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정보과잉 요인과 뉴스 소비 패턴의 관계: 티핑 포인트의 역할을 중심으로

Factors of Information Overload and Their Associations with News Consumption Patterns: The Roles of Tipping Point

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요 약

본 연구는 Jackson and Farzaneh(2012)이 제시한 정보과잉의 세 가지 요소, 즉 시간, 기술, 사회적 네트워크로 구성된 이론적 모델을 뉴스 소비 행위 맥락에서 경험적으로 검증했다. 1,166명의 전국 샘플을 토대로 분석한 결과, 정보과잉 지각과 사회적 네트워크 크기와 다양성은 적극적이고 소극적인 뉴스 소비와 모두 정적인 관련이 있었다. 또한 개인적으로 다양한 수준의 인지적 한계점, 즉 티핑포인트의 존재를 암시하는 연구결과를 토대로, 정보과잉에도 불구하고 개인의 티핑포인트에 따라 정보처리가 중단되지 않고 정보이용을 지속할 수 있다는 점을 확인했다. 특히, 본 연구가 주목한 뉴스 소비자들의 경우 정보과잉 지각에도 불구하고 뉴스의 사실성을 판별하기 위해서 지속적으로 정보를 검색하고 받고자 하는 의도가 높기 때문에 개인의 티핑포인트에 따라 전략적인 뉴스 소비를 채택하는 것으로 보인다. 이러한 결과를 토대로 경영정보시스템과 저널리즘 차원에서 실무적 함의를 논의했다.

키워드 : 정보과잉, 뉴스소비, 시간, 기술, 소셜 네트워크, 티핑 포인트

Ⅰ. Introduction

Experiencing information overload became a widespread phenomenon during an era where some politicians and news networks frame world events in incongruent and divisive ways. Increased channel options and news outlets, especially considering the advances in technology over recent decades, exacerbate the issue of information overload. Many people are overwhelmed by the amount and types of news information they receive and access daily through various outlets (Holton and Chyi, 2012). Researchers have examined relevant issues of information overload such as emotional exhaustion and new avoidance (e.g., Fu *et al.*, 2020;

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Guo *et al.*, 2020; Lee *et al.*, 2017; Zhang *et al.*, 2020), but most have focused on a single aspect of this phenomenon, such as time perception or technology usage, rather than multiple dimensions of information overload simultaneously (Fink *et al.*, 2018). Perception of information overload surely happens at individual cognition; however, information overload is a multilayered phenomenon as Jackson and Farzaneh's model (2012) shows; it has both intrinsic and extraneous sources and various outcomes including further information seeking and exposure (Roetzel, 2019), which has dynamic consequences, particularly in the context of news consumption.

Previous studies have shown perceptions of news information overload are related to several patterns of news consumption such as avoidance, selective exposure, and willingness to pay for contents (e.g., Lee *et al.*, 2016). News consumption was considered one of the major forms of communicative outcomes (i.e., information seeking and exposure) of information overload (Roetzel, 2019). Individual news consumers may have varying levels of cognitive threshold for tolerating the amount of information they can process at one time (i.e., tipping point; Hawes, 1971; Jackson and Farzaneh, 2012) and various factors and conditions impact whether they will keep consuming news or stop and avoid news altogether to not feel overwhelmed by the amount of incoming news (Lee *et al.*, 2016).

However, a simultaneous examination of the relationships between such various sources of information overload (e.g., technology, time constraints, social networks) and distinct types of news consumption (e.g., active, or passive consumption) has not been extensively performed. Due to the change in media technologies and news environment, individual news consumers can now engage in proactive and interactive news consumption by selectively exposing themselves to news they need or want and sharing those with others (Kim and Choi, 2015). This is a significant change from the previous pattern of news consumption, which was rather passively receiving news from the media. Thus, it is necessary to distinguish these two types (i.e., active vs. passive) of news consumption along with the changing media landscape. To fill the gap in existing studies, we first define the practical components of information overload by discussing key factors that have been identified, either theoretically or empirically, as contributing to information overload. Then, the study examines the relationships these factors have with news consumption patterns as a communicative outcome behavior (Roetzel, 2019). We examine multiple sources of information overload, as proposed by Jackson and Farzaneh's (2012) factor-based model that has laid out three unique contributing factors (i.e., intrinsic, extraneous, and mixed [intrinsic/extraneous]) to information overload, which would relate to individuals' tipping point in news consumption decision.

More specifically, we examine time as an intrinsic factor, technology as an extraneous factor, and both size and diversity of social networks as separate mixed (intrinsic/extraneous) factors of information overload (Jackson and Farzaneh, 2012). Time is an important factor of information overload (Guo *et al.*, 2020; Roetzel, 2019) as being a limited resource, it can create cognitive burden when news consumers feel like they spend more time than necessary to search for information. Various communication technology such as email, phone call, texting, social media can increase perceived information overload (Fu *et al.*, 2020) as news consumers may feel they receive more information than they need and can handle through all those outlets (Lee *et al.*, 2017). Individuals' social networks can become both direct and indirect sources of information overload as they provide information directly in-person or indirectly through mediated channels such as social media (Koroleva and Kane, 2016;

Min, 2020; Sasaki *et al.*, 2015).

This study uniquely contributes to understanding the phenomenon of information overload by first empirically testing relationships among theoretical factors of information overload (Jackson and Farzaneh, 2012) in the context of news consumption; and second by recognizing some factors may increase, not lower, the information overload threshold or tipping point (Li and Sun, 2014; Soroya *et al.*, 2021) where an individual is feeling overloaded and cannot process further information (Hawes, 1971). Despite feeling overloaded with information from various sources (i.e., limited time, technology, and social networks), news consumers may not necessarily stop seeking or receiving news according to our research findings.

Ⅱ. Literature Review

2.1 News Consumption and Tipping Point

News consumption can be understood as one type of communication behavior associated with information overload and its related decision-making outcomes (Roetzel, 2019). Lee *et al.* (2016) found that perception of news information overload was associated with selective exposure to news and news avoidance, both of which are considered as coping mechanisms of news information overload. Existing studies have begun to illuminate the effects of news information overload on news consumption patterns (Holton and Chyi, 2012). For instance, some news consumers prefer to access news through their social media as they believe their network contacts would most likely share the news, they might be interested in knowing about, a type of filtering and selective exposure to news (Pentina and Tarafdar, 2014).

Moreover, several factors of information overload, theorized by Jackson and Farzaneh (2012), may also influence both information seeking and news exposure. Lee *et al.* (2016, 2017) examined one extraneous factor of information overload (i.e., technology usage), but accounting for intrinsic and mixed (intrinsic/extraneous) factors causing information overload, suggested by Jackson and Farzaneh, will provide a more comprehensive picture of the overall relationship between information overload and news consumption, specifically in terms of news information seeking and exposure.

Information seeking of news refers to individuals actively pursuing information to both find news sources and share news with their networks (i.e., active news consumption). On the other hand, news information exposure refers to individuals both directly receiving news and indirectly being exposed to news by reading social media posts shared by one’s networks for example (i.e., passive news consumption; Kim and Choi, 2015). It is possible that news consumers overwhelmed by the amount of information may avoid additional exposure to news and decide to just receive whatever information that comes to their feed (i.e., passive news consumption; Lee *et al.*, 2016, 2017). However, others might still engage in active news consumption due to the desire of finding factual and accurate information even if they feel information overload.

According to the theoretical concept of tipping point, or the point where an individual is cognitively overloaded and cannot process further information (Hawes, 1971), individuals may not be overloaded although they may feel overloaded. If they are not actually overloaded and can still cognitively process information, then they may seek additional information to counter anxiety and resolve uncertainty (Soroya *et al.*, 2021). Other studies also show that intensity of communication can increase (Li and Sun, 2014) or decrease (Schneider, 1987) because of information overload. Tipping points or cognitive thresholds vary from person to person or from content to content (Fink *et al.*, 2018). The point at which an individual feels overloaded may be distinct from when they are actually overloaded and cannot process additional information. For example, Fink *et al.* (2018) suggest "the decision threshold is likely to proceed the information overload threshold for free apps and exceed it for paid apps" because consumers of paid apps attribute higher importance to their information processing and thus, they are more likely to experience overload in their decision

〈Table 1〉 Existing Literature on Information Overload and Contrasts with the Current Study

Authors	Focus	Difference from the current study
Holton and Chyi (2012)	Explores areas of news surplus and overload, examining factors associated with the degree of perceived overload across a broad spectrum of news delivery platforms	Focused on a single aspect of information overload, technology (new access platforms)
Misuraca and Teuscher (2013)	Perception of time as a measure of the cognitive workload associated with decision-making types; satisficers adopt a more malleable decision-making process than maximizers.	Focused on a single aspect of information overload, time.
Li and Sun (2014)	Proposes models to capture the characters such as the network, the user behaviors, and the process of information diffusion under information overload	Focused on information overload on specific platforms, social network sites (Facebook-like SNS).
Vacek (2014)	Behavior of email users has not changed much over 12 years and the email overload still occurs and causes many hours being used inefficiently	Focused on communication overload via a specific channel, email.
Pentina and Tarafdar (2014)	Factors influencing news consumption and the role of social media in devising strategies for addressing information overload	Applied information processing lens and sense-making theory to analysis of qualitative data; highlighted the role social media filtering information
Sasaki *et al.* (2015)	Analyzed the number of tweets received, number of friends, and density of a user's egocentric network	Focused on information overload on a specific platform, Twitter
Lee *et al.* (2016)	Antecedents of news information overload and news consumption	Focused on three antecedents: news consumptions through multiple platforms, news attention and interest.
Lee *et al.* (2017)	News access through social media and moderating role of information overload perception	Focused on how social media users' perception of journalism is moderated by their perceived information overload level
Fink *et al.* (2018)	Maximum cognitive load is experienced at lower review lengths for paid apps than for free apps	Focused on a single aspect of information overload, time.
Fu *et al.* (2020)	Examined how system feature, information, and social overload adversely affects users' social media discontinuance	Focused on information overload on specific platforms, social network sites (Facebook) and applied the stressor-strain-outcome framework
Guo *et al.* (2020)	Social network fatigue partially mediates the impact of information overload on information avoidance behavior.	Focused on information overload and avoidance on specific platforms, social network sites.
Zhang *et al.* (2020)	Developed an integrated model to determine the antecedents and consequences of WeChat users' perceived information overload	Focused on a specific platform, WeChat; consequences of information overload were negative emotions and discontinuance.
Soroya *et al.* (2021)	Factors leading to information avoidance during COVID-19 pandemic; only social media exposure results in information overload and information anxiety	Applied stimulus-orientation-response model and focused on information seeking, overload, and avoidance during COVID-19

Note: The list is organized by the year of publication and alphabetic order of authors' last names.

making (p. 34).

This study aims to examine how various factors of information overload, proposed by Jackson and Farzaneh (2012), are simultaneously associated with both active and passive news consumption behaviors. In the following, we discuss each factor of information overload, their relevant research findings (see <Table 1> for a summary of existing literature since 2010 and their distinct foci), and how they relate to the two types of news consumption with a special attention to the concept of tipping point.

2.2 Time as an Intrinsic Factor of Information Overload

Intrinsic factors of information overload are "fundamental elements of the information overload problem and directly influence information overload" (Jackson and Farzaneh, 2012, p. 525). Some empirically supported examples of intrinsic factors are quantity of information (Fink *et al.*, 2018; Fu *et al.*, 2020; Miller, 1994), time constraints (Guo *et al.*, 2020), and information processing capacity (De Jong, 2009). According to Roetzel (2019), time-related perceptions such as feeling pressure or constraints are an important condition that affects further information search and exposure, decision-making, and the occurrence of information overload. Prior research has shown that perception of time can vary by decision-making types (e.g., Maximizer vs. Satisficers) as cognitive workload is different by those types (Misuraca and Teuscher, 2013). However, previous studies did not consider time-related information overload in the context of news consumption along with other sources of information overload.

Time has been found to be a key factor that influences information overload due to increased cognitive burden when the amount of information is vast and time to process such information is limited (Guo *et al.*, 2020). With more strain on cognitive capacity, individuals will experience increased mental exhaustion when time is limited. Therefore, among various intrinsic factors of information overload, the current study first focuses on time-related aspects. Generally, we can expect that the time constraints imposed by the environment, individual, or some other factors contribute to a heightened perception of information overload. In that sense, time-related information overload refers to a perception of time as a limited resource while engaging in information search activities such as news seeking.

However, how news consumers feel about their spending time while searching for information they need, whether they can quickly identify information with little time, or they spend more time than necessary due to the sheer quantity of information available to them can vary by individual and group contexts. In other words, news consumers may feel more constrained in their time while actively seeking for information they need; but it is unclear how such feeling of information overload caused by time pressure would be related to passive news consumption such as receiving and being exposed to news without necessarily seeking them. Particularly, time-related information overload is likely to alter the way individuals seek or avoid news as time pressure (defined as "the perception that there is an inadequate amount of time available to do all that needs to be done"; Guo *et al.*, 2020) strengthens the effect of social network fatigue on information avoidance behavior.

In addition, it is noteworthy that Jackson and Farzaneh's (2012) theoretical assumptions involve a tipping point. They further proposed individuals would choose between pushed and pulled data depending on the level of information overload and control they want to have over it. When individuals begin to experience cognitive discomfort, they may begin to cease pulling data, and instead only receive information pushed to them. Applied to the context of news consumption, individuals may engage in passive news consumption more than actively seeking news once they start feeling overloaded by the amount of news information with a limited time.

While it would be challenging to accurately measure individually varying levels of cognitive threshold for information overload, it is important to note that the tipping point will influence individuals' decision about active and passive ways of news consumption. Thus, depending on the individually varying tipping point, time-related information overload may be positively or negatively related to news consumption patterns. News consumers may stop actively seeking information once they feel overloaded; but they may not stop receiving news (i.e., passive news consumption) until they actually reach the tipping point. Thus, we ask the following research question:

RQ1: How is time-related information overload associated with (a) active and (b) passive news consumption?

2.3 Technology as an Extraneous Factor of Information Overload

Extraneous factors also lead to perceptions of information overload, but only to the extent they influence intrinsic factors (Jackson and Farzaneh, 2012). Examples of extraneous factors include information characteristics (Vacek, 2014), information quality (Guo *et al.*, 2020; Slawson *et al.*, 1994), task and process parameters (i.e., boundary conditions; Bawden, 2001), and personal conditions (Owen, 1992). These factors likely play a role in information overload by altering the level of intrinsic factors' influence.

Specifically, what some scholars would refer to as media control, Jackson and Farzaneh (2012) classified them as pulled and pushed data. When individuals have more control over the presentation of data, it is pulled. An example of pulled data is an interactive website because visitors of the website control the hyperlinks they click on. Pushed data, on the contrary, are media forms where the user has little control over the presentation of data, such as a traditional news broadcast, as the only control the user has is changing the channel. Accordingly, pulled data might be more relevant to active news consumption with more control by individual news consumers and pushed data to passive news consumption with less control by them.

The amount of pushed or pulled data influences not only the extent of information overload individuals experience, but also which media consumers choose to use, based on the degree of control they desire. Technologies therefore impact information source design (Lee *et al.*, 2016; Sasaki *et al.*, 2015) or can become sources of stress in the environment when news consumers rely on them too much (D'Arcy *et al.*, 2014; Kim and Kim, 2014; Tarafdar *et al.*, 2010). Technologies vary in forms, quality, and personal preferences leading to potentially increased or decreased information overload depending on their usage. If individuals use multiple platforms simultaneously to access information and let technologies interrupt their tasks (i.e., multi-tasking), their information processing capacity might decrease (Jackson and Farzaneh, 2012).

However, technology itself does not directly influence information overload, but rather moderates or mediates the amount of information available to individuals. Therefore, technology is an "extraneous" rather than an "intrinsic" factor of information overload (Lee *et al.*, 2017). Among various extraneous factors of information overload, the current study focuses on technology-related information overload considering its importance in the digital age. Increasingly, our daily communication including news consumption is mediated through some sort of technology, be it mobile phone or computer; and people rely heavily on those internet-enabled devices for their various information activities such as news search, news reading, and social communication. Individual news consumers may vary in their extent of using diverse technological platforms and the more varied types of technology they use simultaneously for receiving and retrieving information (e.g., passive, and active news consumption), the more overloaded they may feel.

Technology-related information overload refers to how individuals feel overloaded based on the amount of information they access through various technological outlets, such as social networking sites (Guo *et al.*, 2020; Koroleva and Kane, 2016; Li and Sun, 2014) or mobile applications (Fink *et al.*, 2018), which is likely to change the amount of news received or retrieved through the time it takes to process information in the news. The level of technology-related information overload may then affect both active and passive news consumption patterns indirectly through its association with time-related information overload. While prior studies mostly examined information overload experienced through a specific channel like Twitter (e.g., Sasaki *et al.*, 2015) or Facebook (e.g., Fu *et al.*, 2020), it became necessary to consider multiple types of technologies news consumers use to access news and how overall feeling of overload might be connected to their perception of time constraints. Thus, we propose the following mediation hypothesis between technology-related information overload on news consumption patterns through the perception of time-related information overload:

H1: The relationships between technology-related information overload and both (a) active and (b) passive news consumption will be mediated through time-related information overload.

2.4 Social Networks as Mixed (Intrinsic/Extraneous) Factors of Information Overload

This last category contains factors influencing information overload directly and other factors that lead to information overload indirectly (Jackson and Farzaneh, 2012). The main variable considered intrinsic/extraneous is the source of information (Edmunds and Morris, 2000). For example, a speech presented by a country's leader may have both a direct influence on information overload and an indirect influence through the way it is presented and discussed by other sources like news media. Several dimensions of information source such as databases, social networks, source design, and source preferences have been studied (Roetzel, 2019). Each of these dimensions also has various sub-factors contributing to information overload, and the current study focuses on the aspect of social networks as sources of information considering the significant role of social networking sites in news exposure and circulation (Lee *et al.*, 2017; Pentina and Tarafdar, 2014).

The number of connections people have (i.e., network size), and the diversity of such connections could be influential characteristics of information sources that would impact both intrinsic (e.g., time) and extraneous (e.g., technology) factors of information overload (Koroleva and Kane, 2016; Sasaki *et al.*, 2015). For example, the larger an individual's social network is, the more likely one is to hear about various world events more frequently via in-person or mediated communication. Sasaki *et al.* (2015) found that Japanese Twitter users' number of friends (i.e., network size) had a positive effect on perceived tweet overload. Furthermore, the more diverse an individual's network is, in terms of social and demographic orientations (e.g., politics, religion, sex, age) and tie strength composition (i.e., ratio of strong and weak ties), the more likely one is to hear diverse reports and perspectives of news, which may be contradictory to one another (Siegel, 2009).

Social network literature shows that weak ties (i.e., contacts in one's social network with whom one communicates sparingly and feels less emotional closeness compared to strong/close ties) tend to be larger and more diverse compared to strong ties (Siegel, 2009). News consumers who appreciate the exposure to diverse perspectives may keep relying on their social networks, especially weak ties, for receiving news (Koroleva and Kane, 2016); but others who feel overloaded with the amount of news and conflicting perspectives coming from diverse contacts may end up reducing the amount of exposure, rely only on strong ties, or avoid the sources altogether (Guo *et al.*, 2020; Lee *et al.*, 2016). Thus, social networks, as a type of information source, likely play an important role in the occurrence and management of information overload. As Pariser (2011) discussed the idea of filter bubbles, Facebook and Google users get to interact with like-minded others in the network depending on personal orientations (e.g., politics, preferences, tastes; Kang *et al.*, 2015) and computer algorithms (e.g., search history). Thus, the composition of an individual's social networks in their size and diversity would influence, at least partially, the type of news they are exposed to (i.e., passive news consumption).

Individuals with larger social networks are likely to be exposed to a greater amount of news with varying viewpoints and these various viewpoints may not only influence news consumption patterns directly but also have indirect effects via time-related information overload. Large network size was associated with information overload in previous studies (Koroleva and Kane, 2016; Sasaki *et al.*, 2015; except for Zhang *et al.*, 2020, as their study found number of WeChat subscriptions followed was not associated with information overload) due to the large volume of information brought in by many sources in social networks. Thus, it may take more time for individual news consumers to process such volume of information coming from their large networks, which may consequently influence their active and passive news consumption frequency. Research shows large network size is associated with higher levels of social capital (i.e., resources embedded in social networks) and civic engagement (Gil de Zúñiga *et al.*, 2012); hence, we propose positive relationships between network size and both types of news consumption as engaged citizens will actively seek and receive information relevant to their local and political issues.

H2: Network size will be positively associated with (a) active and (b) passive news consumption

H3: Time-related information overload will mediate the relationship between network size and (a) active and (b) passive news consumption.

Because news consumers with a more diverse social network are more likely to see news from both liberal and conservative channels, in terms of political orientation for instance, they may feel the need to seek out additional information to verify factuality of certain news or have a balanced viewpoint on issues, an active news consumption. Due to the diverse networks that usually accompany a large network size, they would also receive and be exposed to greater amounts of news (thus, passive news consumption) compared to those who have less diverse networks. Along with network size, individuals' network diversity is considered as a mixed factor, which means it could affect information overload both directly and indirectly

(Koroleva and Kane, 2016; Sasaki *et al.*, 2015). Thus, it is also expected that network diversity will be related to news consumption patterns through its association with time-related information overload:

H4: Network diversity will be positively associated with (a) active and (b) passive news consumption.

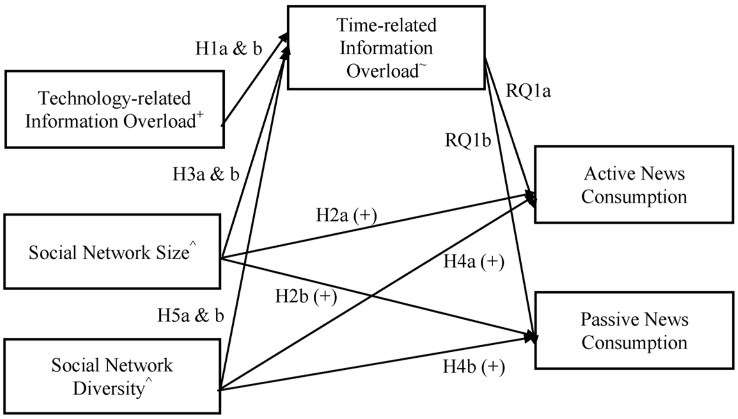
H5: Time-related information overload will mediate the relationship between network diversity and (c) active and (d) passive news consumption.

In addition to the RQ1 and three sets of hypotheses, this research also assesses a theoretical model of information overload and the associations between multiple factors of information overload and both types of news consumption. The model of Jackson and Farzaneh (2012) with various sources of information overload and the theorization of their relationships with social networks and news consumption were utilized as a guide to develop the following research model of information overload and news consumption patterns (see <Figure 1>).

In this model, we theorize technology-related information overload as an extraneous factor and social networks (size and diversity) as mixed factors (intrinsic/extraneous) will be associated with both types of news consumption patterns through the mediation of time-related information overload, an intrinsic factor. Social networks components would also have direct association with both active and passive news consumption as they are theorized as both intrinsic and extraneous factors of information overload.

Ⅲ. Methodology

The sections to follow detail the participants and procedures of this study. Participants were compensated for completing an online survey by the rate determined by a South Korean survey company, Macromill Embrain. The research team hired the company and paid $5 per survey response gathered by them. The study was approved by the Institutional Review Board of the first two authors' school of affiliation when data was collected during August 2015. The response rate was not provided to the researchers as the survey company recruited participants from their panel.



Note: Symbols represent ~ = intrinsic factor, + = extraneous factor, ^ = intrinsic/extraneous factor.

〈Figure 1〉 Theoretical Path Model of Information Overload.

3.1 Participants

Out of 1166 total participants, 50.7% were males, and their age ranged between 20 and 64 (*M* = 42.2, *SD* = 12.1). College graduates were 62.3% of the sample, 27.3% reported less than a college degree as the highest level of education, and 10% of the sample had some graduate school or a graduate degree. The education level of this sample was rather high; but considering the percentage (32.2%) of adults (between 25 and 64 years old) who obtained a college degree or equivalent education in South Korea was highest among 46 OECD countries in 2020, the sample represented the South Korean population to a certain extent. In addition, the tertiary education attainment among younger generations (25 to 34 years old) of South Korea was also the highest among the same comparison group (69.8%). Less than a quarter of the sample (24.2%) earned $2000 or below per month as their income, while 40.2% earned between $2001 and $4000. About a quarter of the sample (25.1%) earned between $4001 and $6000 and the rest (10.5%) earned over $6000 as their monthly income.

〈Table 2〉 Participant Demographics

Variable		%
Sex		
Male		50.7
Female		49.3
Education		
College graduates		62.3
Less than a college degree		27.3
Some graduate school		10.0
Income		
$2000 or less		24.2
$2001 and $4000		40.2
$4001 and $6000		25.1
$6001 and higher		10.5
Geographic Location		
Kyungki-do		22.8
Seoul		19.3
Busan, Daegu, Inchon, Kyoungbuk and Kyoungnam		> 5.0
Gwangju, Daejeon, Ulsan, Gangwon, Chungbuk, Choongnam, Chonbuk and Chonnam		~ 3.5
Occupation		
Office-Based/Clerical		41.5
Homemaker		15.3
Professional		12.2
Service/Sales		10.6
Students		8.3
Production		2.7
Technician		2.1
Other		3.5
	M	*SD*
Age	42.2	12.1

Among major cities and administrative districts of South Korea, residents in Kyungki-do were represented by 22.8% and Seoul, the capital, was represented by 19.3% of the sample. Residents of Busan, Daegu, Inchon, Kyoungbuk, and Kyoungnam were each over 5% of the sample, and the rest of the areas such as Gwangju, Daejeon, Ulsan, Gangwon, Chungbuk, Choongnam, Chonbuk, and Chonnam each represented about 3.5%. Many participants (41.5%) worked for an office-based/clerical job, other reported job categories were full-time homemakers (15.3%), professionals (12.2%), services/sales (10.6%), students (8.3%), production (2.7%), technicians (2.1%), and others (3.5%).

3.2 Procedures

An online survey was used to collect data from South Korean citizens, and participants were asked to complete measures of information overload, news consumption, network size and diversity. The data were checked for common method bias using Harman's single factor score (28.71%), which indicates common method bias is not present (Podsakoff *et al.*, 2003; 2012). Data were also checked for systematic missing data and the missing values analysis with SPSS indicated that data were missing completely at random as Little's MCAR test result was insignificant (p > .05; Bose, 2001).

3.2.1 Information Overload

Participants rated their perceived information overload on a total of twelve statements regarding information overload, adapted from Lee *et al.* (2016). Lee *et al.* identified two types of information overload from their study: general and news information overload. The current research utilized measurement items of general information overload and further explored whether there were any sub-dimensions by performing an exploratory factor analysis (EFA). Participants rated on a 7-point scale (*1 = strongly disagree, 7 = strongly agree*) how well each of the statements represented their recent experiences of information overload. Based on the EFA from these initial 12 items, two factors were generated and named as the following: Time-related information overload and technology-related information overload.

Time-related information overload included four items (M = 3.79, SD = 1.20, Cronbach's alpha = .87) such as "I often felt that I spent too much time searching for information I need." Technology-related information overload included five items (M = 3.35, SD = 1.30, Cronbach's alpha = .90) such as "I often felt that I received more instant messages (texts, instant messenger, WhatsApp) than I could handle." Three items were removed from further analysis due to them being cross-loaded over two factors. The two factors of information overload explained a total of 73.02% of variances and the Kaiser-Meyer-Olkin measure of sampling adequacy was .94 with Barlett's test of sphericity being significant (Approximate Chi-square value = 12292.18, df = 66, p <. 001; see Appendix for more detailed factor analysis results).

3.2.2 News Consumption

A total of 11 items measuring various activities related to news consumption were used with a 7-point scale (*1 = not at all, 7 = very well*; Kim and Choi, 2015). Participants were asked how well each of the statements represents their news consumption behaviors. Based on an EFA, with varimax rotation, of these 11 items, two factors were generated: active and passive news consumption. The two factors explained 71.6% of the variance. Active news consumption (M = 2.94, SD = 1.40, Cronbach's alpha = .89) included five items such as "I have shared news links through social media." Passive news consumption (M = 2.64, SD = 1.35, Cronbach's alpha = .92) also included five items such as "I have received news/headlines through webpages or RSS".

3.2.3 Network Size

Participants' network size was measured by nine different categories of relationships, and then classified into three broader groups (i.e., strong ties, weak ties, and mediated ties). The sum of strong ties (i.e., close friend, family, sibling) average was 19.27 (SD = 27.21, range 0 - 508), weak ties' (i.e., relative, coworker, neighbor, voluntary organization members) average was 40.92 (SD = 90.27, range 0 - 1180), and mediated ties' (i.e., SNS and cell phone contacts) average was 127.35 (SD = 183.60, range 0 - 1800). A total network size variable was calculated aggregating all three groups' average numbers (M = 187.53, SD = 249.40, range 0 - 2716).

3.2.4 Network Diversity

A total of 10 categories of social orientations (i.e., gender, politics, sexual orientation, religion, education, occupation, nationalities, age, ethnicity/race, socio-economic status) were used to measure participants' network diversity on a 7-point Likert-type scale (*1 = not at all, 7 = very frequent* interaction). Based on a scale reliability test (Cronbach's alpha = .90), an aggregated score of total network diversity was created (M = 41.67, SD = 10.00, range 10 - 70). <Table 2> provides a bivariate correlation analysis of all key variables of the study.

Ⅳ. Results

4.1 Results for Active News Consumption (RQ1a, H2a, and H4a)

A stepwise linear regression was performed to answer RQ1a and test H2a through H4a, except H1a (tested later; see section 5.3.) with time-related information overload (RQ1a), network size (H2a), and network diversity (H4a), as independent variables to predict active news consumption. This test was performed using three blocks. The first block included the control variables of participants' sex, age, education, and monthly income. Block two added time-related information overload and technology-related information overload. Block three added network size and diversity. Combined, all predictors explained 30% of the variance in active news consumption. Results showed significant relationships between active news consumption and age (β = -.08, p < .01), sex (β = -.07, p < .01), income (β = .06, p < .05), time-related information overload (β = .16, p < .001), technology-related information overload (β = .27, p < .001), network size (β = .08, p < .01) and diversity (β = .20, p < .001). Participants' education (β = -.05, p > .05) did not show a statistically significant relationship with active news consumption (see <Table 3> for full statistics).

RQ1a asked how time-related information overload would be related to active news consumption. The analysis result showed active news consumption had a statistically significant and positive relationship with time-related information overload after controlling for the effects of demographic variables (see Model 2, <Table 3>). The results meant the higher the level of time-related information overload perceived, the more actively participants consumed news.

Technology-related information overload was theorized as an extraneous factor, which meant no hypotheses

〈Table 3〉 Descriptive Statistics and Bivariate Correlations between Major Variables

Variables	*M (SD)*	1	2	3	4	5	6	7	8	9
1. Passive NC	2.64 (1.35)	1.00								
2. Active NC	2.94 (1.40)	.70**	1.00							
3. Age	42.19 (12.14)	.04	-.07*	1.00						
4. Gender	1.49 (0.50)	-.15***	-.10***	-.02	1.00					
5. Education	3.74 (1.08)	.08**	.03	-.03	-.16***	1.00				
6. Monthly income	3.87 (1.76)	.23***	.14***	.17***	-.08**	.18***	1.00			
7. Network Diversity	41.67 (10.01)	.39***	.37***	-.005	-.11***	.14***	.16***	1.00		
8. Network Size	187.53 (249.40)	.21***	.17***	.09**	-.17***	.07**	.19***	.27***	1.00	
9. Time Info Overload	3.85 (1.21)	.41***	.43***	-.14***	-.00	.03	.07*	.28***	.09**	1.00
10. Tech Info Overload	3.35 (1.30)	.49***	.47***	.02	-.01	.04	.14***	.33***	.11***	.71***

Note: NC = News consumption, Info = Information. $^{*}p$ < .05, $^{**}p$ < .01, $^{***}p$ < .001.

of direct relationships were advanced regarding its relationships with active news consumption (see H1a and b). However, technology-related information overload was found to have a significant direct and positive relationship with active news consumption according to the regression result (see Model 2, <Table 3>); furthermore, this relationship had the highest standard coefficients among all predictor variables. Thus, it seemed technology-related information overload did not just operate as a purely extraneous factor (indirect effect).

H2a proposed that network size would have a positive relationship with active news consumption. This hypothesis was supported as network size predicted active news consumption significantly and positively in the last step of the regression (see Model 3, <Table 3>). The result meant that the larger the participant's network size was, the more frequent active news consumption was reported.

H4a proposed that network diversity would have a positive relationship with active news consumption. This hypothesis was also supported as network diversity predicted active news consumption significantly and positively after controlling for the effects of demographic and two information overload variables (technology- and time-related).

4.2 Results for Passive News Consumption (RQ1b, H2b, and H4b)

The second stepwise linear regression was conducted to examine RQ1b and test H2b through H4b, except H1b (tested later; see section 5.3.) with the same set of control and independent variables as the earlier regression to predict passive news consumption. This test was also performed in three blocks. The first block included the control variables of demographics. Block two added time-related information overload and technology-related information overload. Block three added network size and diversity. Combined, all predictors explained 34% of the variance in passive news consumption. Results showed that several variables had significant relationships with passive news consumption including sex (β = -.11, p < .001), income (β = .12, p < .001), time-related information overload (β = .12, p < .01), technology-related information overload (β = .31, p < .001), network size (β = .07, p < .01) and diversity (β = .21, p < .001; see <Table 4> for complete statistics report).

RQ1b asked how time-related information overload would be related to passive news consumption. The results of analysis showed that time-related information overload had a statistically significant and positive relationship with passive news consumption after controlling for the effects of demographic variables (see Model 2, <Table 4>). The results meant higher levels of time-related information overload perception was associated with participants' report of receiving and being exposed to more news.

H2b proposed that network size would have a positive relationship with passive news consumption. This hypothesis was supported as network size predicted passive news consumption significantly and positively after controlling for the demographic and other types of information overload effect (see Model 3, <Table 4>). The result meant that the larger the network size was, the more frequently the participant was exposed to news.

H4b proposed that network diversity would have a positive relationship with passive news consumption. This hypothesis was supported as network diversity predicted passive news consumption significantly and positively after controlling for the demographic and other types of information overload effect (see Model 3, <Table 4>). The result indicated participants with more diverse social networks tended to receive and be exposed to news more frequently.

〈Table 4〉 Multiple Regression Analysis Predicting Active News Consumption.

Variable	Model 1			Model 2			Model 3		
	B	*SE*	β	*B*	*SE*	β	*B*	*SE*	β
Age	-.01**	.00	-.10**	-.01*	.00	-.07*	-.01*	.00	-.08**
Sex	-.26**	.08	-.09**	-.26***	.07	-.09***	-.20**	.07	-.07**
Education	-.02	.04	-.01	-.03***	.03	-.03	-.06	.03	-.05
Monthly Income	.12***	.02	.15***	.07***	.02	.09***	.05*	.02	.06*
Time information overload				.22***	.04	.18***	.19***	.04	.16***
Technology information overload				.35***	.04	.32***	.29***	.04	.27***
Network Size							.00**	.00	.08**
Network Diversity							.03***	.00	.20***
F	11.03***			66.21***			62.78***		
Adjusted R^2	.03***			.25***			.30***		
ΔR^2	-			.22***			.05***		

Note: *N* = 1166. *p < .05, **p < .01, ***p < .001.

4.3 Results for Mediation Analysis (H1a and b, H3a and b, and H5a and b)

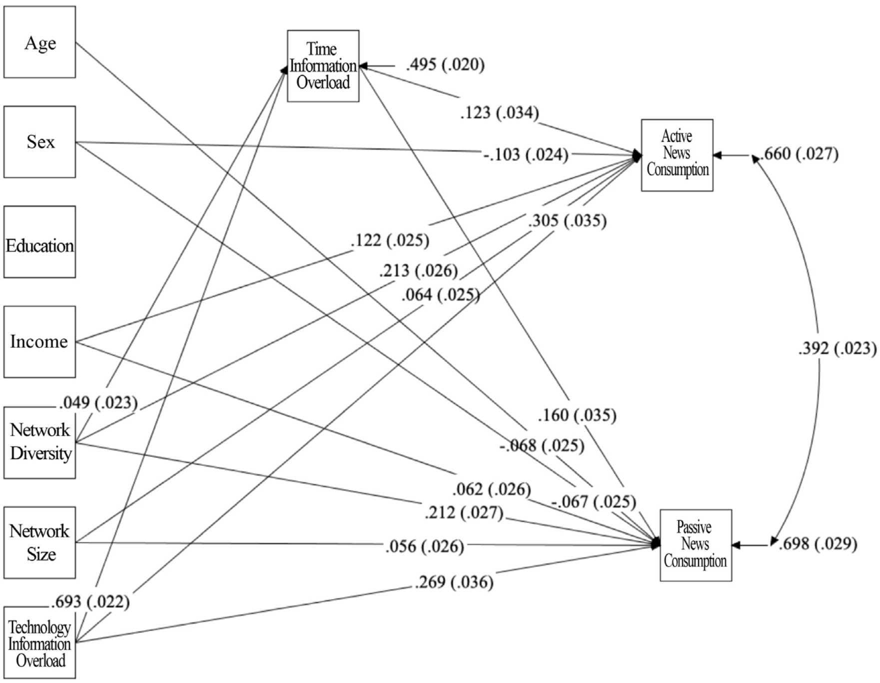
PROCESS macro version 4.1 (Hayes, 2022) was used to test the mediation between technology-related information overload and news consumption patterns via time-related information overload (H1s). Time-related information overload did significantly mediate the relationship between technology-related information overload and news consumptions (indirect effect size = .15, *SE* = .03, CI [.09 - .21] for active news consumption; indirect effect size = .09, *SE* = .03, CI [.04 - .15] for passive news consumption), with a partial mediation due to the direct effects previously mentioned. Thus, H1a and b were supported.

However, no significant direct relationship was found between network size and time-related information overload, meaning H3a and b were unsupported and network size functioned solely as an intrinsic factor of information overload. Time-related information overload significantly mediated the relationship between network diversity and news consumption (indirect effect size = .01, *SE* = .002, CI [.01 - .02] for active news consumption; indirect effect size = .01, *SE* = .002, CI [.01 - .02] for passive news consumption), which supported H5a and b. These mediation analyses were based on 5000 bootstrap samples at the level of confidence, .95 for CIs.

Significant direct paths to active news consumption from time-related information overload (β = .12, *SE* = .03, p < .001), technology-related information overload (β = .31, *SE* = .04, p < .001), network size (β = .06, *SE* = .03, p < .05) and diversity (β = .21, *SE* = .03, p < .001) were identified in addition to those from demographic variables (i.e., sex, income). Also, significant direct paths to passive news consumption from time-related information overload (β = .16, *SE* = .03, p < .01), technology-related information overload (β = .27, *SE* = .04, p < .001), network size (β = .06, *SE* = .02, p < .05) and diversity (β = .21, *SE* = .03, p < .001) were identified in addition to the significant paths from demographics (i.e., age, sex, 〈Table 5〉 Multiple Regression Analysis Predicting Passive News Consumption.

Variable	Model 1			Model 2			Model 3		
	B	*SE*	*β*	*B*	*SE*	*β*	*B*	*SE*	*β*
Age	.00	.00	.00	.00	.00	.03	.00	.00	.02
Sex	-.35***	.08	-.13***	-.36***	.07	-.13***	-.29***	.07	-.11***
Education	.02	.04	.02	.01	.03	.01	-.02	.03	-.02
Monthly Income	.16***	.02	.22***	.12***	.02	.15***	.09***	.02	.12***
Time information overload				.16***	.04	.15***	.14**	.04	.12**
Technology information overload				.38***	.04	.36***	.32***	.04	.31***
Network Size							.00**	.00	.07**
Network Diversity							.03***	.00	.21***
F	21.95***			79.47***			7 4.33***		
Adjusted R^2	.07***			.29***			.34***		
ΔR^2	-			.22***			.05***		

Note: N = 1166. $^{*}p$ < .05, $^{**}p$ < .01, $^{***}p$ < .001.



Note: All paths listed were significant at p < .05 or greater (see <Table 5> for complete descriptions). Values in parentheses are standard errors. Model fit indices: $\chi^2(4)$ = 54.49, p < .001, CFI = 0.98, TLI = 0.86, RMSEA = .10, SRMR = .03.

〈Figure 2〉 Test of the Theoretical Path Model of Information Overload and income). Although some portions of the original hypotheses (H3a and b) were not supported, according to this path analysis, the overall model functioned mostly as hypothesized (see <Figure 2>).

V. Discussion

5.1 Theoretical Implications

This study was based on Jackson and Farzaneh's (2012) distinctive conceptualization of intrinsic, extraneous, and mixed factors of information overload and identified differential association of such factors (e.g., time, technology, and social networks) with news consumption. The research model was held true in many cases although some of our results called for reconsideration of earlier assumptions. The intrinsic factor of time did have a direct relationship with both active and passive news consumption. The extraneous factor of technology was found to have a mediating relationship with active and passive news consumption, via time-related information overload, as predicted by the theoretical model. However, technology-related information overload also had a direct association with

〈Table 6〉 Standardized Estimates for Theoretical Model in 〈Figure 1〉 (N = 1166)

	Estimates	*SE*
Active News Consumption		
Time-related Information Overload	$.12^{***}$	.03
Technology-related Information Overload	$.31^{***}$	.04
Network Size	$.06^{*}$	.03
Network Diversity	$.21^{***}$	.03
Passive News Consumption		
Time-related Information Overload	$.16^{**}$	.03
Technology-related Information Overload	$.27^{***}$	.04
Network Size	$.06^{*}$	.02
Network Diversity	$.21^{***}$	.03
Time-related Information Overload		
Technology-related Information Overload	$.69^{***}$	.02
Network Size	-.00	.02
Network Diversity	$.05^{*}$	.02
Passive News Consumption		
Active News Consumption	$.39^{***}$	.02
Residual Variances		
Time-related Information Overload	$.50^{***}$	.02
Active News Consumption	$.70^{***}$	.02
Passive News Consumption	$.66^{***}$	.02

Note: Estimates for the demographic variables are omitted due to the limit of space and overlap with the regression tables. $\chi^2(4)$ = 54.49, p < .001; CFI = 0.98; TLI = 0.86; RMSEA = .10; SRMR = .03. $^{*}p$ < .05, $^{**}p$ < .01, $^{***}p$ < .001.

both active and passive news consumption, which was not predicted by the initial model, meaning technology acted as a mixed (intrinsic/extraneous) factor.

Both network size and diversity were hypothesized to be intrinsic/extraneous factors, and they did have a direct relationship with both active and passive news consumption patterns. However, network size did not have any indirect relationship with news consumption via time-related information overload, while network diversity did, meaning network size acted solely as an intrinsic, not as a mixed factor of information overload in this study. This finding makes sense considering social networks literature showing large network size increases network diversity (Siegel, 2009). Participants with large social networks may seek news actively and also receive many; but they may not necessarily feel like they spend too much time on searching for information unless their networks are composed of diverse others.

Those who are embedded in diverse networks will be exposed to various perspectives and opinions about social issues and may feel more confused and stressed due to spending much time for verifying large volume of information they see.

Although participants reported feeling overloaded with information, they still continued consuming news in both active and passive ways. According to Jackson and Farzaneh's (2012) model, this finding meant participants had not yet crossed their tipping point or cognitive threshold, for if they had they would not have been able to process or seek out more information. According to their model of information overload, when news consumers do not reach their tipping point, they can search and consume more information.

The findings of this study empirically supported the theoretical components of Jackson and Farzaneh (2012); however, results showed that information overload was associated with increased rather than decreased amount of news that was sought and received. Due to the possibility of a reverse direction of influence from news consumption to information overload, it is critical to include an empirical examination of individually varying cognitive thresholds for information overload in future research.

It is apparent that both network size and diversity are strongly associated with both active and passive news consumption behaviors. Participants who were connected to a large and diverse group of people received more news information. This large volume of information might have brought higher uncertainty of issues and situations, due to potential inconsistency and contradiction among them, which may motivate individuals to seek more news and information. They might have wanted to check the factuality of certain news and form a balanced viewpoint on issues that polarize the public's attitudes and opinions. It is possible those who are the most overloaded might be hyper aware of the amount of information their social networks contacts are providing.

This tension between information overload and information uncertainty will most likely be handled differently by individuals depending on their cognitive tipping point. Such a tension could lead individuals to either actively seek or actively avoid information (Fu *et al.*, 2020). For example, Guo *et al.* (2020) showed social media fatigue partially mediated the relationship between information overload and information avoidance behavior and fully between social overload and information avoidance. The vast amount of information and social support requests on social media can make one feel tired and want to avoid further exposure to information.

On the other hand, Fink *et al.* (2018) found a curvilinear relationship between variation in information overload and information usage from studying online review lengths. Their participants experienced the highest cognitive load when reviewing shorter lengths for paid applications than for free applications, which demonstrated product-related differences in information processing motivations matter. The researchers also provided explanations based on the elaboration likelihood model (Petty and Cacioppo, 1986) that participants were more elaborated in using paid applications, so their information processing route was rather central than peripheral, which made them feel more overloaded even when they read shorter reviews compared to using free applications. This finding highlights the importance of not only product-related differences, but also individually varying motivations related to tipping point in examining information overload. Even while experiencing information overload, motivated individuals with higher cognitive thresholds may seek further information for clarifying and strengthening their viewpoints.

In summary, our analysis results confirmed that all three factors of information overload were indeed influential in their associations with news consumptions; however, the test of mediation results indicated technology-related information overload seemed to function as a mixed factor whereas network size as an intrinsic factor. These results meant that experiencing time- or technology-related information overload did not necessarily decrease the level of active or passive news consumption, and the theoretical concept of tipping point (or cognitive threshold) of information overload might indeed exist. Large and diverse social networks did not seem to abate news consumption, either, as long as news consumers' threshold is not crossed. The results of mediation analyses were particularly meaningful for potential revision of the original theoretical model as they suggested feeling overloaded by uses of various communication media could not only influence news consumption directly but also indirectly by affecting one's feeling of time-related overload. Considering the prevalence and magnitude of news access through multiple channels, the direct effect of technology-related information overload on news consumption seemed reasonable. However, why individual news consumers still actively sought out news even when they felt time-related information overload, connected to various technology usage, needs to be examined further.

5.2 Practical Implications

Practical application of the current research findings can be discussed at multi-levels and multi-disciplines. First, the implications will be discussed for both individuals and organizations.

Based on the positive and significant associations between technology- and time-related information overload and news consumption patterns identified in this study, we can infer if individual news consumers decrease their active and passive news consumptions, they may feel less overwhelmed by the amount of information available through various technological venues and by the lack of time available for their information processing. Due to the limitation in individuals' cognitive capacity and time, selectively exposing oneself to trusted news sources and maybe paying for quality news contents can be considered coping strategies for information overload (Lee *et al.*, 2016). Some news consumers use social media to access news as they believe contacts in their social networks would operate as filters for finding and sharing interesting and meaningful information for them (Pentina and Tarafdar, 2014).

An organization consists of many members who contribute to adding information and iteratively updating and retrieving information from the organization's information sources (Jackson and Farzaneh, 2012). As a whole, the organization is greater than the sum of its parts, individuals, and the organization can create an environment of information overload when its members continue to collect and store information individually. Research in organizational information overload has focused on email and other electronic document management systems that create too much information while solutions to that problem have been suggested as introducing new systems or reducing the flow of information (Klausegger *et al.*, 2007). Findings of this study showed feeling overloaded did not necessarily stop individuals from seeking further information (news). As both technology- and time-related information overload had direct associations with news consumptions, reducing the number of technologies used in the workplace communication (simplifying the choice options) and allowing more response time to task-related communication may help reduce organizational information overload.

Second, the implications for practice will be suggested for the field of Management of Information Science (MIS). Many existing MIS studies deal with issues related to social networks in the context of online social networking sites (SNSs) or social media more broadly. Few have focused on the issue of information overload related to individual social networks themselves (e.g., Guo *et al.*, 2020; Koroleva and Kane, 2016; Li and Sun, 2014), and those who did still did not examine network-specific characteristics such as size or diversity as in this study (except Koroleva and Kane, 2016; Sasaki *et al.*, 2015). People's social networks are not only important as intrinsic sources of information overload, but they also relate to active and passive news consumption patterns.

While Facebook's popularity is decreasing among young generations and Instagram, Snapchat, and TikTok are gaining more traffic, a future SNS developer may consider a venue where users can have minimal number of contacts and maintain a small circle of close friends or followers. This probably sounds counterintuitive as it defies the benefit of being able to connect with large and diverse groups on social media. However, there would be users who feel too overwhelmed by all the contents shared by many sources and want to gain some control back in managing the amount of information (i.e., pulled media) coming from their social networks. A recently developed iPhone app, called "Locket" that only allows adding up to five friends to share their immediate photos may serve as an example (Molina, 2022). When the competition is very high in the market, this unique niche may be worth pursuing for any future platform.

Finally, findings of this study are not necessarily "bad news" for the journalism field as various sources of information overload including technology, time, and social networks were not associated with decreased levels of news consumption. As news consumers might be motivated to verify factuality of certain information and reaffirm their existing stance on issues when faced with conflicting information, unless they reach the cognitive threshold (i.e., tipping point), they seem to still seek out or receive news while feeling overloaded in relation to time, technology, and social networks. Along with previous research findings that show social media news access tend to negatively influence news consumers' perceptions of journalism ethics and practices, which is moderated by their perceived information overload (Lee *et al.*, 2017), the current study's findings suggest news consumers' perceiving information overload does not necessarily make them avoid or stop news consumption. Ironically, it is those who think they are not overloaded access news via social media frequently and disagree with traditional journalism ethics such as fairness and objectivity (Lee *et al.*, 2017). Therefore, information overload from various sources can make news consumers feel humbler and realize they need to seek further information to verify and strengthen their position.

5.3 Limitations and Future Directions

One of the limitations of this research is our inability to measure the actual level of information overload with tipping point. We can attempt to assess these latent variables (i.e., perception) with scales, but employing superior measurements of cognitive functions to empirically test tipping points would improve the validity and reliability of such measurement. Another limitation is the focus on news consumption behavior only in two aspects (i.e., active and passive). Future researchers should consider an experimental design where not only information overload factors such as time, technology, and networks vary, but also the subject of information and its relevant activities (not just news, but other areas and types of activities) to assess if participants respond differently to topics of varying interest and engagement levels. In addition, considering the finding of technology-related information overload being directly associated with news consumption (being a mixed factor with both direct and indirect effect), future research can also explore potential mediating relationship between social network characteristics and news consumption via technology-related information overload. Finally, the cross-sectional data collected for this study cannot guarantee any causal relationships hypothesized in the theoretical model. Thus, it is possible that high levels of time- and technology-related information overload accompany high levels of active and passive news consumption and vice versa.

VI. Conclusion

The findings of this research provide some support for the theoretical model of information overload proposed by Jackson and Farzaneh (2012) and support the idea of a tipping point by providing empirical evidence to earlier theorizing. After controlling for the effects of demographics, social network and information overload variables all showed positive associations with news consumption patterns. Particularly, time-related information overload partially mediated the relationships between technology-related information overload and news consumption. In addition to the theoretical contribution, research findings also provide some practical insights on individual coping strategies for information overload, development of new social networking applications potentially serving a niche market, and the relationships between perceived information overload and journalism practice.

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〈Appendix〉

Exploratory Factor Analysis Results of Information Overload (IO) Measurement Items

	Factors of IO	
	Tech IO	Time IO
I often felt burdened about handling phone calls and messages simultaneously through various information and communication means.	.831	
I often felt that I received more instant messages (texts, instant messenger, WhatsApp) than I could handle.	.819	
I often felt that I received more cellular phone calls than I could handle.	.806	
I often felt burdened about replying to emails.	.786	
I often felt stressed about receiving too many emails.	.743	
*I often felt less motivated about working due to the amount of information I had to process.	.638	.573
*I often felt insecure about the amount of information I had to process.	.637	.568
I often felt I spent too much time using communication tools (laptop, desktop, tablet, smart phones) to seek information from others.		.819
I often felt that I spent too much time searching for information I need.		.811
I often felt stressed about the amount of information I had to process.		.719
I often felt confused about the amount of information I had to process.		.710
*I often felt overwhelmed about the amount of information I had to process.	.604	.649

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
*Removed from further analysis due to cross-loading over two factors.

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Factors of Information Overload and Their Associations with News Consumption Patterns: The Roles of Tipping Point

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Abstract

A theoretical model of information overload (Jackson and Farzaneh, 2012) with its three influential components (i.e., time, technology, and social networks) was empirically tested in the context of news consumption behavior considered as a communicative outcome. Using a national sample of South Korean adults (*N* = 1166), data analyses identified perceived information overload and large/diverse social networks positively associated with active and passive news consumption. Findings may imply the existence of individually varying cognitive threshold (i.e., tipping point), if crossed individuals cannot process information any further. News consumers may keep searching and receiving information to verify factuality of news even when they feel overloaded.

Keywords: Information Overload, News Consumption, Time, Technology, Social Networks, Tipping Point

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