09*	.03	.07*	−.04	.43*	−.05*	.05	.04	.38*	.41*	.35*
(13)	.10*	.11*	.09*	.08*	.52*	−.04	−.01	.03	.37*	.35*	.42*
(14)	−.03	−.05*	.02	.04	−.07*	.01	−.05*	−.05	−.35*	−.07*	−.13*
(15)	−.02	−.02	−.08*	.33*	.03	−.08*	−.11*	−.03	−.12*	−.04	.09*
(16)	.12*	.08*	.19*	.01	.21*	−.004	−.10*	−.09*	.11*	.14*	.13*
(17)	.03	.13*	.10*	−.07*	.11*	.04	.09*	.09*	.14*	.08*	.10*
(18)	.01	.13*	.14*	−.03	.09*	.05	.15*	.12*	.13*	.05	.03
(19)	.03	.09*	.12*	−.05	.18*	.02	.05	.08*	.19*	.16*	.17*
(20)	.02	.05	.07*	−.02	.14*	.005	.01	.11*	.12*	.14*	.15*
(21)	.06*	.14*	.10*	−.02	.17*	.005	.04	.08*	.16*	.12*	.13*
(22)	.10*	.19*	.10*	.01	.15*	.02	.12*	.07*	.19*	.06*	.06*
M	3.26	3.51	2.82	.41	54.23	.05	.63	.29	11.66	2.49	2.77
SD	7.92	1.25	.79	.35	18.50	.35	1.30	.78	5.07	2.01	1.90

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(12)	-										
(13)	.34*	-									
(14)	−.09*	−.15*	-								
(15)	−.04	.07*	.13*	-							
(16)	.20*	.14*	−.03	−.02	-						
(17)	.10*	.06*	−.10*	−.10*	.33*	-					
(18)	.06*	.03	−.13*	−.06*	.24*	.35*	-				
(19)	.17*	.15*	−.21*	−.06*	.41*	.40*	.40*	-			
(20)	.17*	.16*	−.16*	−.02	.40*	.25*	.26*	.48*	-		
(21)	.14*	.12*	−.14*	−.04	.35*	.32*	.32*	.45*	.45*	-	
(22)	.08*	.09*	−.15*	−.03	.23*	.30*	.32*	.29*	.30*	.38*	-
M	2.62	2.70	.46	.41	3.87	2.51	2.05	3.00	3.45	2.87	2.62
SD	2.13	1.99	.27	.34	.65	1.36	1.05	1.24	1.04	1.16	1.11

*p <.05, **p <.01, ***p <.001.