[a] and

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ARTICLE HISTORY
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ABSTRACT

KEYWORDS

1. Social Isolation in China

1.1. Introduction

Research is quite mixed when it comes to identifying the relationship between social media use and feelings of isolationism. Early research suggested that the internet would build social capital, or an interconnectedness between people, and that social media platforms were the ultimate way to bring people together. Since then, research on the subject has been decidedly more mixed. On one hand, some authors have found social media may encourage social isolation, and ultimately, social media users may feel more disconnected from others than those who do not use social media. On the other hand, others have found that there is only a minimal relationship between these two variables. More recent scholarship has suggested that social media may produce heterogeneous effects on individuals. This study uses the little-studied Chinese social media environment to try and gain leverage on this question - the Chinese online environment has certain features that should both moderate and exacerbate key causal pathways previously identified in the literature. To we employ a large survey of Chinese internet users and test a variety of regression specifications.[1] The main result is that social media use is generally negatively related to social isolation, though the nature of this relationship changes depending on the urbanicity of the respondent - being in a rural area amplifies this relationship. This finding lends support both to the previous negative relationship findings and also reinforce the findings that emphasize heterogeneous effects.

1.2. Literature Review and Theory

The existing literature on social isolation and social media use generally finds a negative to null relationship between the two variables, while the most recent research has suggested that social media has heterogeneous effects. Based on this existing literature, we then develop some testable hypotheses regarding how the relationship between usage and isolation may vary in the context of China. The result of these hypotheses tests will help to better understand the possible mechanism that links these two variables.

Initially, scholars imagined that social media would create more opportunities for users to create unique and fulfilling social relationships. The early theorizing about the possible benefits of social media hypothesized three important mechanisms by which social media could decrease loneliness. 1) creating more opportunities for online to offline meetups and 2) helping to alleviate feelings of isolation for those who have difficulty making in-person social connections via joining an online communities, and 3) facilitating keeping in touch with family and friends [@ellison2007; @steinfield2008; @subrahmanyam2008].

More recent studies on the subject have found significantly more mixed and often negative evidence regarding the impact of social media on feelings of isolation. Primack et al. found a negative relationship between social media use and social isolation in youth in a representative sample [@primack2017]. A meta-review of the literature on adolescent social media usage notes that while the effect size is often small the relationship in most studies on social media's linkage to ill-being is negative [@valkenburg2022] while emphasizing the importance of heterogeneous effects. There are relatively fewer studies that consider all ages. However, those that have been conducted also emphasize that

[1] All data and analysis files for this research are available at the author's website.

the relationship between social media use and well-being has possible negative effects but the effects seem to vary by personality type [@appel2020]. More recent research has reinforced the finding that the effect of social media on measures like social isolation may be highly heterogeneous across individuals; for some individuals, the effect may be quite negative for some while for others social media usage may have a modestly positive impact on well-being [@beyens2020; @ostic2021].

While most of the studies agree that the causal direction flows from social media use to feelings of isolation (though see [@nowland2018; @kim2017]), there is disagreement among authors about the specific mechanisms and causal pathways through which this relationship exists. For those who find a negative relationship between social media and well-being, one set of mechanisms suggests that the social media itself that is the problem. Cyberbullying, or more generally, repeated and aggressive online attacks against users has been systematically linked to feelings of social isolation [@ademiluyi2022]. Another proposed mechanism is upward comparisons of others and the weak nature of online connections - both of these have been found to generate social anxiety and social isolation [@alabri2022; @büttner2022]. A third set of mechanisms primarily concern themselves with the physical changes that social media causes. Social media use has been shown to displace face to face activity, which leads to greater social isolation [@larson2018]. Heavy social media use also decreases hours of sleep, leading to greater feelings of anxiety and more social isolation [@twenge2017]. The current research suggests that which of these mechanisms is dominant depends on the age/demographic group in question and the societal context [@twenge2019].

Most of the existing research on the subject focuses on Western highly developed societies, and this focus may limit variation on key independent variables given the similar social and institutional context in which users are embedded. To address this problem, this study aims to understand how these complex dynamics interact in the non-Western setting of China. Relatively little is known about China's level of social isolation, though what evidence that does exist suggests that it is on the rise. Twenge et al.'s study found that adolescent feelings of loneliness have generally been on the rise in comparable East Asian countries [@twenge2021]. News reports have highlighted the increasing number of people who consider themselves to be online outcasts or losers (*diaosi*) [@nan2013; @szablewicz2014; @chinas2016]. We do not aim to make a direct comparison between China and Western countries but rather highlight the way in which China's unique context helps shed light on which contextual factors matter in understanding the linkage between the two variables.

The most important of these contextual factor in China is that social media space that is highly controlled online environment. Many people are aware that the Chinese government heavily censors politically sensitive content on online platforms. Fewer are aware that the Chinese government spends as much, if not more, effort to clean up non-political negative or distressing content on the Chinese internet, such as scams, instances of cyber bullying, disturbing videos, and vulgar content [@wang2020]. This control impulse also extends content the government views as spiritually polluting, such as pornography, scantily dressed women, and other escapist content. While the Chinese government and online platforms are not 100 per cent effective in their ability to completely stamp out such content, the default is that such content is actively restricted, while US platforms tent to take a more pro-speech regulatory position [@liu2022]. If one of the main mechanisms through which social media promotes social isolation occurs is exposure to negative content, then this highly regulated online environment should lead to a weaker relationship between social media use and isolation. Suggestive of this is a a study by Liu and Liu that finds Chinese who consumed more commercialized and sensationalized media reported more trauma during the first COVID-19 outbreak in China than those who followed government sources [@liu2020].

On the other hand, China also has a highly robust online influencer culture. While social media influencers are a global phenomena, China has perhaps the most commercialized version of influencing. Social media influencers are developed by large agencies and work in an almost assembly-line fashion to promote products on livestreams or pitch sponsored products. In this influencer culture, less attention is paid to authenticity and personality and relatively more emphasis is placed on consumerism, brand promotion, and image [@tam2019; @wei2023]. Given that previous research has suggested one of the main channels through which social media creates feelings of isolation is negative personal comparisons with online content (so-called "FOMO" - fear of missing out), heavy social media use may increase the strength of the relationship between social media use and social isolation through consumption of such highly commercialized content. These influencers are most popular among young consumers so one may expect that only younger users would experience these effects.

Additionally, China's social media environment is relatively unique in that the dominant messaging platform is also the largest social media app (WeChat). Users can use it simply to chat with family and friends, they can use it to post photos and other content about their life in a feed that works similarly to Facebook, or they can browse videos of others in a method similar to Tiktok. Previous research has indicated that while, on the whole, social media increases social isolation, for users that primarily use it to contact friends and family, its use can counteract the negative effects [@hajek2019; @lim2020]. In this way, those that heavily use these type of combined platforms may engage in multiple uses of social media that tend to cancel each other out. Given the ubiquity of WeChat in China, such a relationship seems plausible.

Finally, the nexus of social isolation and social media use in China has played out in the context of one of the most rapid periods of urbanization in human history. Hundreds of millions of people have shifted from rural subsistence farming to participating in an urban market economy. The existing literature finds that urbanicity is an important factor in levels and mechanisms for social isolation; many studies of Western societies have found that rural residents, while having stronger familial bonds, also can more easily experience social isolation without those bonds [@kaye2017; @koning2017; @henning-smith2018]. In China, less is known about the differential effects of the urban rural divide on feelings of social isolation but the research that does exist suggests that urban environments can be especially isolating, particularly for rural to urban migrants particularly due to lack of access to traditional support systems and familial connections [@li2017].

Given the existing literature and the context of China, this leads to a series of testable hypotheses.

- **H1a:** social media use should have a weak or possibly positive connection to social isolation due to strengthened government control over online content
- **H1b:** social media use should have a strongly negative connection to social isolation due to the dominance of influencer culture in China, possibly moderated by age.

- **H2:** those who are able to use social media to make new friends will have lower social isolation scores than those who do not
- **H3:** the urban/rural divide will produce differential impacts in the above hypotheses on the relationship between social media use and social isolation

1.3. Data, Measurement, and Descriptives

The data used in this study are original. We designed a survey instrument in English, and translated it into Chinese, to measure a range of concepts including social isolationism and various dimensions of social media and digital information consumption. We employed Qualtrics to collect the data. They randomly selected 2292 respondents from their existing panel[2] from November 25 to December 2, 2015. This sample size on provides for a roughly ± 2 margin of error.[3]

Our dependent variable, *social isolationism*, is a three-item additive index. Respondents were given the following introduction: The next question is about how you feel about different aspects of your life. Could you tell me for each one if you feel that way always, almost always, some of the time, rarely or never? Then they were asked: A) How often do you feel that you lack companionship, B) How often do you feel isolated from others?, and C) How often do you feel left out? Response options were recoded so that higher responses equated to feeling more socially isolated, they were all three added together, and then rescaled to range from 0 through 1 maintaining the original intervals ($\alpha = 0.86$). The distribution of that index is presented in Figure 1. The distribution is relatively normal centered around the midpoint with a slight skew to the right. Most respondents appear to be on the low end, indicating the the majority of those in our sample do not feel particularly isolated. Conversely, the right skew in the distribution does suggest that a sizable chunk of folks feel quite socially isolated. Altogether, the spread out distribution indicates quite a bit of variance ($\mu = 0.41$, $sd = 0.20$).

```r
figure1 = ggplot(china_isolation_data, aes(x=isolation)) +
  geom_histogram(aes(y=..density..), colour="black", fill="seashell")+
  geom_density(alpha=.2, fill="#FF6666") +
  xlab("Social Isolationism") +
  ylab("Density") +
  theme(panel.border = element_rect(color = "black",fill = NA))
figure1
```

```
Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
i Please use `after_stat(density)` instead.
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
Warning: Removed 9 rows containing non-finite values (`stat_bin()`).
```

[2] Qualtrics recruits a large pool of respondents for various survey projects through online advertising. Recruits who update their profiles at least once every 6 months are randomly invited to participate. These recruits are awarded online points that can be exchanged for cash or various other country-specific gifts. The number of points is based on the length of the survey, and since our survey had over fifty questions, respondents received a relatively high number of points.

[3] We were able to first collect a small sample ($n = 286$) to check the reliability and adjust the instrument after before proceeding with the final data collection. We made three adjustments, none of which are related to the measures used in the current study.

```
Warning: Removed 9 rows containing non-finite values (`stat_density()`).
```

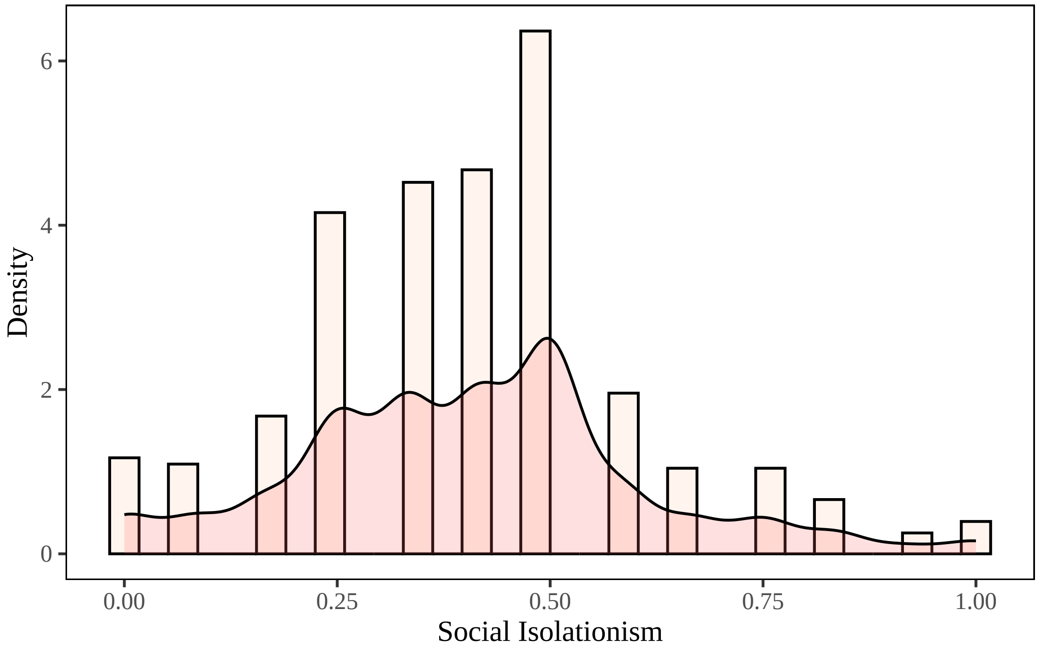

Figure 1.: Distribution of Social Isolationism Index

We have several primary independent variables including human interaction, online to offline relationships, general social media use, and urbanicity. We measured human interaction with a single item: "Has the internet and phone applications increased your contact with the following groups of people (check yes to all that apply)?" The response options were: 1) Family that lives nearby, 2) Family that lives far away, 3) Friends that live nearby, 4) Friends that live far away, 5) People you met on the internet that live nearby, and 6) People you met on the internet that live far away. We simply counted the number of selected responses so the item ranged from 0 to 6, and then for the models that come later, we rescaled it to range from 0 through 1 maintaining the original intervals. Online to offline relationships was also measured with a single item: Have you met someone offline that you initially met online? Response options were: 1) Yes, many times, 2) Yes, several times, 3) Yes, once, and 4) No, never. We inverted this scale so that higher values represented more offline relationships, and again, rescaled it to range from 0 through 1 for the models that follow.

The distributions of these ordinal independent variables are reflected in Figure 2. Very few people claimed to never have increased their contact/connections with others through the internet. The modal number of increased connections respondents claimed to have made through the internet was 2, followed closely by 1, but a sizable proportion of the sample, about 48% claimed to have increased their number of personal connections by 3 or more through the internet. Perhaps not surprisingly, the modal response when asked whether one had met someone online and that relationship moved offline was "No, never". On the other hand, we were surprised that about 37% of those sampled claimed to have moved relationships offline several times, over 10% said they had done so many times, and about 13% did so once. Taken altogether, a large proportion of our respondents seem to using the internet to facilitate social relations.

```
figure2a = ggplot(data = subset(china_isolation_data, !is.na(human_interaction_cat)), a
  geom_bar(aes(y = (..count..)/sum(..count..))) +
  scale_y_continuous(labels=scales::percent) +
  labs(x = "Human Interaction", y = "Percent") +
  coord_flip() +
  theme(panel.border = element_rect(color = "black",fill = NA, size = 1))
```

```
Warning: The `size` argument of `element_rect()` is deprecated as of ggplot2 3.4.0.
i Please use the `linewidth` argument instead.
```

```
figure2b = ggplot(data = subset(china_isolation_data, !is.na(online_offline_cat)), aes
  geom_bar(aes(y = (..count..)/sum(..count..))) +
  scale_y_continuous(labels=scales::percent) +
  labs(x = "Online to Offline Relationships", y = "Percent") +
  coord_flip() +
  theme(panel.border = element_rect(color = "black",fill = NA, size = 1))

grid.arrange(figure2a, figure2b)
```

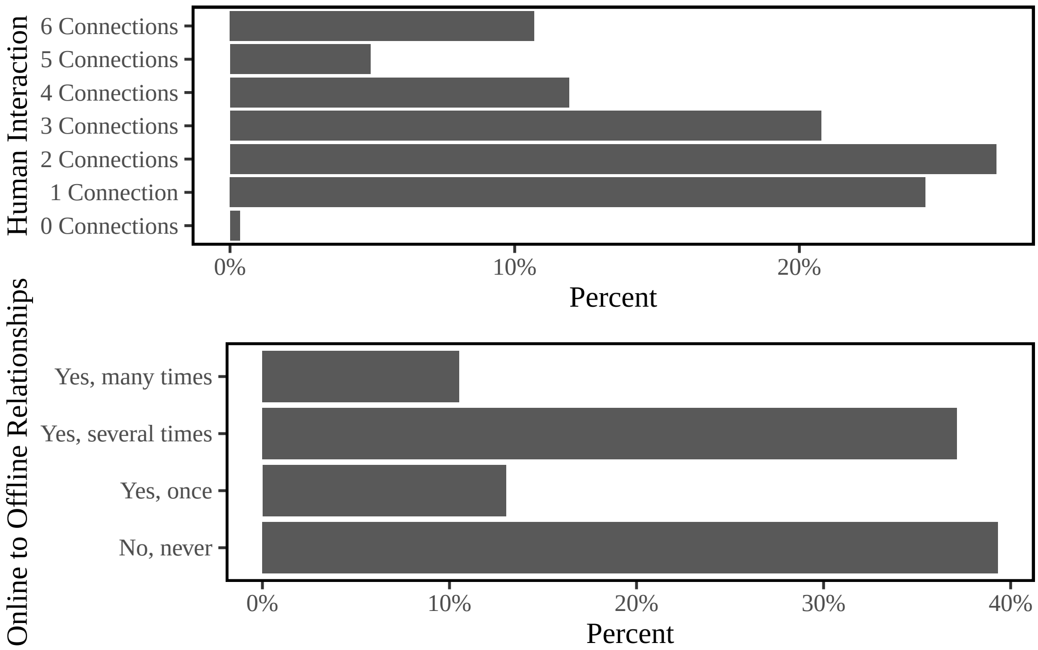

Figure 2.: Primary Independent Variables Distributions

We measured general social media use with an index based on the following three items: 1) About how many hours a day would you estimate you spend using only social media? Social media means applications like Weibo, QQ, Renren, Kaixin001, Douban, WeChat or other sites and services that allow users to interact with each other. (0-1, 1-2, 2-3, 3-4, 4-5, 5-6, 6-7, 7-8, 8-9, or More than 9), 2) Do you check email, read websites, and use social media (social media means applications like Weibo, QQ, Renren, Kaixin001, Douban, WeChat or other sites and services that allow users to interact with each other) more than you did five years ago? (Yes, No), and 3) How often do you read news stories about political events that have been posted on social media (social media means applications like Weibo, QQ, Renren, Kaixin001, Douban, WeChat or other sites and services that allow users to interact with each other)? (More than once a day, Everyday, Three-to-five days per week, One-to-two days per week, Less often, Never). Each was recoded so that higher values represented more social media use, rescaled to range from 0 through 1, added together, and then again, rescaled to range from 0 through 1 maintaining all original intervals. The distribution of this index is presented in Figure 3. The distribution is relatively normal and tightly centered around the mean 0.63 with a standard deviation of 0.17, but there is a left skew suggesting that a portion of the population is not that social media active, but clearly the bulk of the population are.

```
figure3 = ggplot(data = subset(china_isolation_data, !is.na(gen_social_med)), aes(x=ge
  geom_histogram(aes(y=..density..), colour="black", fill="seashell") +
  geom_density(alpha=.2, fill="#FF6666") +
  xlab("Social Media Use") +
  ylab("Density")  +
  theme(panel.border = element_rect(color = "black",fill = NA))
figure3
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

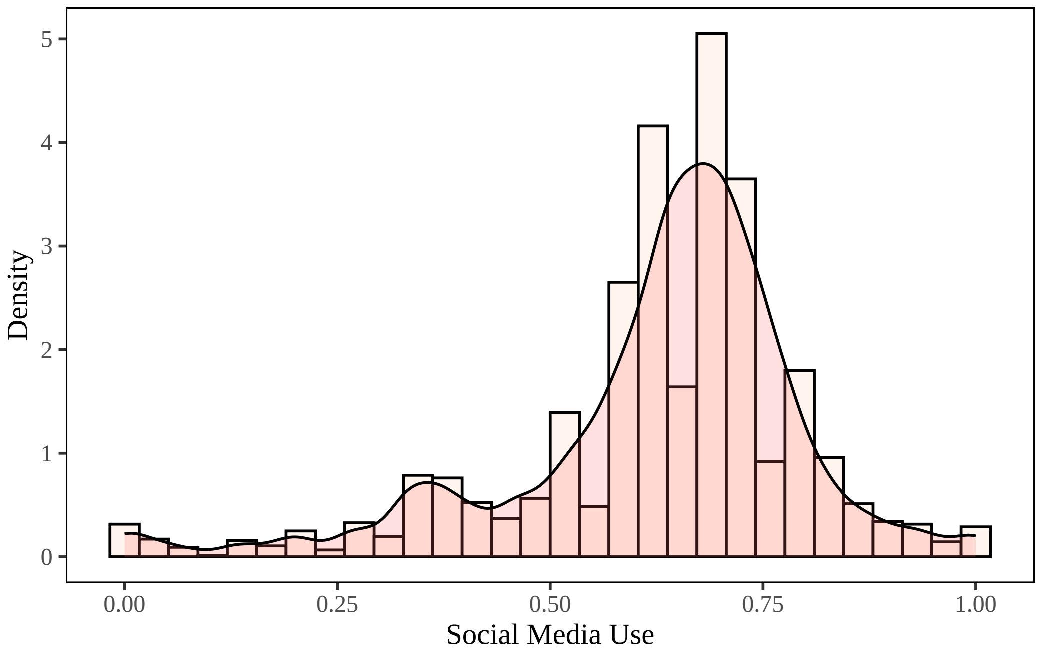

Figure 3.: General Social Media Use Distribution

Our final primary independent variable, urbanicity, was measured using a single item: Which of these best describes the place in which you live? (Countryside/Village, Small City, Mid-Sized City, Suburban Area of a Big City, Big City). For the purpose of the models, we rescaled this item to range from 0 through 1 maintaining the original intervals. The distribution is reflected in Figure 4. Given the rural to urban Chinese migration since the founding of the People's Republic [@xia1995], it is not surprising to see that nearly 45% of those in our sample live in cities, 7% in suburbs, and about 27% in mid-sized cities. About 16% say they live in small cities and only about 5% say they live in villages.

```
figure4 = ggplot(data = subset(china_isolation_data, !is.na(urbanicity_cat)), aes(x = u
  geom_bar(aes(y = (..count..)/sum(..count..))) +
  scale_y_continuous(labels=scales::percent) +
  labs(x = "Urbanicity", y = "Percent") +
  coord_flip() +
  theme(panel.border = element_rect(color = "black",fill = NA, size = 1))

figure4
```

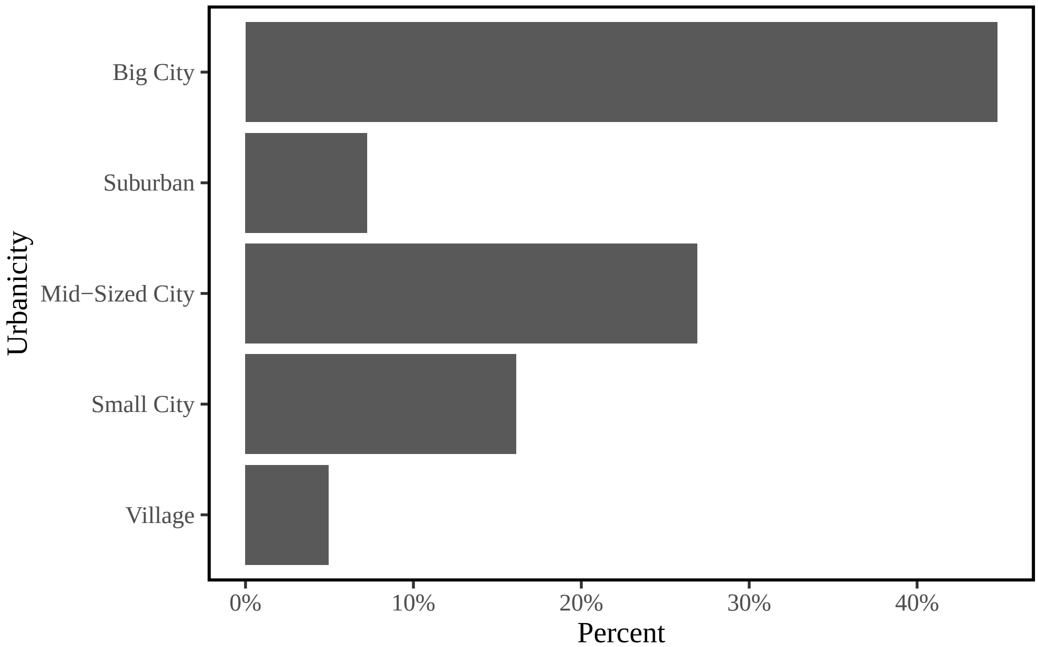

Figure 4.: Urbanicity Distribution

Our modeling strategy that follows is straightforward. We begin by modeling each of our internet communication independent variables as function of socio-economic status (SES), gender, Chinese Communist Party membership (CCP), and age to create an individual profile of each type of digital user (see the Online Appendix for the operationalization of these variables). This provides some context for the models that follow which are intended to test our primary hypotheses, that is that internet communication can deter social isolation and that this is particularly true for those who do not have the convenience of the high social interaction opportunity provided by urban living. For those we begin by fitting an additive model of our index of social isolationism as function of each of our primary independent variables while also controlling for the same variables included in our profile models. Finally, we refit three models with the same specification but introduce an interactive term between each of our internet communication indicators, respectively, with our measure of urbanicity. This allows us to test whether the observed additive effects are stronger for those living outside cities.

1.4. Results

Given that the first two dependent variables (human interaction, online to offline to offline relationships) in our profile models are distributed ordinally, we initially estimate linear models of those outcomes and examine the residual behavior to determine if a linear model fits the data well or if an ordered outcome model is a better fit. The results were clear, a linear model is not a good fit for either outcome (see the figures in the Online Appendix), so we fit the models using ordered logit. Because our measure of general social media is based on an additive index, we treat it as continuous, and accordingly fit a linear model.

```
mod1_ord = polr(human_interaction_cat ~ ses + female + CCP_member + age, data = china_i
mod2_ord = polr(online_offline_cat ~ ses + female + CCP_member + age, data = china_isol
mod3 = lm(gen_social_med ~ ses + female + CCP_member + age, data = china_isolation_data

models <- list(
  "Human Interaction" = mod1_ord,
  "Online/Offline Interaction" = mod2_ord,
  "General Social Media" = mod3
)

gof.included <- list(
  list("raw" = "nobs", "clean" = "N", "fmt" = "%i"),
  list("raw" = "r2.nagelkerke", "clean" = "Pseudo R2", "fmt" = "%.2f"),
  list("raw" = "r.squared", "clean" = "R2", "fmt" = "%.2f"))

n <- "Human Interaction and Offline/Online Relationships estimates are derived from ord

modelsummary(models,
             coef_omit = ".*Connect|.*Intercept|.*No|.*Yes",
             coef_rename = c("ses" = "SES",
                             "female" = "Female",
                             "CCP_member" = "CCP Member",
                             "age" = "Age"),
             fmt=2,
             stars=c("*" = 0.05),
             output="kableExtra",
             gof_map = gof.included) %>%
  footnote(general = n, threeparttable = TRUE)
```

```
#gof_omit = "R2 Adj|AIC|BIC|Log.Lik.|RMSE"
```

The results of our profile models are presented in Table 1. When it comes to SES, the relationship across all three of our internet communication is consistent. As SES

Table 1.: Modeling Profiles of Digital Communication

	Human Interaction	Online/Offline Interaction	General Social Media
SES	2.35*	2.16*	0.24*
	(0.27)	(0.28)	(0.03)
Female	−0.03	−0.35*	0.01
	(0.08)	(0.08)	(0.01)
CCP Member	−0.17	0.23*	0.01
	(0.09)	(0.09)	(0.01)
Age	0.51*	−0.82*	−0.12*
	(0.26)	(0.27)	(0.02)
N	2277	2276	2198
Pseudo R2	0.07	0.05	
R2			0.05

* $p < 0.05$

Note:
Human Interaction and Offline/Online Relationships estimates are derived from ordered logit and General Social Media from ordinary least squares.

goes up so does digital human interaction, the move from online to offline relationships, and general social media use. That gender is only statistically significant in the model of the move from online to offline relationships where women are less likely to do so. Interestingly, being a CCP member has inverse relationships with human interaction and the move from online to offline, where members are less likely to increase digital human interaction but are more likely to move online relationships offline. Finally, the older respondents were the more likely they were to increase human interaction, and the less likely they were to move relationships offline and use social media. These profile results provide background context for the models that follow. The internet communication indicators are our primary independent variables, so these profile models give us a sense for whom they matter the most when it comes to deterring social isolation.

```
mod4 = lm(isolation ~ human_interaction + online_offline + gen_social_med + urbanicity

mod5 = lm(isolation ~ human_interaction*urbanicity + online_offline + gen_social_med +

mod6 = lm(isolation ~ online_offline*urbanicity + human_interaction + gen_social_med +

mod7 = lm(isolation ~ gen_social_med*urbanicity + human_interaction + online_offline +

n <- "Estimates are derived using ordinary least squares"

mods <- list(mod4, mod5, mod6, mod7)

modelsummary(mods,
```

```
                coef_omit = ".*Connect|.*Intercept|.*No|.*Yes",
                coef_rename = c("ses" = "SES",
                                "female" = "Female",
                                "CCP_member" = "CCP Member",
                                "age" = "Age",
                                "urbanicity" = "Urbanicity",
                                "online_offline" = "Online-Offline",
                                "human_interaction" = "Human Interaction",
                                "gen_social_med" = "Social Media",
                                "human_interaction:urbanicity" =
                                  "Human Interaction*Urbanicity",
                                "online_offline:urbanicity" =
                                  "Online-Offline*Urbanicity",
                                "gen_social_med:urbanicity" =
                                  "Social Media*Urbanicity"),
                fmt=2,
                stars=c("*" = 0.05),
                output="kableExtra",
                gof_map = gof.included) %>%
  footnote(general = n, threeparttable = TRUE)
```

The results of our models of social isolation are presented in Table 2. The additive estimates in model (1) provide mixed results regarding whether internet communication is a positive force in deterring social isolation. Not surprisingly, there is a negative relationship between the number of digital connections (human interaction) folks make and feelings of social isolation. On the other hand, though, both moving online relationships offline and general social media use are positively related to feelings of social isolation. The latter is consistent with much of the literature outlined above, but the former is not. The results also indicate that those living in more urban environments tend to feel less socially isolated.

Models (2) - (4) in Table 2 include each of the interactions between our three internet communication measures and urbanicity. The consistent result across the interactions is that the relationships are dulled for those living in more rural areas. The interaction between digital humna interaction and urbanicity is statistically significant ($p < 0.01$), as is that between the move from online to offline relationships and urbanicity ($p < 0.001$), and that between general social media use and urbanicity only slightly misses the arbitrary 0.05 threshold ($p = 0.07$). The interactions are most easily interpreted graphically (see Figure 5).

```
a <- plot_model(mod5, type = "pred", title = "", terms = c("human_interaction", "urban
               , legend.title = "Urbanicity") +
  scale_color_discrete(labels = c("Village", "Small City", "Mid-sized City", "Suburb",
  ylab("") +
  xlab("Digital Human Interaction") +
  theme(panel.border = element_rect(color = "black",fill = NA, size = 1))
```

```
Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```

Table 2.: Modeling Social Isolation

	(1)	(2)	(3)	(4)
Human Interaction	−0.14*	−0.04	−0.14*	−0.14*
	(0.02)	(0.04)	(0.02)	(0.02)
Online-Offline	0.07*	0.07*	0.15*	0.07*
	(0.01)	(0.01)	(0.03)	(0.01)
Social Media	0.05*	0.05*	0.05*	0.13*
	(0.03)	(0.02)	(0.02)	(0.05)
Urbanicity	−0.04*	0.02	0.01	0.04
	(0.01)	(0.03)	(0.02)	(0.05)
SES	−0.04	−0.04	−0.04	−0.04
	(0.03)	(0.03)	(0.03)	(0.03)
Female	0.02*	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
CCP Member	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Age	−0.19*	−0.20*	−0.20*	−0.20*
	(0.03)	(0.03)	(0.03)	(0.03)
Human Interaction*Urbanicity		−0.14*		
		(0.05)		
Online-Offline*Urbanicity			−0.12*	
			(0.03)	
Social Media*Urbanicity				−0.13
				(0.07)
N	2173	2173	2173	2173
R2	0.08	0.08	0.09	0.08

* $p < 0.05$

Note:
Estimates are derived using ordinary least squares

```r
b <- plot_model(mod6, type = "pred", title = "", terms = c("online_offline", "urbanici
                , legend.title = "Urbanicity") +
  scale_color_discrete(labels = c("Village", "Small City", "Mid-sized City", "Suburb",
  ylab("") +
  xlab("Online to Offline Relationships") +
  theme(panel.border = element_rect(color = "black",fill = NA, size = 1))
```

```
Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```

```r
c <- plot_model(mod7, type = "pred", title = "", terms = c("gen_social_med", "urbanici
                , legend.title = "Urbanicity") +
  scale_color_discrete(labels = c("Village", "Small City", "Mid-sized City", "Suburb",
  ylab("") +
  xlab("Social Media Use") +
  theme(panel.border = element_rect(color = "black",fill = NA, size = 1))
```

```
Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```

```r
grobs <- list(a, b, c)

grid.arrange(grobs=grobs, ncol=2, left="Feelings of social isolation")
```

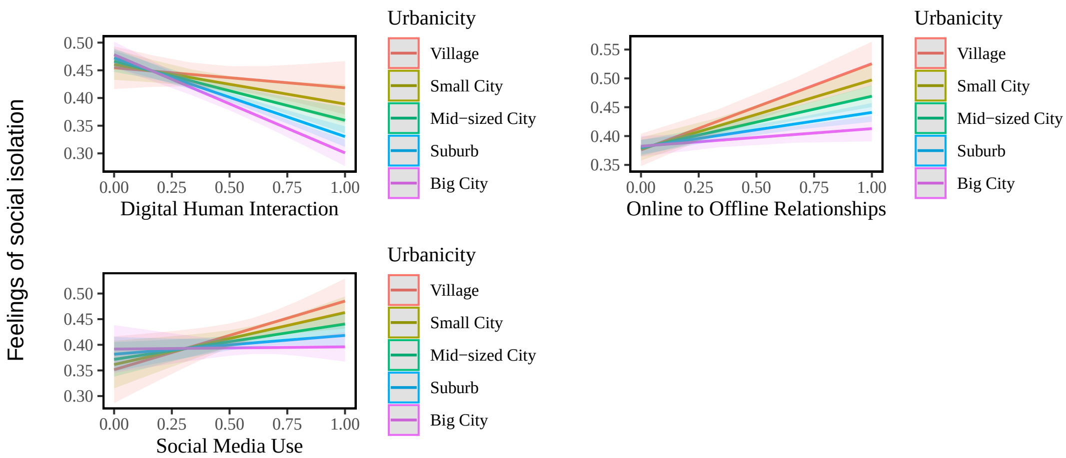

Figure 5.: Modeling Social Isolation: Interaction Results

The model (2) results are graphed in the upper left hand figure. Here it is clear that the negative relationship between digital human interaction and feelings of social isolation is considerably stronger for those in cities. For that matter, notice that the relationship for those in villages is basically flat; the 95 percent confidence interval around the slight negative slope indicates that the relationship could be flat.

The results from the interaction between online to offline relationships and urbanicity are displayed in the graph in the upper right hand corner of Figure 5. Again, here, the main effects run in the opposite direction than those of digital human interaction. Those who are more likely to move relationships from online to offline tend to feel more isolated, and the interactive results presented here suggest that this relations is stronger for those living in less urban spaces. Likewise, the same is the case for those using social media more frequently. In fact, the relationship here for those living in the largest cities is completely non-existent.

In terms of our original hypotheses, we find support for the idea that China's social media environment is not particularly unique with respect to generating feelings of social isolation (**H1b**). Whether or not this is due to the influencer culture or other factors, we cannot say with our data, however age is a consistently negative predictor of social isolation even when controlling for amount of social media use. This result is at least suggestive of the negative online influencer culture. We also find, as has been found in other studies, that users who use the internet to create new connections are less likely to feel isolated (**H2**). However, this does not seem to extend to those that use the internet to facilitate offline meetups. Finally, we find that the impact of the internet and social media vary significantly according to the level of urbanicity (**H3**) - this matches with previous findings that suggest that there is significant heterogeneity in the impact of social media on social isloation.

1.5. Conclusion

Cyberoptimists heralded the internet as means by which people could connect, build social capital, and some suggested this could deter social isolationism. On the other hand, more recent research and popular media coverage of the subject has presented a deeply negative view of the role of social media. Our results do lean toward supporting the negative conclusions but add important contextualization and are suggestive of which of the hypothesized mechanisms are most relevant.

Firstly, we found no evidence that the internet could serve as bridge to build connections for those living outside of cities. The optimistic view that internet use could lower the costs of making connections for those who have less social opportunity, those living in less populated areas, and as a result, help them to feel less isolated. We, in fact, found the opposite. Internet communication had either less positive effect or more negative effect on feelings of social isolation for those living in less urban spaces. This finding lends support to the FOMO channel - viewing lots of content from influencers in a rural area compounds feelings of isolation.

Additionally, given the robustly negative relationship between social media use and social isolation even in the context of China's highly policed internet, our results cast some doubt on theories that suggest it is the negative content, such as cyberbullying or violent/graphic posts, that drives the relationship. Finally, our results also further suggest more work needs to be done in identifying important hetergeneous effects - in our results, those living in a big city experienced almost no change in social isolation as social media use increased while the relationship becomes increasingly negative by ruralness. This specific heterogeneous effect may be unique to China but the strength of it suggests that important inter-personal factors may be relevant in other contexts.

While our study is far from the last word on the subject, we hope this paper further helps move researchers away from considering the binary question of whether social media use has a negative relationship with social isolation to more productively considering the contextual and personal attributes that moderate and mediate this relationship.

1.6. References

1.7. Online Appendix

1.7.1. Variable Operationalization

SES is an additive index of these two questions regarding income and education. Each of the following questions were rescaled to range from 0 through 1, then the two questions were summed, and then rescaled to range from 0 through 1 again.

- Here is a table showing the range of monthly incomes that people have. Which of the letters on this table best represents the total monthly income of your household (after tax)?
  - 0 - 3,000,
  - 3,000 - 6,000,
  - 6,000 - 10,000,
  - 10,000 - 15,000,
  - 15,000 - 25,000,
  - 25,000 - 40,000,
  - More than 40,000
- What is the highest level of education that you have obtained?
  - No formal education,
  - Primary,
  - Middle school,
  - High school,
  - University,
  - Advanced Studies/Graduate School

Other important predictor variables are operationalized as follows:

- Gender
  - 0 = male,
  - 1 = female
- Are you a member or probationary member of the CCP?
  - 0 = no,
  - 1 = yes
- How old are you? (rescaled to range from 0 through 1)

1.7.2. Residual Analysis

```
resid_panel(mod5, plots = "R")
```

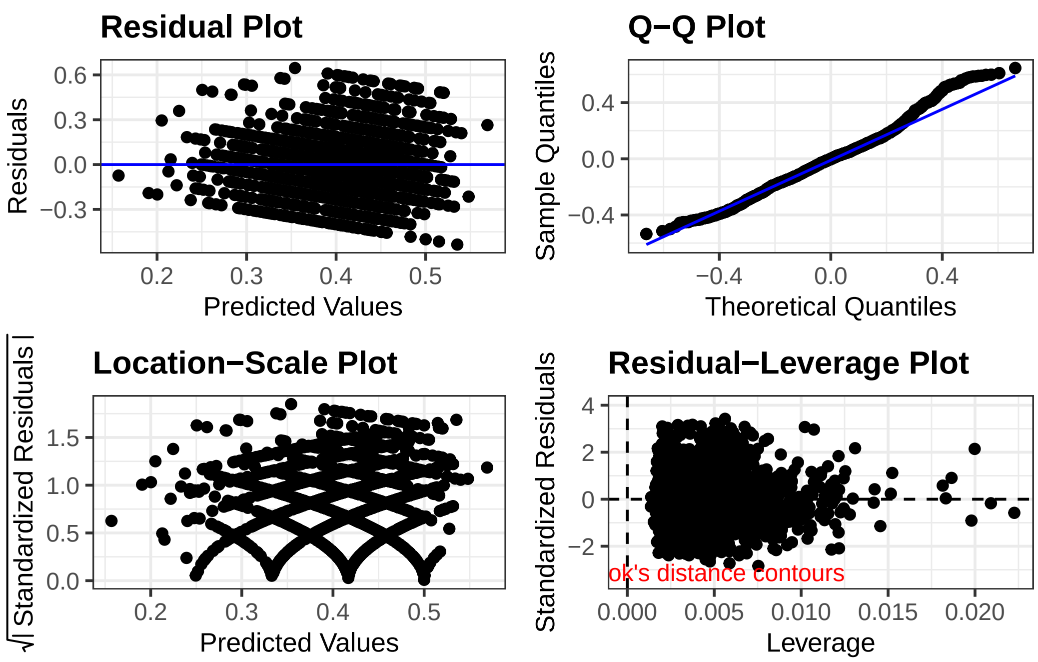

Figure 6.: Human Interaction Model Residuals

```
resid_panel(mod6, plots = "R")
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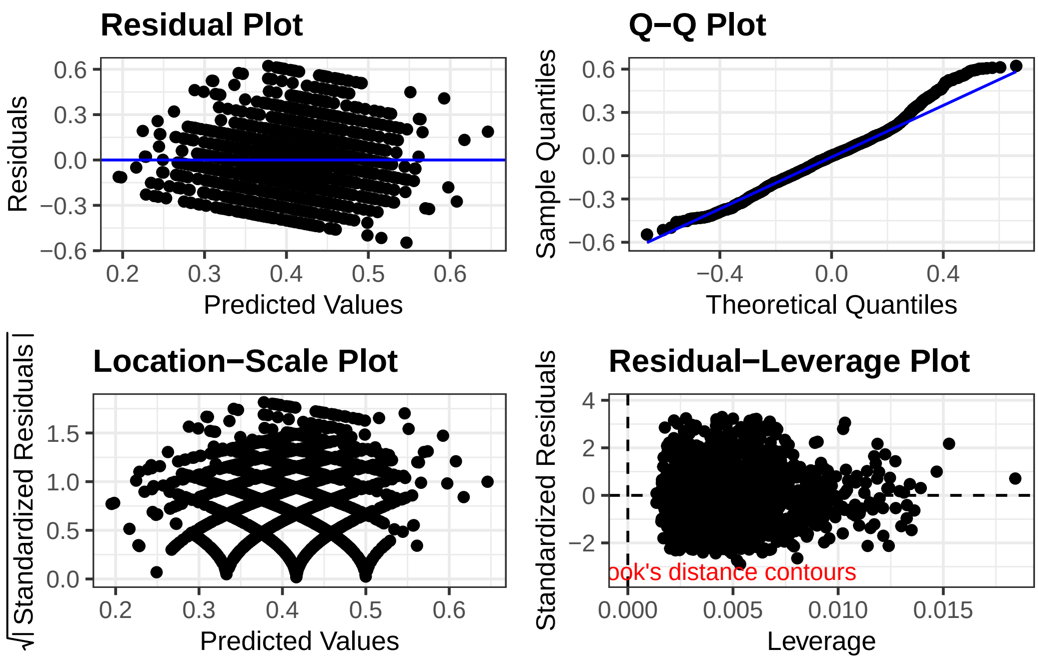

Figure 7.: Online/Offline Model Residuals