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*Completed Research Paper*

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## Abstract

*While public transit is a major place where people devote their time to smartphones, particularly social media usage, the literature has paid scant attention to how contextual factors in public transit affect the individual usage behavior of social media. Building upon prior literature on stress and social media as a stress reliever, this study examines the impact of physical crowdedness on users' content consumption and generation behaviors on social media platforms. In collaboration with a major wireless telecom provider in China, we collect detailed information on smartphone usage behavior among 200,000 randomly selected individuals on a major public subway line in Qingdao, China. The results demonstrate a positive causal relationship between crowdedness and content consumption and generation on social media platforms, even after controlling for potential endogeneity of crowdedness.*

**Keywords:** Crowdedness, social media, content generation, content consumption, stress

## Introduction

Physical crowdedness, as a prevalent and important contextual factor, has received extensive attention in the field of marketing. For example, previous studies have found that crowdedness will stimulate users to be more attached to brands (Huang et al., 2018), reduce shopping time (Harrell et al., 1980), prefer safety-oriented (Maeng et al., 2013) or more distinctive products (Xu et al., 2012), and make more verified and unique choices (Levav & Zhu, 2009).

Crowding always occurs in daily life, especially in public transit (Andrews et al., 2016). In recent years, there has been a growing trend towards the utilization of low-cost and environmentally friendly public transit among citizens, particularly among commuters.[1] This phenomenon is not limited to a specific geographic location, as individuals around the globe spend significant amounts of time utilizing public transit for daily commutes (Ghose et al., 2019). The advancement of mobile communication technology has facilitated the ability of individuals to engage in social activities, such as social media usage, during their commutes on

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[1] https://www.census.gov/newsroom/press-releases/2021/public-transportation-commuters.html

public transit, which can often be lengthy and tedious (Bohmer et al., 2011; Liang & Huang, 1998): A survey found that 66% of commuters use social media during their daily commutes (Bohmer et al., 2011).[2]

The public transit context has unique features that may alter individuals' mobile usage behavior, including psychological stress (Ghose et al., 2019), boredom (Andrews et al., 2016; Olsson et al., 2013), and crowdedness (Andrews et al., 2016). Previous business studies have primarily focused on how these contextual factors in public transit can be exploited for business, including stimulating redemptions of mobile coupons (Ghose et al., 2019) and responses to mobile targeting (Andrews et al., 2016). Several studies have focused on the use of smart devices in public transit, exploring the relationships between crowdedness and phone calls or texting (Guo et al., 2015; Van der Waerden et al., 2009). However, there is a limited understanding of the causal impact of crowdedness in public transit on the way users consume and generate content across different types of mobile social media platforms. This is particularly important as public transit is a context where individuals spend a significant amount of time engaging with social media, and thus multiple social media services compete for user engagement. Understanding how individuals use their social media apps in public transit can provide valuable insights for social media providers and advertisers on such platforms to optimize user engagement, content consumption and generation, marketing responsiveness, and overall user experience.

This study fills the gap by investigating how physical crowdedness affects individuals' social media usage in public transit. To this end, in collaboration with a major wireless telecom provider in China, we collect proprietary information on smartphone usage behavior among a sample of 200,000 individuals randomly selected from a major public subway line in Qingdao, China. Utilizing the granular spatial-temporal information in the data, we identify subway passengers and their respective routes, allowing us to measure the extent of crowdedness each passenger encountered during their public transit journey. We then examine the impact of crowdedness on passengers' content consumption and generation behavior across various social media apps (i.e., based on the social network structure such as private, public, and business social platforms (Kwon et al., 2017), and based on multi-media types such as text-based, image or video-based social platforms (Pittman & Reich, 2016)), using passenger-fixed-effect models. To address concerns of potential endogeneity of crowdedness, we account for the systematic difference in crowdedness at various times of day and between weekdays and weekends. We also employ an instrumental variable approach, utilizing the extent of crowdedness in the previous week as an instrumental variable. Additionally, we use an external shock that unexpectedly caused an increase in crowdedness to validate the causal effect of crowdedness on social media usage.

The key findings of this study demonstrate that crowdedness has a positive impact on users' social media usage, including both content generation and consumption behaviors. Additionally, the effects of crowdedness appear to vary depending on the types of social relationships and content each platform facilitates. The results indicate that the positive impact of crowdedness is more pronounced for social media apps that are used to manage private social networks, compared to those used for public and work-related social relationships. Additionally, text-based social media apps appear to benefit more from crowdedness than image- or video-based apps.

The present study makes significant contributions to the existing literature. Specifically, the findings of this study extend our understanding of the effects of crowdedness and resultant stress, which have traditionally been viewed as negative in offline retail contexts (e.g., Harrell et al., 1980; Maeng et al., 2013), into positive effects in a novel mobile context. Additionally, this study adds to recent findings regarding the positive impact of crowdedness on responsiveness to mobile promotions (Andrews et al., 2016) and the relationships between crowdedness and phone usage (Van der Waerden et al., 2009), making it one of the pioneering studies to link offline physical crowdedness to mobile social media behaviors. Furthermore, this study offers unique perspectives on the boundary conditions for the impact of crowdedness, an area that has been largely under-explored in previous studies (e.g., Eroglu et al., 2005; Harrell et al., 1980; Huang et al., 2018; Levav & Zhu, 2009; Maeng et al., 2013; Xu et al., 2012), by examining the roles of service characteristics. In addition, this study expands upon previous research by delving deeper into factors affecting individuals' social media usage. While previous studies have examined the effects of specific times and locations on social media usage (e.g., Bohmer et al., 2011; Do et al., 2011; Karikoski & Soikkeli, 2013),

[2] http:// www.marketingdive.com/news/study-commuters- spend-more-time-shopping-ordering-food-on-phones/538571/

this study examines the interactions between these factors, specifically how contextual information on crowdedness impacts social media usage.

# Background and Hypothesis

## *Literature on Social Media Usage*

Social media allows individuals to create, share, and communicate content with others (Demirtepe-Saygili, 2020). Researchers have investigated various factors that influence social media usage, including both internal and external motivations. Internal needs include self-enhancement (Fu et al., 2017; Oh & Syn, 2015), recognition (Leung, 2013; Oh & Syn, 2015) and information seeking (Gan, 2018), and escapism (Wang et al., 2015). Externally driven motivations, including social effects (Susarla et al., 2012; Zeng & Wei, 2013) and spatial (Do et al., 2011; Karikoski & Soikkeli, 2013) and temporal (Bohmer et al., 2011) factors, also play a role in driving social media usage. In addition, different categorizations of social media platforms have been proposed to investigate how different types of social media platforms shape different user behaviors. For instance, Pittman and Reich (2016) have suggested categorizing them based on their primary mode of communication, such as text-based, image-based, or video-based. Kwon et al. (2017) categorized social media platforms based on the degree of openness of the social networks they host, such as public versus private ones. Nevertheless, a hyper-context, which can be identified by integrating spatial-temporal information, such as physical crowdedness, has received limited attention as a driving factor of social media usage. In addition, the lack of investigation into the types of social media platforms as potential boundary conditions for the contextual impact on social media usage remains in the literature. This study aims to contribute to this research gap.

## *Literature on Crowdedness*

Previous studies have extensively examined the impact of crowdedness on offline individual behavior and proposed various underlying mechanisms for this effect. Behavioral constraint theories suggest that crowdedness instills *avoidance motivation* in individuals, thereby influencing consumer behavior. For instance, Harrell et al. (1980) found that high physical density stimulates individuals to reduce their shopping time to avoid the shop environment. Huang et al. (2018) demonstrated that consumers in crowded areas tend to avoid interacting with others, leading to a greater attachment to brands. Additionally, crowdedness may *threaten individuals' inherent needs*, stimulating them to engage in coping behaviors. Specifically, Xu et al. (2012) illustrated that physical proximity to other people makes individuals tend to purchase distinctive products as a way to restore threatened individuality. Levav and Zhu (2009) revealed that consumers tend to make more verified and unique choices to restore and assert freedom when they are in spatially confined conditions. Lastly, crowdedness is also suggested to affect consumer behavior by *lowering individuals' perceived social status* or *creating distraction*. Specifically, O'Guinn et al. (2015) demonstrated that people in crowded conditions judge things to be less valuable due to their reduced perceived social status. Hock and Bagchi (2018) observed that perceived human crowding and physical proximity led to increased distraction, causing greater affective information processing and a corresponding rise in calorie consumption.

In addition to the extensive studies on how crowdedness influences offline behavior, a few recent studies have investigated the effects of physical crowdedness on user behavior in online and mobile environments. For example, Andrews et al. (2016) illustrated how crowdedness influences users' responsiveness to mobile advertisements in public transit. The authors provide support for the avoidance mechanism in a mobile context, under which increased crowding motivates users to be more immersed in their mobile channel as a way to avoid the environment, leading to more effective mobile promotions. Several studies have observed negative or insignificant correlations between crowdedness and smartphone usage behavior (Guo et al., 2015), or ICT-based activities in public transit context (Keseru et al., 2020; Van der Waerden et al., 2009; Varghese et al., 2020). These studies have not explored the underlying mechanism behind the correlation relationships. Our study extends these studies by investigating how physical crowdedness causally affects users' mobile social media usage behavior and its mechanism based on stress literature.

## *Literature on Stress*

Several studies have investigated the behavioral modifications exhibited by individuals in response to stressful circumstances. It has been observed that individuals often engage in compensatory behaviors in an attempt to regain a sense of control over their environment. Durante and Laran (2016) observed that consumers tend to increase their savings and prioritize spending on essential items during periods of stress. Moreover, individuals tend to seek social support when experiencing stress. Bae (2023) discovered that individuals were more inclined to fulfill their social interaction needs through engagement on social media platforms during the stressful conditions brought about by the pandemic. Galaif et al. (2003) indicated that perceived stress leads to a heightened desire for seeking social support. Additionally, researchers have examined the connection between stress and compulsive behaviors. Zheng et al. (2020) found a positive association between perceived stress and compulsive online buying behavior. Ali et al. (2021) identified that stress related to social interaction anxiety could contribute to an increase in compulsive social media usage.

## *The Effect of Crowdedness on Social Media Usage*

Crowdedness has been shown to negatively impact the psychological state of individuals, leading to feelings of stress (Aiello et al., 1977; Collette & Webb, 1976; Lundberg, 1976; Maeng et al., 2013). As a result, individuals may employ coping strategies to avoid and mitigate the negative consequences of this crowded environment. First, when individuals are unable to escape the crowded environment, they may experience a lack of control over their surroundings, leading to feelings of stress (Epstein, 1981). In response, they may engage in compensatory behaviors to restore a sense of control, such as strengthening social connections and expressing themselves (Derrick, 2013; Kay et al., 2010). As a result, individuals may be motivated to consume and generate content on social media platforms as a means of satisfying their needs for social connection and self-expression (Fu et al., 2017; Leung, 2013; Matikainen, 2015; Oh & Syn, 2015). Second, individuals may also seek social support when facing the negative effects of stress in crowded environments (Appley & Trumbull, 2012; Cohen & Wills, 1985). Social media platforms offer a means for individuals to access and share social support (Oh & Syn, 2015). Therefore, the psychological stress of crowdedness in public transportation may lead to increased use of social media as a means of gaining social support. Lastly, the frequent occurrence of crowdedness in public transportation may lead to chronic, rather than acute, stress (McGonagle & Kessler, 1990). Chronic stress has been linked to impulsive behavior (Ghose et al., 2019), and research has demonstrated a positive correlation between impulsivity and social media use (Savci & Aysan, 2016). Thus, it is expected that crowdedness in public transportation and the resultant stress may result in increased use of social media as individuals seek to satisfy their needs for social connection, self-enhancement and social support, or as a direct behavioral reflection of the negative effects of chronic stress such as impulsivity. Hence, we posit the following hypothesis:

***Hypothesis 1****: Physical crowdedness increases individuals' social media usage.*

The use of social media platforms can elicit different psychological states in users depending on the nature of the social networks they are managing on platforms, such as professional, public, and private networks (Mark et al., 2014; Shu et al., 2017). Platforms specifically designed for professional networking, such as DingTalk, are commonly utilized for communication with colleagues and the handling of work-related matters (Mark et al., 2014). However, the use of such platforms in non-working contexts may exacerbate users' perceptions of a lack of control (Karkoulian et al., 2016), which may not be desirable for stressed individuals in crowded public transit settings. As a result, we expect that the positive effect of crowdedness would be marginal for business-oriented social media platforms.

Previous research has consistently demonstrated variations in user behavior across public and private social media platforms, as each type of platform is specifically designed to foster distinct types of relationships and networks. Public social media, such as Facebook, typically host communication with a broad range of individuals in a publicly visible manner, whereas private social media platforms, such as WhatsApp, facilitate communication primarily within smaller groups of closely connected individuals. Studies have shown that relationships formed and cultivated on private social media tend to be characterized by stronger ties between individuals who share greater similarities and homogeneities, including demographic factors such as age and gender (Kwon et al., 2017). As a result, it is posited that private social media is more effective in satisfying users' needs for social support and connection in the face of crowdedness, compared to public social media (Krämer et al., 2021). Overall, it is expected that the positive effect of crowdedness on private

social media use will be the strongest, followed by public and professional social media platforms. Hence, we posit the following hypothesis:

***Hypothesis 2****: The positive impact of physical crowdedness on social media usage is more pronounced for private social media compared to public and professional social media.*

Various forms of social media employing distinct communication modes may elicit diverse levels of stress among users. Specifically, text-based communication modes are generally considered to be less complex and convey less information than image- and video-based formats (Lim & Benbasat, 2000). Studies have demonstrated that the cognitive and emotional demands associated with processing visual information, such as images and videos, are typically greater than those associated with processing textual information (Moreno & Mayer, 2002) given that visual cue necessitates more cognitive resources and mental effort to process, comprehend, and interpret the information. Hence, text-based social media would offer a more straightforward and less demanding communication mode, which would be more appealing to users who are experiencing crowdedness-related stress or anxiety. Therefore, as much as reading and sharing text-based content is less taxing for users, the positive effect of crowdedness on text-based social media would be stronger than on image- and video-based social media. Moreover, the congestion-induced instability of internet connectivity can hinder users' capacity to consume and create image- and video-centric content on social media platforms. Hence, we posit the following hypothesis:

***Hypothesis 3****: The positive impact of physical crowdedness on social media usage is more pronounced for text-based social media compared to image- and video-based social media.*

# Empirical Analyses

## *Research Context*

We investigate the relationship between crowdedness and social media usage in public metro systems. We focused on Qingdao Metro Line 2 in Shandong, China which started operations on December 10th, 2017, and serves over 260,000 daily passengers through 21 underground stations.

To measure crowdedness and social media usage in the metro, we partnered with a major wireless telecom provider in the region, which covers about 30% of the regional population. We then randomly selected its 200,000 customers representing 7% of the company's customer base who used the metro line during the data period. We obtained detailed information on their data upload and download behavior across all websites and apps from November 19th to December 17th, 2021. This includes when each user starts and terminates their use of each app and website, the amount of data uploaded and downloaded at each app and website, and the location of each user during data transfer (i.e., longitude and latitude).

## *Variables and Measures*

***Dependent variables***: To measure each individual's content consumption and generation behavior on various social media apps in public transit, we first define route $j$ of user $i$ as a trip starting and ending at different stations in the Qingdao Metro Line 2. Thus, each user can have multiple routes even in a single day, such as commuting to and from work, and traveling for shopping or visiting friends. We then generally define content consumption (generation) as the amount of downloaded (uploaded) data. Our two dependent variables $ContConsumption_{ij}$ ($ContGeneration_{ij}$) are measured as the amount of downloaded (uploaded) data for content consumption (generation) by user $i$ during route $j$ (measured in bytes).

We also measure the extent of content generation and consumption on various social media apps with different characteristics. Social media services can be divided into three categories based on the nature of social networks and the relationships they facilitate: Professional, Public, and Private (Kwon et al., 2017). Professional social media platforms focus on work-related networks and interactions. Public social media provides a platform for communication between a large, publicly visible group of people. Private social media is designed for communication within smaller, close-knit groups of relationships. The other way of classifying social media is based on the major media form of communication conducted on each social media platform (Pittman & Reich, 2016). Specifically, text-based social media includes WeChat, while TikTok (Instagram) exemplifies video-based (image-based) social media. Table 1 presents a comprehensive list of social media services organized by classification categories. Accordingly, $ProfessionalCC_{ij}$, $PublicCC_{ij}$,

and $PrivateCC_{ij}$ ($ProfessionalCG_{ij}$, $PublicCG_{ij}$, and $PrivateCG_{ij}$) indicate the amount of downloaded (uploaded) data for content consumption (generation) on professional, public, and private social media by user *i* during route *j*, respectively. Similarly, $TextCC_{ij}$, $ImageCC_{ij}$, and $VideoCC_{ij}$ ($TextCG_{ij}$, $ImageCG_{ij}$, and $VideoCG_{ij}$) indicate the amount of downloaded (uploaded) data for content consumption (generation) on text-, image-, and video-based social media by user *i* during route *j*, respectively.

| Classification criteria | Classification category | APP List |
|---|---|---|
| Network type | Professional | DingTalk, TIM, 263 云通信, 全时云会议, 安司密信 |
| | Public | Facebook, In, Instagram, NOTHING, Qzone, Weico, 百度贴吧, 波波网, Douban, 天涯, 人人, Tencent Weibo, Weibo International Edition, Sina Weibo, 知乎, Tiktok, 抖音火山版, 快手, 美拍, 秒拍, 微视, 西瓜视频, 酷狗短酷, 画吧, 美篇, 火柴盒, 麦萌对手戏, 色影无忌 |
| | Private | WeChat, QQ, Azar, Blued, LESDO, Skype, Soul, 百度 Hi, 百合相亲, 触宝电话, 来往, Momo 陌陌, 平行世界, , 世纪佳缘, 情侣我和你, 有信电话, 对缘, 珍爱网 |
| Communication modes | Text | WeChat, QQ, LESDO, Soul, TIM, 安司密信, 百度 Hi, 百度贴吧, 百合相亲, DingTalk, 263 云通信, Douban, 天涯, 火柴盒, 来往, Momo 陌陌, 平行世界, 世纪佳缘, 情侣我和你, 对缘, 珍爱网, 知乎 |
| | Image | Facebook, In, Instagram, NOTHING, 波波网, 画吧, 美篇, 色影无忌 |
| | Video | Azar, Blued, 全时云会议, Tiktok, 抖音火山版, 快手, 美拍, 秒拍, 微视, 西瓜视频, 酷狗短酷 |

**Table 1. List of Social Media Services**

***Independent Variable***: Following the way of previous studies (e.g., Andrews et al., 2016), we operationalize the average level of crowdedness around user *i* during route *j*, $Crowdedness_{ij}$, as the average number of passengers per square meter on the train that user *i* is traveling on during route *j*. Specifically, we first identify the number of *passengers within our sample* based on their location and timestamp information in our dataset. Given that our sample rate is 7% of the customer base, and the penetration rate of the collaborating telecom provider into the regional population is 30%, we calculate the number of *actual passengers* by dividing the number by 0.07 and 0.3. We divide this number further by the total area of each train; each train consists of six cars with a total area of 319.2 square meters (6 *19m * 2.8m). Table 2 shows the descriptive statistics of our main variables. Figure 1 shows that the passenger volume in our sample almost follows the same trend as the passenger volume that the metro provider reported officially, verifying the accuracy of the proposed method to measure our key independent variable to a certain extent.

| Variables | Description | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Crowdedness | The average crowdedness of the route | 1.23 | 0.716 | 0.15 | 7.683 |
| ContCons | Content consumption through all social media | 5,328,877.1 | 16,679,509 | 0 | 1.630e+08 |
| ContGen | Content generation through all social media | 230,629.23 | 657,069.56 | 0 | 6,996,308 |
| Breakdown by Network Types | | | | | |
| ProfCC | Content consumption through professional social media | 4,505.915 | 531,941.24 | 0 | 1.451e+08 |
| PubCC | Content consumption through public social media | 80,514.42 | 1,347,132.1 | 0 | 1.560e+08 |

| | | | | | |
|---|---|---|---|---|---|
| PrivCC | Content consumption through private social media | 5,241,867.7 | 16,474,766 | 0 | 1.628e+08 |
| ProfCG | Content generation through professional social media | 33.858 | 2,551.731 | 0 | 807,285 |
| PubCG | Content generation through public social media | 8,860.098 | 69,136.95 | 0 | 6,476,978 |
| PrivCG | Content generation through private social media | 221,708.86 | 646,298.67 | 0 | 6,996,308 |
| Breakdown by Communication Modes | | | | | |
| TextCC | Content consumption through text-based social media | 5,256,494.5 | 16,503,143 | 0 | 1.629e+08 |
| ImageCC | Content consumption through image-based social media | 707.262 | 95,889.017 | 0 | 31978247 |
| VideoCC | Content consumption through video-based social media | 55,905.312 | 1,236,060 | 0 | 1.560e+08 |
| TextCG | Content generation through text-based social media | 222,696.78 | 647,839.3 | 0 | 6,996,308 |
| ImageCG | Content generation through image-based social media | 55.952 | 1,666.732 | 0 | 363,583 |
| VideoCG | Content generation through video-based social media | 7,616.445 | 60,439.942 | 0 | 6,471,487 |
| Control Variables | | | | | |
| Stations | The number of stations a route contains | 3.038 | 2.142 | 2 | 21 |
| Routes | The number of routes for a user on the same day | 2.357 | 1.629 | 1 | 14 |

**Table 2. Descriptive Statistics**

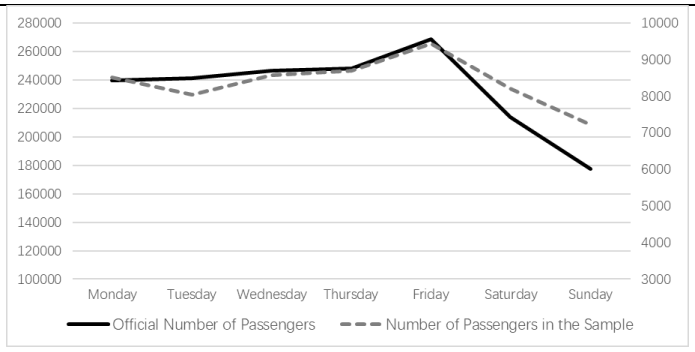


**Figure 1. The Number of Reported and Identified Passengers**

## *Model Specification*

We construct the following model to identify the effect of crowdedness on social media usage:

$$ContentConsumption_{ij}\ (or\ ContentGeneration_{ij}) = \beta_0 + \beta_1 Crowdedness_{ij} + \beta_2 Stations_{ij} + \beta_3 Routes_{ij} + \beta_4 PeakHour_{ij} + \beta_5 Weekend_{ij} + \alpha_i + \varepsilon_{ij},$$

where the dependent variables are log-transformed to enhance their normality. $Stations_{ij}$ represents the number of metro stations route $j$ of user $i$ contains, and $Routes_{ij}$ is the number of routes for user $i$ on the same day of route $j$. To further control for the potential source of endogeneity from the systematic differences in crowdedness between peak and nonpeak hours, and weekdays and weekends, we include variables representing whether each route is taken on peak hours or weekends. Specifically, $PeakHour_{ij}$ consists of two dummy variables, each of which indicates whether route $j$ of user $i$ is taken between 7 am and 9 am (i.e., morning peak hour) or between 5 pm and 7 pm (i.e., evening peak hour). $Weekend_{ij}$ represents whether route $j$ of user $i$ is taken on weekends. We also include the user-fixed effects $\alpha_i$ in the model to take account of time-invariant user-specific unobservable characteristics.

## Empirical Results

Table 3 shows the results regarding the impact of crowdedness on content consumption and generation behavior on overall social media platforms (see Column 1 and 2 of the table, respectively). The results demonstrate that crowdedness has significantly positive impacts on both content consumption and generation behavior ($p < 0.01$). This implies that users are inclined to consume and generate more content on social media platforms when they are in physically crowded environments, supporting Hypothesis 1.

| | **(1) ContCons** | **(2) ContGen** |
|---|---|---|
| Crowdedness | 0.086***(0.010) | 0.093***(0.011) |
| Stations | 0.563***(0.005) | 0.598***(0.005) |
| Routes | -0.055***(0.008) | -0.055***(0.008) |
| Time Dummy (PeakHour & Weekend) | Yes | Yes |
| User Fixed Effects | Yes | Yes |
| Observations | 233,828 | 233,828 |
| R-Squared | 0.2861 | 0.2834 |

**Table 3. Main Results**

Note. * p<0.1, ** p<0.05, *** p<0.01. 5,337 singleton observations are excluded from the estimation.

We replicate the main analyses for individuals' content consumption and generation behaviors across social media platforms with different networks and relationships, the first three columns of Table 4 show that the effect of crowdedness on content consumption is positive for all the professional, public, and private social media platforms ($p < 0.01$). In addition, the positive impact of crowdedness on content consumption is most pronounced for private social media (coef. = 0.084) while professional social media enjoys the least benefit from crowdedness (coef. = 0.016). The last three columns of Table 4 illustrate that only content generation on public and private social media benefits from crowded environments (p<0.01), whereas content generation on professional social media is not statistically significantly associated with crowdedness. Moreover, compared to public social media (coef.= 0.017), the positive crowdedness impact on content generation is more prominent for private social media (coef.= 0.095), supporting Hypothesis 2.

| | **(1) PrivCC** | **(2) PubCC** | **(3) ProfCC** | **(4) PrivCG** | **(5) PubCG** | **(6) ProfCG** |
|---|---|---|---|---|---|---|
| Crowdedness | 0.084*** (0.010) | 0.036*** (0.007) | 0.016*** (0.003) | 0.095*** (0.011) | 0.017*** (0.006) | 0.002 (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 |
| R-Squared | 0.2854 | 0.2435 | 0.2163 | 0.2835 | 0.2470 | 0.1635 |

**Table 4. Results for Social Media Platforms with Different Network Types**

Note. * p<0.1, ** p<0.05, *** p<0.01. Controls include Stations, Routes, PeakHour, and Weekend.

We conduct an additional formal statistical test proposed by Clogg et al. (1995) to confirm whether significant differences exist across professional, public, and private social media in terms of the extent to which crowdedness affects content consumption and generation. The results further confirm that private social media experiences a significantly greater impact of crowdedness on content consumption and generation compared to professional and public social media ($p < 0.01$). The results lend further support for Hypothesis 2.

Table 5 shows the results regarding the crowdedness effects for social media platforms with different communication modes. The first three columns of the table illustrate that all three types of social media platforms enjoy significant benefits from crowded environments in terms of users' content consumption amount ($p < 0.01$). Moreover, the positive impact of crowdedness on content consumption is most pronounced for text-based social media (coef. = 0.084) compared to image- or video-based one (coef. = 0.007 and 0.021, respectively), supporting Hypothesis 3. Regarding content generation, the last three columns of Table 6 indicate that only text- and image-based social media enjoy significant benefits from crowding ($p < 0.01$), whereas the relationship between crowdedness and content generation on video-based social media is statistically insignificant ($p > 0.1$), provide further support for Hypothesis 3. A formal statistical test (Clogg et al., 1995) confirms that text-based social media enjoys significantly greater benefits from crowded environments compared to image- and video-based social media ($p < 0.01$). The results collectively support Hypothesis 3.

| | (1) TextCC | (2) ImageCC | (3) VideoCC | (4) TextCG | (5) ImageCG | (6) VideoCG |
|---|---|---|---|---|---|---|
| Crowdedness | 0.084*** (0.010) | 0.007*** (0.002) | 0.021*** (0.006) | 0.095*** (0.011) | 0.004*** (0.001) | 0.006 (0.005) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 |
| R-Squared | 0.2856 | 0.2853 | 0.2385 | 0.2836 | 0.1580 | 0.2461 |

**Table 5. Results for Social Media Platforms with Different Communication Modes**

Note. * p<0.1, ** p<0.05, *** p<0.01. Controls include Stations, Routes, PeakHour, and Weekend.

# Robustness Checks

## *Instrumental Variable Approach*

The relationship between crowdedness and social media usage could also be affected by unobservable factors as passengers may self-select into different trains (Andrews et al., 2016), raising another endogeneity concern. To address this potential endogeneity concern for unobservable, we adopt an instrumental variable approach (in this section) and exploit sudden, unanticipated variations in crowdedness that can be considered exogenous (see the next section – Exogenous Shock of Crowdedness).

First, we adopt an instrumental variable approach, i.e., two-stage least square (2SLS), to address the endogeneity concern (Angrist & Krueger, 1994). An instrumental variable should meet both relevance and exclusion restriction assumptions (Wooldridge, 2010). In other words, the instrumental variable should be highly correlated with the endogenous variable and uncorrelated with the error. In this study, we utilize the lagged value of the endogenous variable, $Crowdedness_{ij}$, as its instrumental variable $PrevCrowd_{ij}$ (Siebert & Zubanov, 2010). Specifically, for route $j$ of user $i$, we retrieve the average level of crowdedness for the same route and time from the previous week and define it as $PrevCrowd_{ij}$.

The first column in Table 6 shows the first-stage regression results. As expected, the one-week lagged crowdedness is significantly positively associated with crowdedness in the current week ($p < 0.01$). Also, the F-statistics for the first-stage estimations is significant and higher than 10 ($F = 4110.32$, $p < 0.01$), suggesting that the selected instrumental variables are not weak, and they meet the relevance condition. The passenger flow in a subway during a specific hour follows a relatively stable weekly pattern. Thus, weekly lagged variables are expected to have a high correlation with the current level of crowdedness during

that hour. Regarding the exclusion restriction, the crowdedness in the previous week would not determine unobserved factors of smartphone usage, such as social media usage, in the current week. Hence, it's reasonable to expect that the lagged instrumental variables meet the exclusion restriction condition.

| | **First Stage** | **Second Stage** | |
|---|---|---|---|
| | **(1) Crowdedness** | **(2) ContCons** | **(3) ContGen** |
| Crowdedness | | 0.492***(0.073) | 0.468***(0.077) |
| Stations | 0.0039***(0.0011) | 0.559***(0.005) | 0.594***(0.006) |
| Routes | -0.0440***(0.0019) | -0.038***(0.010) | -0.040***(0.010) |
| PrevCrowd | 0.6991***(0.0109) | | |
| Time Dummy (PeakHour & Weekend) | Yes | Yes | Yes |
| User Fixed Effects | Yes | Yes | Yes |
| Observations | 174,970 | 174,970 | 174,970 |
| R-Squared | | 0.0611 | 0.0627 |
| F-value | 4110.32 | | |

**Table 6. Results of Two-Stage Least Square Analyses**

Note. * p<0.1, ** p<0.05, *** p<0.01.

Table 6 shows the results of two-stage least square analyses, which are consistent with our main findings. In other words, crowdedness enhances both content consumption and generation behaviors on social media platforms ($p < 0.01$), supporting Hypothesis 1. To confirm the validity of our instruments, we check both the relevance and the exclusion restriction conditions. We then further replicate the results of Tables 4 and 5, which are about the crowdedness impact for social media platforms with different network types and communication modes, respectively. Table 7 shows that the results remain qualitatively consistent even after addressing the concern for potential endogeneity, providing further support for Hypotheses 2 and 3.

| **Panel A** | **(1) PrivCC** | **(2) PubCC** | **(3) ProfCC** | **(4) TextCC** | **(5) ImageCC** | **(6) VideoCC** |
|---|---|---|---|---|---|---|
| Crowdedness | 0.502***(0.073) | 0.113**(0.054) | 0.045**(0.022) | 0.499***(0.073) | 0.016(0.012) | 0.036(0.047) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 174,970 | 174,970 | 174,970 | 174,970 | 174,970 | 174,970 |
| R-Squared | 0.0608 | 0.0248 | 0.0069 | 0.0609 | 0.0030 | 0.0169 |
| **Panel B** | **PrivCG** | **PubCG** | **ProfCG** | **TextCG** | **ImageCG** | **VideoCG** |
| Crowdedness | 0.467***(0.077) | 0.101**(0.042) | -0.003(0.009) | 0.467***(0.077) | 0.005(0.009) | 0.043(0.039) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 174,970 | 174,970 | 174,970 | 174,970 | 174,970 | 174,970 |
| R-Squared | 0.0635 | 0.0116 | 0.0011 | 0.0634 | 0.0015 | 0.0079 |

**Table 7. 2SLS Results for Different Social Media Types**

Note. * p<0.1, ** p<0.05, *** p<0.01. Controls include Stations, Routes, PeakHour, and Weekend.

### *Exogenous Shock of Crowdedness*

To further address the concern for the potential endogeneity of crowdedness, we exploit variations in crowdedness exogenously driven by an unexpected event. Specifically, on December 3rd, 2021, an equipment failure occurred on Qingdao Line 2 around 8:40 am, resulting in a suspension of train operations. The failure was resolved around 9:05 am, leading to a return of train operations to normal by 9:30 am. This resulted in a subsequent increase in unmet demand for trains and the level of crowdedness. Specifically, the average crowdedness level during the half-hour period from 9:30 am to 10:00 am on December 3rd, 2021 (Friday) was significantly higher than the average crowdedness level during the same period from November 29th (Monday) to December 2nd, 2021 (Thursday) ($p < 0.05$).

In this section, we examine the effect of this sudden, unexpected increase in crowdedness on social media usage. To this end, we first scrutinize the specific time frame from 9:30 am to 10:00 am to rule out potential effects of the hour of the day. Our analyses include passengers only who traveled during this interval on both December 3rd, 2021 and any date between November 29th to December 2nd, 2021. We then define $Shock_{ij}$ as a binary variable indicating whether route $j$ of user $i$ was taken on December 3rd, 2021 when passengers experienced the exogenous shock, or not. Thus, the estimated coefficient of $Shock_{ij}$ in the following model (i.e., $\beta_1$) would represent the impact of the exogenous increase in crowdedness on social media usage:

$$ContentConsumption_{ij}\ (or\ ContentGeneration_{ij}) = \beta_0 + \beta_1 Shock_{ij} + \beta_2 Stations_{ij} + \beta_3 Routes_{ij} + \alpha_i + \varepsilon_{ij}.$$

Panels A and B of Table 8 show the results regarding the impact of the exogenous shock on content consumption and generation behavior on social media platforms, respectively. The results demonstrate the significant positive impact of the shock on both content consumption ($p < 0.05$) and generation ($p < 0.1$) on overall social media platforms, providing additional supporting evidence for Hypothesis 1. Furthermore, such a positive impact of the shock on content consumption ($p < 0.05$) and generation ($p < 0.1$) is present only for private and text-based social media platforms, lending further support for Hypotheses 2 and 3, respectively. These results further address the potential endogeneity concern for unobservable factors.

| **Panel A** | **(1) ConCons** | **(2) PrivCC** | **(3) PubCC** | **(4) ProfCC** | **(5) TextCC** | **(6) ImageCC** | **(7) VideoCC** |
|---|---|---|---|---|---|---|---|
| Shock | 1.326** (0.625) | 1.645** (0.686) | 0.052 (0.742) | 0.168 (0.217) | 1.659** (0.684) | -0.127 (0.240) | -0.265 (0.649) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 103 | 103 | 103 | 103 | 103 | 103 | 103 |
| R-Squared | 0.7265 | 0.6939 | 0.6003 | 0.4195 | 0.6959 | 0.3998 | 0.6206 |
| **Panel B** | **ConGen** | **PrivCG** | **PubCG** | **ProfCG** | **TextCG** | **ImageCG** | **VideoCG** |
| Shock | 1.159* (0.669) | 1.165* (0.663) | 0.083 (0.538) | | 1.170* (0.663) | -0.074 (0.115) | -0.054 (0.486) |
| Controls | Yes | Yes | Yes | | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | | Yes | Yes | Yes |
| Obs. | 103 | 103 | 103 | | 103 | 103 | 103 |
| R-Squared | 0.6922 | 0.6934 | 0.4191 | | 0.6938 | 0.1663 | 0.4610 |

**Table 8. Results for the External Shock**

Note. * p<0.1, ** p<0.05, *** p<0.01. Controls include Stations and Routes. The result for ProfCG is omitted as content generation on professional social media platforms is not captured in this sample.

### *Alternative Measurement of Content Consumption and Generation*

We also adopt an alternative approach to measure the dependent variables. Specifically, we quantify content consumption and generation by the number of downloaded and uploaded records. We replicate the main

analyses using this alternative measurement, and the results are presented in Table 9. Panel A and B of Table 9 reveal a positive influence of crowdedness on users' content consumption and generation, particularly in relation to private and text-based social media platforms. These findings are consistent with our main findings.

| **Panel A** | **(1) ConCons** | **(2) PrivCC** | **(3) PubCC** | **(4) ProfCC** | **(5) TextCC** | **(6) ImageCC** | **(7) VideoCC** |
|---|---|---|---|---|---|---|---|
| Crowdedness | 0.051*** (0.004) | 0.051*** (0.004) | 0.012*** (0.002) | 0.003*** (0.001) | 0.051*** (0.004) | 0.002*** (0.000) | 0.007*** (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 |
| R-Squared | 0.3085 | 0.3082 | 0.2643 | 0.2181 | 0.3084 | 0.2709 | 0.2629 |
| **Panel B** | **ConGen** | **PrivCG** | **PubCG** | **ProfCG** | **TextCG** | **ImageCG** | **VideoCG** |
| Crowdedness | 0.051*** (0.003) | 0.051*** (0.003) | 0.004*** (0.001) | 0.000 (0.000) | 0.051*** (0.003) | 0.001** (0.000) | 0.002*** (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| User FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 | 233,828 |
| R-Squared | 0.3129 | 0.3125 | 0.2378 | 0.1575 | 0.3128 | 0.1346 | 0.2310 |

**Table 9. Results of the Alternative Measurement of Content Consumption and Generation**

Note. * p<0.1, ** p<0.05, *** p<0.01. Controls include Stations, Routes, PeakHour, and Weekend. 5,337 singleton observations are excluded from the estimation.

## Conclusions and Discussions

In this study, we utilize comprehensive smartphone usage data obtained from a leading telecom operator in China to assess the effects of physical crowdedness on individuals' social media usage behaviors. The results demonstrate a positive causal relationship between crowdedness and content consumption and generation on social media platforms, even after controlling for potential endogeneity of crowdedness using instrumental variable approaches and exploiting exogenous shocks on crowdedness. We hypothesize that stress caused by crowdedness leads to increased social media usage. In other words, stress engendered by crowdedness prompts individuals to seek more social connections, social support, and self-expression, or engage in impulsive behavior in the mobile world, all of which can be facilitated by social media. In addition, we find that the positive effect of crowdedness is more pronounced on private and text-based social media, which can better relieve individual stress.

Some limitations of the study are also noteworthy. The dataset was procured from a top telecommunications provider in China, however, the customer base may not be representative of the broader population, leading to questions of generalizability. To address potential issues of endogeneity with both observable and unobservable variables, a series of supplementary analyses were conducted. However, to fully establish causality from crowdedness to social media usage, randomized experiments are necessary. Moreover, as a result of privacy considerations, we lack access to users' income and occupation data, thus impeding our ability to investigate how the positive influence of crowdedness may differ based on these demographic characteristics. Additionally, it is worth noting that while this study examines the impact of crowdedness within a subway context, the effects may vary across different scenarios. Hence, future research endeavors could explore the relationship in various settings, thereby enhancing the generalizability and robustness of the findings.

Nevertheless, this study offers significant theoretical and managerial implications. First, it enhances our understanding of the effects of crowdedness and resultant stress. Specifically, crowdedness has been widely

investigated in offline retail environments, where its negative effects have been documented extensively (e.g., Harrell et al., 1980; Maeng et al., 2013). However, this study illustrates the positive impact of crowdedness on social media usage in the context of mobile social media. This is a novel contribution to the recently emerging body of research that highlights the positive impact of crowdedness in mobile settings, such as increased responsiveness to mobile promotions (e.g., Andrews et al., 2016). Moreover, despite the widespread recognition of social media as a modern source of stress in individuals (Apaolaza et al., 2019; Demirtepe-Saygili, 2020; Karim et al., 2020; Mark et al., 2014), this study also highlights the potential of social media as a means of alleviating the stress caused by crowdedness in public transit.

Second, this study advances previous research on social media by demonstrating that environmental contexts, such as crowding in public transit, play a significant role in determining social media usage, making it a pioneering study in linking offline contextual information on crowdedness to mobile social media usage. Previous studies on social media usage have revolved around the roles of specific times and locations (e.g., Bohmer et al., 2011; Do et al., 2011; Karikoski & Soikkeli, 2013). However, this study delves into a contextual factor, which can be defined by the synthesis of both spatial and temporal factors, and identifies its impact on social media usage. Crowding in public transit has particular importance as a contextual determinant of social media usage given that public transit constitutes a crucial scenario for social media usage (Andrews et al., 2016; Ghose et al., 2019).

Third, this study contributes to the literature by exploring the boundary conditions that influence the impact of crowdedness on social media usage. Specifically, we demonstrate that the positive impact of crowdedness on social media usage is most pronounced for social media platforms facilitating private social networks and relationships through text-based content. However, platforms hosting public or business-related networks and relationships through visual and auditory means do not typically enjoy benefits from users in crowding. This extends our theoretical understanding of the varying effectiveness of social interactions in alleviating stress, depending on the types of social networks and communication modes.

Our research has valuable managerial implications for social media providers and advertisers. Social media providers can develop competitive strategies that are tailored to individual users, taking into account factors such as the type of service offered (e.g., network and content) and the level of crowdedness each user is now facing. Advertisers can also leverage contextual information on public transit to optimize the effectiveness of their promotional campaigns that target customers in different locations at different times across various social media platforms.

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