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GOING DIGITAL? HOW BLACK AND HISPANIC SENIORS ADAPTED DURING COVID

Mark A. Scanlan, Stephen F. Austin State University

ABSTRACT

The COVID-19 pandemic required isolation for many people at its peak. This isolation was especially prevalent and painful for seniors who became cut-off from friends and family. This study examines access to information and communication technologies by older adults and extends previous research by focusing on outcomes for racial and ethnic minorities within this population. Census data from 2017 and 2021 is used to compare online activities by older adults before and during the COVID-19 pandemic. Our results indicate that Black and Hispanic individuals aged 65 or older were less likely to own a computer or access the Internet than their White peers in both 2017 and 2021, but that the gap between these groups decreased during the pandemic. We also find that older Black Internet users were significantly less likely to engage in most activities online than their White peers. This deficiency, however, closed significantly between 2017 and 2021, especially in relation to social media use where no deficiency was found to exist. Hispanic Internet users who were 65 or older were found to be less likely to participate in half of the studied online activities in both years. Older Hispanic adults still lagged in online shopping and searching for health information online, while this group was equally as likely as their White peers to do activities such as use social media and engage in finances online. Our results indicate real progress for racial and ethnic minorities in the acceptance of information and communication technologies in their daily lives, but we also find that large benefits could still be achieved by targeting policy towards these groups.

INTRODUCTION

The sudden onset of the COVID-19 pandemic resulted in widespread uncertainty and panic as governments scrambled to understand the virus and control its spread. While the virus negatively impacted all demographics, it has been particularly dangerous for the elderly, who suffered significantly higher death rates than the general population. Early in the pandemic Americans over the age of 65 were at a 16- to 52-fold higher risk of dying from COVID-19 than their younger counterparts (Ioannidis et al., 2020). To date there have been over 1.1 million deaths in the U.S. from COVID-19 with adults aged 65 and older accounting for nearly 800,000 of these cases. In the month of September 2022 alone, the elderly represented 88% of COVID related deaths (Freed et al., 2022).

As it became apparent that the elderly were at an elevated risk from COVID-19 they began to self-isolate to avoid contracting the disease. At the same time, family members began to limit physical proximity with this group out of fear of unintentionally spreading the virus to them (Markowitz et al., 2022). This combination resulted in extended periods of isolation and increased loneliness among the elderly (Paulin, 2020). It had already been well documented before the pandemic that older adults who are socially isolated experience adverse health outcomes including higher rates of dementia, obesity, heart diseases, depression, and premature death (NAS, 2020; Gerst-Emerson et al., 2015; Santini et al., 2020). The extended isolations that resulted from the spread of the COVID-19 virus magnified these effects, especially for those living in assisted care facilities, those who lived alone, and those who had socioeconomic disadvantages (Armitage et al., 2020; Kasara et al., 2021; Santini et al., 2020). One potential way to mitigate the feelings of isolation and loneliness is through the use of information and communication technologies (ICT's), specifically through online connections. Internet use can help, not only with shopping and receiving health related information during the pandemic, but it can also serve as a way to stay connected with friends, family, and society as a whole (Kasara et al., 2021; Berg-Weger et al., 2020).

Given the benefits of having access to technology, particularly during a pandemic, it becomes important to determine whether older adults lag behind the general population in adoption of ICT's. If a gap does exist, it is crucial to determine which groups of seniors are most at risk of lacking access to ICT's so that policies and programs can be better targeted to those groups. This study aims to fill this gap in the current literature by first examining the digital divide between the elderly and the young before and during the pandemic, then determining whether specific racial and ethnic groups among the older generations are at a greater risk of not being connected. We then answer the question of whether, once online, do Black and Hispanic seniors engage in online activities in the same way as their White peers? In the next section, we look at research that describes the digital divide in technology access and Internet use for older adults. Next, we describe the data in this study and outline the model and methodology that are employed to achieve our results. We then present our initial results on computer ownership, Internet access, and online activities. These activities include e-commerce, online banking, social media use, and finding health information online. The subsequent section extends these results by implementing interaction effects between race/ethnicity and age variables. We conclude by discussing the implications of our findings and recommending future research that should be conducted in this area.

LITERATURE

It was discovered early in the computer revolution that older adults are consistently slower to adopt computers and connect to the Internet. It follows, therefore, that the pandemic did not cause a shortage of computers for the elderly or limit their access to the Internet; instead it highlighted a problem that already existed. Studies by Lenhart et al. (2003), Goolsbee (2001), and Scanlan (2007) all noted that a person's age was inversely related to the likelihood that they would own a computer or connect to the Internet. Morris and Brading (2007) referred to this gap as the "Grey Divide". Anderson and Perrin (2017) find that Internet use among people 65 or older increased by 55% between 2000 and 2016, to a 67% overall usage rate. Even with this progress, they find older adults still significantly lag behind younger Americans who achieved a 90% usage rate. Therefore, while we observe the adoption rate of technology among older adults is increasing, it still falls short of the general population, even after controlling for income and educational differences using multivariant regression analysis (Friemel, 2016; Scanlan, 2022; Song et al., 2021).

As Internet usage among older adults has expanded, so has the literature on how this group consumes online content. One such area, eHealth, relates to searching for, receiving, and understanding health information found online (Hong et al., 2017). Opportunities for eHealth have broadened over time due to expansions in telehealth services, access to medicines online, health intervention services, and health information being shared on social media. Taking advantage of these resources has been shown to bring about a variety of health benefits such as improved access to doctors and medicine, participation in support groups, and improved diets (McCully et al., 2013; Chou et al., 2011). In one such example, Muellmann et al. (2018) and Van Dyck et al. (2016) find that intentional web-based health interventions lead to improved physical activity among older adults. Given these quality-of-life benefits, eHealth literacy becomes acutely beneficial to older adults as they begin to face the health challenges that arise with age. However, even after controlling for access to computers and the Internet, older adults are still found to have low eHealth literacy and are less likely to use the Internet to search for health-related information online (Levy et al., 2015). Furthermore, older adults that are in good health are found to be more likely to use computers than those who were unhealthy, while Black and Hispanic seniors were less likely to use ICTs for health-related activities (Heart et al., 2013; Mitchell et al., 2019; Yoon et al., 2020; Walker et al., 2020). Our results confirm that older Black and Hispanic Internet users were less likely to engage in eHealth before the pandemic, we then extend this research by showing that this did not improve significantly after the pandemic began.

Beyond the health-related benefits of social media discussed above, the use of social networks during the pandemic became a way for friends and families to stay connected when direct contact became difficult. Historically older adults have been slow to adopt social media usage due to security and privacy concerns, uncertainty regarding social norms online, and an initial feeling that it lacked personal relevance for them (Leist, 2013). Yu et al. (2016a) find that older adults become less likely to use social media as they age but find older Black and Hispanic users are not significantly less likely to use social media than their White peers. Once older adults do become active on social media, they often fully incorporate it into their daily lives and view it as an effective resource in maintaining contact with friends and family (Quan-Haase et al., 2017; Yu et al., 2016b).

A final area of related literature for this study deals with the move by consumers towards shopping and banking online since the start of the pandemic. Anxiety over being exposed to COVID-19 while in public places convinced many consumers to move a large portion of their banking and consumer purchases online. According to the U.S. Census Bureau, e-commerce in the U.S. increased by 43% in 2020 alone, rising from $571.2 billion to $815.4 billion (Brewster, 2022). Truong and Truong (2022) explain that age was positively related to online shopping during the pandemic, indicating older adults were spending more than younger adults on e-commerce. They also find racial and ethnic minority shoppers were less likely to shop online than White consumers. Shaw et al. (2022) find that while older adults still lag in e-commerce, all age groups are expected to shop online significantly more in the coming years, relative to before the pandemic, due to the increased convenience.

STUDY OUTLINE AND FINDINGS

Our study builds from the broad concept in Friemel (2016) and Kampfen and Maurer (2018) who find that it is inappropriate to group all older adults into a single category when exploring technology use. Specifically, they find that activities such as having used a computer before retirement and exhibiting technical interest significantly increases the likelihood of technology use among older adults. They also find that key socio-economic variables such as income and years of schooling have significant effects on computer and Internet use among older adults. Related studies have focused on traits such as the difference between male versus female

Internet use among older adults. Van Deurson et al. (2015) find that Internet use is a male dominated activity among seniors with female seniors showing a greater propensity to avoid using the available Internet access at home. Hargittai, Piper, and Morris (2018) however, find that this difference disappears completely when they controlled for income, education, and level of autonomy.

This study extends the previous research by examining computer ownership, Internet access, and the online habits of Black and Hispanic seniors relative to their White counterparts both before and after the COVID-19 outbreak. We are the first to use a large, well respected, data set to study a wide range of connectivity issues and online activities for minority seniors over this timeframe. We are able to make unique observations regarding how habits may have changed for these older adults since the pandemic began by using data from both 2017 and 2021. Our research questions include whether Black and Hispanic seniors lagged behind their White peers in 2017 with respect to computer ownership, Internet access, social media use, eHealth activity, e-commerce, and online finances. We then address whether the incentives to increase Internet access created by the pandemic significantly changed the connectivity and online habits of this group of older adults. Our results indicate that Black and Hispanic seniors were less likely, in 2017, to own a computer and access the Internet than White seniors. Further, we find that the digital divide between minority and White users expands significantly in most areas for those over the age of 65, hitting Black seniors especially hard. Finally, we find that while there has been significant progress in closing the digital divide since 2017 large gaps still persist for Black and Hispanic seniors relative to their White peers.

DATA

The data for this study comes from the 2017 and the 2021 Current Population Surveys (CPS) conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics. We take advantage of the Computer and Internet Use Supplement survey that was included in the November 2017 and 2021 surveys (NTIA). This supplement asks detailed questions about computer ownership, Internet access, and online activities for over 52,000 households and receives responses from over 123,000 individuals within those households. The breadth of questions asked in this survey allows us to address a wide variety of research questions, while the large sample size helps in the identification issues within the regression analysis. By using these data sets we can analyze how the spread of COVID-19 impacted online behavior among older adults.

The dependent variables of interest are only asked during the Computer and Internet Use Supplement survey and are described in the Table 1.

Table 1	
Dependent Variable	**Description**
Computer Ownership	Does anyone in the household own a desktop, laptop, or tablet?
Internet Access	Does anyone in the household use the Internet from home?
Shop Online	In the past 6 months have you used the Internet for online shopping, travel reservations, or other consumer services on the Internet?
Finance Online	Do you use the Internet for financial services such as banking, investing, or paying bills online?
Social Media	Do you use social networks such as Facebook, Twitter, or Instagram?
Health Search Online	Did you use the Internet to communicate with a doctor or health professional, access health records or health insurance records, or research health information online, such as with WebMD?

The explanatory variables of interest are presented in Table 2 and are separated into three categories. The first is the entire sample, the second compares computer owners to those that do not own computers, and the third compares Internet users with non-users. The household income and education questions ask the respondent to select a range in which their household income or education falls. These variables are therefore set up as categorical variables that correspond to the midpoints of each given range. The table shows that computer owners compared to those that do not own a computer are younger, have higher income and education levels, are married, and are more likely to live in a metropolitan area. It also indicates that Black, Hispanic and people with disabilities are less likely to own a computer. The same pattern for each of these variables holds true when comparing those who connect to the Internet from home to those who do not.

Table 2
Summary Statistics 2021

Variable	Entire Sample	Computer		Internet	
		Owners	Non Owners	Users	Non-Users
N	84,206	63,620	20,586	65,648	18,558
Age	48.55	47.144	52.889	47.263	53.096
	(19.61)	(19.138)	(20.831)	(19.02)	(20.923)
White	0.804	0.814	0.773	0.812	0.773
	(0.397)	(0.389)	(0.419)	(0.39)	(0.419)
Black	0.103	0.09	0.145	0.096	0.131
	(0.304)	(0.286)	(0.352)	(0.294)	(0.337)
Hispanic	0.136	0.125	0.17	0.128	0.165
	(0.343)	(0.33)	(0.376)	(0.334)	(0.371)
Native Am.	0.012	0.01	0.019	0.011	0.018
	(0.087)	(0.101)	(0.136)	(0.103)	(0.134)
Asian	0.058	0.064	0.041	0.059	0.057
	(0.235)	(0.245)	(0.199)	(0.235)	(0.231)
# People in HH	2.883	3.00	2.56	2.909	2.791

	(1.600)	(1.542)	(1.569)	(1.532)	(1.652)
HH Income	86,234	94,841	59,635	90,840	69,940
	(56,077)	(54,999)	(50,779)	(55,589)	(54,750)
Own Business	0.130	0.144	0.085	0.137	0.105
	(0.336)	(0.352)	(0.279)	(0.344)	(0.306)
Married	0.500	0.533	0.394	0.516	0.44
	(0.500)	(0.500)	(0.489)	(0.500)	(0.496)
Education	13.579	13.906	12.566	13.83	12.691
	(2.689)	(2.595)	(2.722)	(2.575)	(2.900)
Female	0.520	0.518	0.521	0.521	0.511
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Metro Area	0.812	0.826	0.768	0.819	0.785
	(0.391)	(0.379)	(0.422)	(0.385)	(0.411)
Disability	0.131	0.107	0.207	0.112	0.200
	(0.338)	(0.309)	(0.405)	(0.315)	(0.400)

METHODOLOGY

Each dependent variable of interest in this study, described in Table 1, is presented in the survey as a “Yes” or “No” question resulting in discrete dependent variables in each specification. To account for this restriction, we employ probit regression analyses and present the marginal effects in our findings. The explanatory variables will include age and race along with a variety of demographic and socioeconomic variables, as described in Table 2. Dummy variables for region are also included in each specification. The model will be defined as follows:

$$Y_i^* = X_i \beta + u_i \tag{1}$$

where X_i is a vector of explanatory variables, β is their corresponding coefficient estimates, and u_i is the error term. The observable outcome is defined as:

$$Y_i = \begin{cases} 1 \text{ if } X_i\beta + u_i > 0 \\ 0 \text{ if } X_i\beta + u_i \leq 0 \end{cases}$$

Questions on the survey relating to online activities are only asked to respondents who indicated they have access to the Internet. This allows for a better comparison of online activities based on race and ethnicity among those who are already online. This restriction on the data however can introduce selection bias into the results. To account for this structure of survey questions an inverse mills ratio is implemented in the regression analysis to avoid any bias in the results (Heckman 1979).

RESULTS ON COMPUTER OWNERSHIP AND INTERNET ACCESS

In this section we investigate whether older adults are still less likely than younger generations to own a computer or access the Internet in both 2017 and 2021. The independent variables of interest include age, race, and ethnicity variables. Other independent variables that are included in the probit regression, but not shown, are disability status, sex, marital status, the number of people living in the household, living in a metro area, whether they own their own business, household income (logged), highest education level, and regional dummies. The results of the multivariate regression analysis are included in Table 3 where columns (1) and (2) represent data from 2017 and columns (3) and (4) represent data from 2021.

Columns (1) and (3) of Table 3 relate to computer ownership based on age, race, and ethnicity for the entire sample in 2017 and 2021 respectively. We find that, similar to past studies, coefficients on age, Black, and Hispanic are all negative and highly significant for both years of study. This confirms the continued existence of digital divides in computer ownership based on age, race, and ethnicity, though it appears the divide has modestly shrunk between 2017 and 2021 for both Black and Hispanic individuals. Columns (2) and (4) of Table 3 examine the computer ownership of individuals who are 65 years of age or older in 2017 and 2021 respectively. Again, we find highly significant negative coefficients on both the Black and Hispanic variables. Like before we do find that the coefficients are less negative in 2021 suggesting the divide is shrinking.

Comparing column (1) to column (2) shows that in 2017 the negative coefficients on both the Black and Hispanic variables increased substantially (were more negative) for older adults relative to the entire sample. This indicates the racial divide in ICT's was larger for seniors than

Table 3
Probit Regressions for Computer Ownership in 2017 and 2021

	(1)	(2)	(3)	(4)
	2017		2021	
	Own a Computer	Own a Computer Age 65+	Own a Computer	Own a Computer Age 65+
Age	-0.004***	-0.011***	-0.004***	-0.009***
	(0.001)	(0.001)	(0.0001)	(0.001)
Black	-0.092***	-0.153***	-0.078***	-0.115***
	(0.006)	(0.013)	(0.006)	(0.014)
Hispanic	-0.117***	-0.159***	-0.093***	-0.138***
	(0.005)	(0.016)	(0.006)	(0.017)
N	105,596	22,189	83,051	20,479
LR chi(2)	19,431.29	5,121.39	12,449.59	3,809.24

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

for the general population in that year. A similar analysis can be done for 2021 by comparing columns (3) and (4). The results show that the coefficients on the Black and Hispanic variables are again more negative for older adults than for the general population. There were some positive changes over this period, however, as older Black individuals closed the gap on their White peers between 2017 and 2021. In 2017 Black individuals overall were 9.2% less likely to own a computer than their White counterparts, while those aged 65 or older were 15.3% less likely to own a computer than their White peers. This translates to a 6.1% additional lag faced by older Black adults in 2017. This gap shrank in 3.7% in 2021 signifying progress in bridging this aspect of the Grey Divide, as older Black adults began catching up with their White peers more quickly than Black individuals in general. The gap for Hispanic individuals over this period actually increased slightly, changing from 4.2% in 2017 to 4.5% in 2021.

Table 4 presents results from the probit regressions on whether the respondent had Internet access at home in 2017 and 2021. We again verify previous research by finding that

Table 4
Probit Regressions for Internet Access in 2017 and 2021

	(1)	(2)	(3)	(4)
	2017		**2021**	
	Internet Access	Internet Access Age 65+	Internet Access	Internet Access Age 65+
Age	-0.005***	-0.013***	-0.003***	-0.010***
	(0.0001)	(0.001)	(0.0001)	(0.0001)
Black	-0.067***	-0.153***	-0.039***	-0.081***
	(0.005)	(0.013)	(0.005)	(0.013)
Hispanic	-0.046***	-0.098***	-0.035***	-0.073***
	(0.005)	(0.016)	(0.005)	(0.015)
N	105,596	22189	83,051	20,479
LR chi(2)	14,328.67	4,854.61	5,452.46	2,757.17

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

Black, Hispanic, and older individuals have lower Internet penetration rates than younger White individuals in both 2017 and 2021. Columns (2) and (4) extends this result by again focusing solely on computer owners who are aged 65 or older. Our results reiterate that the racial digital divide is magnified for those who are 65 or older in all instances. Interestingly, there are positive signs in the results for older adults as the gap between young and old Black users decreased from 8.6% down to 4.2%. Older Hispanic users also saw progress in this area as their gap shrank from 5.2% to 3.8%.

ONLINE HABITS

This section explores the online habits of Black and Hispanic seniors in areas related to social media use, online searches for health information, online shopping, and online finances. Since the CPS survey only asks about online activities for those who have access to the Internet, the results will directly measure the online habits of each group instead of capturing the underlying differences in access to technology. As before, independent variables that are included but not shown in each of the tables in this section are disability status, sex, marital status, the number of people living in the household, whether they live in a metro area, whether they own their own business, household income (logged), highest education level, and regional dummies. Additionally, the Mills Ratio (Lambda) is included to account for selection bias, as discussed in the section on methodology.

Table 5
Probit Regressions for Social Media Use in 2017 and 2021

	(1)	(2)	(3)	(4)
	2017		**2021**	
	Social Media	Social Media Age 65+	Social Media	Social Media Age 65+
Age	-0.010***	-0.012***	-0.008***	-0.004
	(0.0004)	(0.002)	(0.001)	(0.002)
Black	-0.086***	-0.138***	-0.022*	-0.037
	(0.01)	(0.031)	(0.011)	(0.026)
Hispanic	-0.057***	-0.05	-0.009	-0.012
	(0.009)	(0.032)	(0.010)	(0.031)
N	43,902	8,989	36,097	9,563
LR chi(2)	5,271.06	273.86	4,004.79	371.24

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

Table 5 focuses on social media activity for the general population and those 65 and older in 2017 and 2021. The negative coefficients on the Black and Hispanic variables in Column (1) indicate that minorities overall were less likely to use social media than White users in 2017. Column (2) shows that Black Internet users who are 65 or older were significantly less likely than their White peers to use social media in that year. Contrary to this, in Column (2) we see that Hispanic Internet users who are 65 or older are just as likely to use social media as their White counterparts in 2017. Columns (3) and (4) of Table 5 show that during the pandemic the divide in social media use across race and ethnicity almost completely disappeared. Only Black Internet users overall were found to still lag behind White Internet users, but only by 2.2% and with only a 10% significance level.

Table 6 shifts the focus to whether individuals utilize the Internet to find health information of any type online. Column (1) of Table 6 shows Black and Hispanic Internet users were far less likely than White users to lookup up health information online in 2017. Column (2)

Table 6
Probit Regressions for Online Health Searches in 2017 and 2021

	(1)	(2)	(3)	(4)
	2017		**2021**	
	Health Search Online	Health Search Age 65+	Health Search Online	Health Search Age 65+
Age	-0.002***	-0.010***	-0.003***	-0.013***
	(0.0005)	(0.002)	(0.001)	(0.002)
Black	-0.126***	-0.202***	-0.138***	-0.202***
	(0.011)	(0.032)	(0.012)	(0.027)
Hispanic	-0.163***	-0.218***	-0.168***	-0.197***
	(0.009)	(0.031)	(0.012)	(0.032)
N	43,902	8,989	36,097	9,563
LR chi(2)	5,508.06	955.57	4,671.04	1,114.19

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

indicates that for seniors this gap not only persists, it expands, with each minority group lagging even further behind their White peers in that year. Unlike social media use, we find, in Columns (3) and (4), that Black and Hispanic users made very little progress bridging the gap in online health searches between 2017 and 2021. In fact, the results for the coefficients in 2021 are very similar to those in 2017. In both 2017 and 2021 Black Internet users who were age 65 or older were 20.2% less likely than their White counterparts to search for health information online. For Hispanic Internet users this changed from 21.8% in 2017 to 19.7% in 2021, showing a modest improvement over this period relative to White users.

Results from probit regressions related to the online shopping habits of the general population and seniors are presented in Table 7. Column (1) of the table provides evidence that Black and Hispanic Internet users were less likely to shop online than White users overall in both 2017 and 2021. These marginal effects are relatively large and highly significant. Given the mobility concerns and transportation limitations faced by many seniors, actively participating in

Table 7
Probit Regressions for Shopping Online in 2017 and 2021

	(1)	(2)	(3)	(4)
	2017		**2021**	
	Shop Online	Shop Online Age 65+	Shop Online	Shop Online Age 65+
Age	-0.006***	-0.014***	-0.005***	-0.010***
	(0.0005)	(0.002)	(0.001)	(0.002)
Black	-0.125***	-0.193***	-0.082***	-0.106***
	(0.011)	(0.034)	(0.011)	(0.027)
Hispanic	-0.109***	-0.121***	-0.102***	-0.114***
	(0.01)	(0.033)	(0.011)	(0.032)
N	43,902	8,989	36,097	9,563
LR chi(2)	7,602.94	1,038.46	5,376.03	1,111.37

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

online shopping could be very beneficial for their overall well-being. These potential benefits were magnified during the pandemic since e-commerce allowed people to avoid close contact in a public setting with people who may have been exposed to COVID-19. However, Column (2) of Table 7 shows that in 2017 Black and Hispanic Internet users that were aged 65 or older were 19.3% and 12.1% less likely to engage in e-commerce than their White peers respectively. Column (4) shows that while there was measurable progress in 2021, especially by older Black Internet users, there still existed a large and significant divide. In 2021 Black and Hispanic seniors were 10.6% and 11.4% less likely to shop online than their White peers.

The final area of online activity that we investigate relates to financial activities done over the Internet, such as online banking, investing, and bill payment. Similar to the benefits described for online shopping, completing financial services online helps seniors circumvent any transportation difficulties they may face and lets them avoid unneeded exposure during a pandemic. The results in Columns (1) and (3) of Table 8 show that in both 2017 and 2021 Black and Hispanic Internet users in general lagged behind White Internet users in online finance activities. In 2017 Black users in general were 13.7% less likely to engage in online finance while Black users who were 65 or older were 17% less likely. Older Black users showed incredible progress between 2017 and 2021 ending up only 10.7% less likely to participate in online finance than their White peers. This is important progress, but the gap is still large and significant. Older Hispanic Internet users fared much better in this online activity. In 2017 the coefficient for Hispanic Internet users who were 65 or older was almost identical to that for the Hispanic population in general, and only showed significance at the 10% level. By 2021, Column (4) of Table 8 indicates that older Hispanic users were just as likely to use online finances as their White peers.

Table 8
Probit Regressions for Finances Online in 2017 and 2021

	(1)	(2)	(3)	(4)
	2017		**2021**	
	Finance Online	Finance Online Age 65+	Finance Online	Finance Online Age 65+
Age	-0.009***	-0.017***	-0.008***	-0.012***
	(0.0005)	(0.002)	(0.001)	(0.002)
Black	-0.137***	-0.170***	-0.093***	-0.107***
	(0.011)	(0.032)	(0.012)	(0.027)
Hispanic	-0.086***	-0.083*	-0.084***	-0.050
	(0.01)	(0.032)	(0.011)	(0.031)
N	43,902	8,989	36,097	9,563
LR chi(2)	6,817.94	727.12	4,961.55	902.43

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

INTERACTION EFFECTS

To determine whether there is a persistent relationship between age and minority status across ICT usage we add interaction effects to each general specification. Table 9 presents the results from including an interaction effect between the age and Black variables. Columns (1) and (2) show that the racial divide relating to computer ownership and online access are persistent across age ranges. Columns (3) through (6) show that this connection disappears when focusing on online habits with the divide created by older individuals being offset by other age groups. Table 10 illustrates the results from including an interaction effect between the variables age and Hispanic. Again, there is a significant negative coefficient for computer ownership but no significant impact in relation to Internet access. Columns (3), (4) and (5) show positive and significant interaction effects for online shopping, online finances, and social media use. These results are driven heavily by younger users, but may be an indication of future progress in this area.

Table 9
Probit Regressions with Black and Age Interaction Term Included

	(1)	(2)	(3)	(4)	(5)	(6)
	Computer Ownership	Internet Access	Shop Online	Finances Online	Social Media	Health Online
Age	-0.004***	-0.005***	-0.006***	-0.009***	-0.01***	-0.002***
	(0.001)	(0.0001)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Black	-0.035***	0.007	-0.119***	-0.164***	-0.047*	-0.088***
	(0.013)	(0.011)	(0.023)	(0.024)	(0.023)	(0.023)
Black*Age	-0.001***	-0.002***	-0.0001	0.0005	-0.001	-0.001
	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.001)

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

Table 10
Probit Regressions with Hispanic and Age Interaction Term Included

	(1)	(2)	(3)	(4)	(5)	(6)
	Computer Ownership	Internet Access	Shop Online	Finances Online	Social Media	Health Online
Age	-0.004***	-0.01***	-0.01***	-0.009***	-0.010***	-0.002***
	(0.001)	(0.0001)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Hispanic	-0.055***	-0.031**	-0.18***	-0.219***	-0.113***	-0.191***
	(0.012)	(0.011)	(0.022)	(0.022)	(0.023)	(0.022)
Hispanic*Age	-0.001***	-0.0003	0.001***	0.003***	0.001**	0.001
	(0.0003)	(0.0002)	(0.0004)	(0.0005)	(0.0004)	(0.001)

Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level or smaller.

DISCUSSION

In this study we find that older adults, along with those identifying as Black and Hispanic, still lag behind the general population in computer ownership, Internet access, and participation in many online activities. Our results go beyond updating the existence of the racial and Grey Divides by explicitly focusing on how age and race interact in these areas. By using Census data from before and during the pandemic, we investigate whether older adults were motivated to transition online as a way to maintain social distancing during the spread of COVID-19. We find that the racial divide does not only persist for those who are 65 or older relative to the general population, it is magnified in most cases. On a positive note, we do find the gap in technology use between Black and Hispanic older adults and the rest of the population shrank significantly in most areas between 2017 and 2021.

Older Black adults, in 2017, were 15.3% less likely to own a computer than their White peers, but this outcome decreased to 11.5% in 2021. This 3.8% improvement in computer ownership shows a step in the right direction, but also that deficiencies still exist. Positive changes in other activities experienced by Black seniors include a 7.2% improvement in Internet access, an 8.7% improvement in online shopping, and a 6.3% improvement in online finances. There were two surprising results for older Black Internet users. The first was a complete lack of improvement in searching for health care information online between 2017 and 2021. The second was the improvement in social media usage for this group who went from being 13.8% behind their White peers in 2017 to showing no statistical difference in this activity from their White peers in 2021.

Older Hispanic adults only made limited progress in computer ownership and Internet access, but were moderately more successful at bridging the divide in online activities with their White peers than were older Black adults. Between 2017 and 2021 Hispanic seniors experienced little change in their rates of online shopping and researching health information online. This group however was just as likely as their White peers to use social media and to engage in financial activities online in 2021. Surprisingly, we also found that in 2017 Hispanic Internet users in general were 5.7% less likely to use social media than their White counterparts, while in the same year Hispanic Internet users over the age of 65 were equally likely as their White peers to connect to social networks.

Results presented here are meaningful since they provide evidence that gaps still exist across race and ethnicity even after controlling for differences in income, education, and connectiveness to the Internet. These concepts have always been important to study but have taken on grave importance, especially for seniors, after experiencing a worldwide pandemic. The COVID-19 pandemic highlighted how isolated seniors can become during times of national or international emergencies. Without modern information and communication technologies in place, many older citizens can become effectively cut off from their friends, family, and society. Providing adequate access to computers and the Internet is crucial but is lacking for some groups. Racial and ethnic minorities still face a substantial digital divide. For minorities over the age of 65, this divide can seem more like a chasm that cannot be easily traversed. Effective policy moving forward must include increased access along with training aimed at this underrepresented group. This will ensure fewer people become isolated in the face of future pandemics or national emergencies.

Future research in this field needs to address two key issues: whether the positive trends in access and online activity continue after the pandemic has subsided, and what technology interventions are most meaningful for underrepresented seniors. This paper uses data from 2021 which is in the heart of the pandemic, and as of writing this study the country is still dealing with the very contagious Omicron variant of COVID-19. Once the pandemic has eased more substantially it will be important to determine if Black and Hispanic seniors persisted in their use of technology, or if the large divides re-emerged. One method of keeping technology use relevant for seniors is to provide targeted training in technical skills that promote safe and meaningful online engagement. Experimental research on different intervention techniques will provide invaluable insights on the most effective ways to get older adults comfortable with online activities. Documenting what types of trainings are successful for Black and Hispanic seniors in particular can help guide policy and resources to appropriate areas.

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MODELING COVID-19 EPIDEMIC TO GUIDE DECISION MAKING

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ABSTRACT

A coronavirus has many crown-like spikes on its surface. Two recent examples of these viruses are SARS-CoV-1 and SARS-CoV-2. The former caused the 2003 outbreak of severe acute respiratory syndrome (SARS), that according to the World Health Organization (WHO), as of July 5, 2013, infected a total of 8,439 people and 812 died worldwide. The latter caused the coronavirus disease 2019 (Covid-19), that the WHO declared a pandemic on March 11, 2020. Unlike the SARS-CoV-1, the SARS-CoV-2 is much more contagious and widespread, and it has adversely affected life in almost every country. The Centers for Disease Control and Prevention (CDC) reported that as of July 24, 2020, there were over 15 million confirmed cases of Covid-19 in the world, among them the US had 4,024,492 cases out of which 72,219 were new cases as of July 25, within a 24- hour period. It reported 143,868 total deaths in the US due to this disease that included 1,113 new deaths during this 24-hour period. Among the US cases, one million new cases were added during July 9-24, 2020, indicating an exponential growth of new Covid-19 cases relative to the timeline of SARS-CoV-1.

One way to understand and predict the impact of Covid-19 is to formulate a mathematical model to predict the spread of illness, hospitalization, death, recovery, etc. based on assumptions about the characteristics of the disease and behavior of individuals. Many institutions, universities, and organizations have formulated mathematical models for this purpose. Some notable organizations for this purpose include the Covid-19 Forecast Hub that hosts over 30 international research groups and their models, the CDC, and the FiveThirtyEight (Best & Boice, July 24, 2020; ABC News Internet Ventures, 2020).

The purpose of this research is to introduce basic terminology about the spread of infectious diseases and to formulate basic epidemic models to analyze Covid-19 to guide managerial decisions.

THE CHARACTERISTICS OF COVID-19 EPIDEMIC

Dr. Gro Harlem Brundtland, Director-General of the WHO (2003), said “We do not mark the end of SARS today, but we observe a milestone: the global SARS outbreak has been contained.” He said “SARS is a warning, SARS pushed even the most advanced public health systems to the breaking point. Those protections held, but just barely. Next time, we may not be so lucky. We have an opportunity now, and we see the need clearly, to rebuild our public health protections. They will be needed for the next global outbreak, if it is SARS or another new infection."

Thirteen years later, Dr. Brundtland's warning came true with the arrival of SARS-CoV-2 virus that causes Covid-19 disease and was first reported on December 31, 2019 (World Health Organization, 2021). Covid-19 has directly or indirectly affected most individuals, organizations, and countries. The economic and social life in most countries was severely affected. This study explores the parameters that govern the dynamics of this infectious disease and should be of interest to public healthcare policy planners, managerial decision makers, and individuals who want to minimize the chance of getting infected by Covid-19 disease.

The CDC reports that seven human coronaviruses have been identified since the mid-1960s and four of which (HKU1, NL63, 229E, and OC43) cause common illness in people while three coronaviruses, namely, MERS-CoV, SARS-CoV, and SARS-CoV-2, have evolved from animals to become human coronaviruses.

On January 21, 2020, the CDC confirmed the first US case of Covid-19 in Snohomish County, Washington, where a 35-year-old man, who had travelled to Wuhan, China, showed up at an urgent care clinic with Covid-19 symptoms (Holshue et al., 2020). The SARS-CoV-2 is a new virus for which people do not have a natural immunity and, at that time, there was no vaccine for it. The Covid-19, the **co**rona **vi**rus **d**isease that originated in 20**19**, caused a public health crisis that has resulted in an economic crisis. Almost every industry was adversely affected by the Covid-19 epidemic. In the US, the economy shrank 5% in the first quarter of 2020 followed by 9.5% in the second quarter.

The economic and business activity could not recover without controlling Covid-19. The government administrators, public health officials, business leaders, school administrators, employees, households, parents, and individuals tried to gain a better understanding of Covid-19 to control its spread so they could return to normal operations. The target audience of this study is everyone who is interested in how an infectious disease like Covid-19 spreads through a population and what measures are useful to minimize its impact and reduce and eliminate this disease.

Basic and Effective Reproductive Rates, R_0 and R_E

The reproductive rate or reproduction number measures the contagiousness of a disease. The spread of an infectious disease is controlled by its reproduction number. The basic reproductive rate, R_0, is the average number of secondary infections caused by an individual in a fully susceptible population. The effective reproductive rate, R_E, is the average number of secondary cases generated by an infected individual in a population where some individuals have been previously infected or immunized so not everyone is susceptible to the disease. R_0 plays a key role in the spread of a disease and in determining the population size that must be vaccinated to attain herd immunity. SARS-CoV-2 virus continues to mutate and spawn new variants and subvariants. WHO names coronaviruses using Greek alphabet. The following presents selected literature on reproduction number for different variants and subvariants of SARS-CoV-2 virus.

Esterman (2022) provides that the basic reproduction numbers, R_0, for various strains of SARS-CoV-2 virus. The ancestral strain in Wuhan, China: R_0 = 3.3. Delta strain that appeared in India: R_0 = 5.1. Omicron BA.1 in Botswana and South Africa: R_0 = 9.5. Omicron BA.2 has R_0 = 13.3. He summarizes the impact of these variants and subvariants as follows:

- *Three subvariants of Omicron (BA.1, BA.2, and BA.3) appeared in late November 2021 in South Africa. In early January 2022, BA.1 rapidly spread across Australia replacing Delta and causing more than 100,000 cases per day at the peak (early January 2021) of the first wave of Omicron. The second Omicron wave was caused by BA.2 and peaked in early April 2022 at more than 60,000 cases a day. Omicron BA.2 was even more transmissible than BA.1.*
- *Omicron BA.4 and BA.5 were detected in South Africa in January 2022 and February 2022 respectively. The third wave in Australia was caused by BA.4 and BA.5 started in July 2022, as BA.4 and BA.5 became the dominant Covid-19 strains. BA.4 and BA.5 are more infectious than previous variants and subvariants and are better able to evade immunity from vaccines and previous infections. BA.4 and BA.5, however, did not cause more sever disease compared with the previous subvariants of Omicron possibly due to previous infections or vaccinations.*

Katella (2022) notes the following characteristics for some variants and subvariants of SARS-CoV-2.

- *Alpha (B.1.1.7) first appeared in Great Britain in November 2020. It was 30%-50% more contagious than the original SARS-CoV-2 strain and created 66% of cases in the US by mid-April 2021. It also caused more severe disease than the original virus.*
- *Beta (B.1.351) appeared in South Africa at the end of 2020 and was 50% more contagious than the original virus. Beta may have caused more severe disease than the other variants, but it did not become the dominant variant in the US.*
- *Delta (B.1.617.2) first appeared in India in late 2020 and spread around the world to become the dominant variant. It was 80%-90% more contagious than the Alpha variant. Starting in June 2021, Delta spread across the US and caused some breakthrough infections among fully vaccinated individuals. More contagious variants of Delta later emerged and infected many people.*
- *Omicron (BA.1) appeared in Botswana and South Africa in late November 2021 and quickly spread across the world. BA.1 was more contagious than Delta but tended to cause less severe disease. In the US in December 2021, Omicron caused daily infections that exceed one million cases. Omicron generated many subvariants including BA.5, BQ.1, BQ.1.1.*

Liu and Rocklöv (2022) conduct extensive literature review of articles publications in Chinese and US journals and conclude that the reproduction number for Omicron is 5.08 which is higher than that of the Delta variants.

Selected Covid-19 Modelling Across the World

The following presents selected model building efforts by researchers to understand the dynamics of Covid-19 in different parts of the world.

Biswas, Khaleque, and Sen (2020), in a pre-print (not peer-reviewed) study use data from China and Italy in an SIR framework. They use a Euclidean network of interactions among individuals to show that the new infections of Covid-19 are inversely proportional to Euclidean distance (raised to power ~1.85) from the epicenter of the disease. They calculate that the exponent of distance from the epicenter Wuhan is 0.268 for China and from the epicenter Bergamo is 0.383 for Italy. So generally, infections would be larger the closer the individuals are located to the epicenter of this disease and this spatial dependence follows an approximate power law with exponent ~1.85.

Cooper, Mondal, and Antonopoulos (2020) utilize a classical susceptible-infected-removed (SIR) model to study the spread of Covid-19 in China, South Korea, India, Australia, USA, Italy and the state of Texas in the USA. They consider data from January-June 2020. They make predictions regarding various parameters of disease dynamics and the numbers of individuals in S, I, R compartments of the populations until September 2020. They note: "This allowed us to estimate the development of Covid-19 spread in these communities by obtaining estimates for the number of deaths D, susceptible S, infected I and removed Rm populations in time." By comparing recorded data with the results of their predictions they claim that the spread of this disease can be controlled by early implementation of proper restrictions and strong control policies. They make a few statements that are incorrect. Here are our observations on this study.

- The authors utilize a typical closed SIR model where births and deaths (other than those due to COVID-19) can be neglected due to short duration of the study.
- They claim that their total population, N, is not specified or held constant. They specify three compartments of individuals in their three SIR equations so N in their model can be obtained by adding these three compartments. Thus, $N(t) = S(t) + I(t) + R(t)$. Adding their three SIR equations results in $\frac{dN}{dt} = N'(t) = 0$. So, their model requires a constant total population even though the authors do not acknowledge it.
- They claim that unlike in the classic SIR model, the susceptible population does not monotonically decrease in their modified SIR model but can increase to accommodate new surges in infections. Contrary to their claim, however, their equation (1) specifies the typical susceptibles function with a monotonically decreasing slope. $\frac{dS}{dt} = S'(t) = -aS(t)I(t) < 0$. So, the disease incidence, $aS(t)I(t)$, decreases monotonically in their model.
- They acknowledge that deaths and recoveries are not generated directly by their SIR model, so they estimate them separately. A better approach is to model them directly in and extended SIR model. For example, Ndaïrou, Faïçal, Iván Area, Juan J. Nieto, and Delfim Torres (2020) extend the SIR model to directly incorporate the number of deaths, recoveries, reinfections, hospitalizations, serious infections, etc.

- To estimate S, I, and R, they set initial values between 0-1 and scale their variables to fit the data. They set initial conditions of the SIR model as S(0) = 1, and I(0) = R(0) <= 1. This indicates that initially everyone is susceptible, and some people may be infected or removed (recovered or dead). However, although everyone is susceptible to the new pathogen, some people have to be infected at the start of the epidemic, thus S(0) < 1 and I(0) > 0 and R(0) = 0 since the infected individuals will be moved from the susceptible compartment to the infected compartment, while none will have recovered or died at the very beginning of the epidemic.
- They do not specify N(0), the initial population size in the SIR model. However, by definition, N(0) = S(0) + I(0) + R(0). The sum of the components (as fractions) will be one. They do not specify but their approach normalizes N to 1 (or 100%).
- They fit their model to the data by trial-and-error and visual inspection thus introducing bias in their estimates and predictions since the result are not produced automatically by applying the model itself but by active intervention by the researchers to fit the model to results. So different researchers will obtain different results from the same data set.
- They estimate and plot total infections, active infections (I), recoveries (R), deaths (D), and active susceptibles (S) over time for different countries and the state of Texas. Their plots show that the researchers have achieved good approximation in fitting their model to actual data. However, their SIR model does not extend to their data analyses.
- Their theoretical SIR model does not extend to their actual data analysis regarding deaths (D), recoveries (R), and surges based on increasing S and I. This is because their SIR model does not directly incorporate deaths and recovered individuals, nor does it accommodate surges due to increased numbers of usucaptible individuals.
- They state that during a surge, the number of susceptible individuals increases, and the number of infected individuals also increases. They conclude that in the absence of a vaccine, drastic actions should be taken to control the spread of disease in its early stages. So, the disease could be eliminated by reducing the susceptible population to zero.
- They recommend that in the absence of an effective vaccine the authorities should enforce strict measures to the spread of epidemic at its early stages.
- They do not share their code or data, so the readers are unable to replicate their results.

Ndaïrou, Area, Nieto, and Torres (2020) study transmission dynamics of Covid-19 in Wuhan (population about 11 million people) with a modified SIR model. This model utilizes a constant total population size N that is subdivided into eight epidemiological classes: susceptible, exposed, symptomatic and infectious, super-spreaders, infectious but asymptomatic hospitalized, recovery, and fatality. This model allows for surges in susceptible class and does not require a monotonically decreasing susceptible class of individuals. These authors adjust the Wuhan population of 11 million by dividing by 250 to account for strict lock downs. They simulate results of the model and compare them with actual data and find good approximations of their model performance with actual data. They estimate the basic reproductive number for Wuhan as $R_0 = 0.945$. This is less than 1 indicating that the authorities quickly contained the spread of Covid-19 through strict Zero-Covid measures of quarantine and lock-down of communities with infected individuals. For a preprint (not peer-reviewed) of a study on the index case in Wuhan, China, please refer to Pekar, Worobey, Moshiri, Scheffler, and Wertheim (2020).

THE STUDY

This study takes a mathematical model building approach to generate insights to control Covid-19. This study addresses the following research questions:

- RQ #1. What types of mathematical models are useful in understanding Covid-19?
- RQ #2. What parameters determine the spread of an infectious disease like Covid-19 through the population?
- RQ #3. What proportion of the population will become infected with Covid-19 *if no preventive measures are taken* to stop the spread of this epidemic?
- RQ #4. What level of *vaccine-induced herd immunity* is required to control the disease?
- RQ #5. What steps should individuals and organizations take to control the spread of this disease?

THE SUSCEPTIBLE-INFECTIOUS-RECOVERED MODEL AND ITS VARIATIONS

The following two research questions are addressed here.

- RQ #1. What types of mathematical models are useful in understanding Covid-19?
- RQ #2. What parameters determine the spread of an infectious disease like Covid-19 through the population?

The SIR Model of Epidemics

The SIR model (Kermack & McKendrick, 1927) describes the diffusion of an infectious disease through a susceptible pupation by dividing the population into three different compartments of susceptibles (S), infectious (I), and recovered (R). The relationships among the number of S, I and R can be described as $S \rightarrow I \rightarrow R$. The SIR model may be closed or open where the closed model assumes that the overall population does not change while the open model allows new births and deaths (other than those due to the pathogen).

Closed SIR system

An SIR model can be represented with a deterministic ordinary differential equation (ODE) system given below:

$$\frac{dS}{dt} = -\beta I \frac{S}{N} \qquad equation\ (1)$$
$$\frac{dI}{dt} = \beta I \frac{S}{N} - \gamma I \qquad equation\ (2)$$
$$\frac{dR}{dt} = \gamma I \qquad equation\ (3)$$

- Equation (1) describes the dynamics of the susceptibles compartment in terms of outflow of individuals from the susceptibles compartment to the infectious compartment.
    - β is the probability of disease transmission times the contact rate between susceptible (S) and infectious (I) individuals that independently and randomly mix with one another.
    - $\frac{S}{N}$ is the fraction of encounters with susceptible individuals.
    - βIS is the *incidence rate*, the number of newly infected individuals per unit time.
    - $\beta I \frac{S}{N}$ is the *incidence fraction*. The negative sign in equation (1) represents removal of individuals from the susceptible compartment.
- Equation (2) describes the dynamics of the infected compartment in terms of inflow of individuals from the susceptibles compartment and outflow of individuals to the recovered compartment.
    - Equation (2) describes disease *prevalence*, which is the number of infected individuals at time t.
    - $\beta I \frac{S}{N}$ is the *incidence fraction*. The positive sign in equation (2) represents addition of individuals to the infected compartment.
    - γ represents *the recovery rate.* It is the rate of transition from infectious to recovered.
    - $\frac{1}{\gamma}$ is the average infectious period.

  - γI is the number of individuals who recover per unit of time. The negative sign indicates that these individuals are removed from the infected compartment.
- Equation (3) describes the dynamics of the recovered department.
  - γI is the number of individuals who recover per unit of time. The positive sign indicates that these individuals are added to the recovered compartment.
- N represents population size. N was operationalized by normalizing it to 1 indicating 100% of the population. So, $S + I + R$ would be expressed as fractions.
- $N = S + I + R$.
- N is constant in a closed SIR system, so $\frac{dN}{dt} = 0$. This can be confirmed by adding equations (1)-(3).
- The basic reproductive ratio, R_0, is the expected number of secondary infections from an index case in a randomly mixing pupation. For the SIR model, $R_0 = \frac{\beta}{\gamma}$.
- If $R_0 > 1$, each index susceptible case <u>infects more than one other person</u> so the infection spreads among susceptible population resulting in an expanding epidemic.
- If R_0<1, then each infected individual <u>infects less than one other person</u> on average and the epidemic dies out.

Open SIR System

In an open SIR model, there is "background" death rate (μ) that is balanced by per capita birth rate (μ). In this model, the relationships among the number of susceptibles (S), infectious (I) and recovered (R) can be described as follows:

$$\frac{dS}{dt} = \mu(N - S) - \beta I \frac{S}{N} \quad equation\ (4)$$
$$\frac{dI}{dt} = \beta I \frac{S}{N} - (\mu + \gamma)I \quad equation\ (5)$$
$$\frac{dR}{dt} = \gamma I - \mu R \quad equation\ (6)$$

In the open SIR system, the basic reproductive ratio, $R_0 = \frac{\beta}{\gamma + \mu}$.

ESTIMATING SIR MODEL WITH R SOFTWARE

The following two research questions are addressed here.

- RQ #3. What proportion of the population will become infected with Covid-19 *if no preventive measures are taken* to stop the spread of this epidemic?
- RQ #4. What level of *vaccine-induced herd immunity* is required to control the disease?

The SIR model has been extended to incorporate other aspects like exposed status, hospitalizations, deaths, etc. The model parameters can be estimated from published studies, discussed above, about the behavior of infectious pathogen, SARS-CoV-2.

This system of equations can be solved by numerical integration by using the *deSolve* package in R (R Development Core Team, 2022). *R is an open-source software and environment that can be utilized by the reader to reproduce the results of this study.* The appendix describes how the reader can utilize R to run programs.

The following annotated code is adapted from Bjornstad (2018) to estimate a closed SIR model. The main steps are described below.

1. In an R script, specify a gradient function (sir_mod) containing the following arguments: time t, a vector y representing the state variables (S, I, R, N) of the SIR model, and a variable *parms* containing parameter values (μ, β, and γ, and N).
2. Specify the time points in weeks, and time-increments per week, for example, 26 weeks with 10-increments per week.
3. S + I + R = N and N = 1. So, S, I, R are modeled here as fractions of N.
4. Specify *parms* values, for example, $\mu = 0$, $\beta = 2$ (so disease transmission rate is 2), and $\gamma = 1/2$ (so the infectious period is 2 weeks). For $\beta = 2$ and $\gamma = 1/2$, the basic reproductive rate, $R_0 = \frac{\beta}{\gamma} = 4$.
5. The starting values of the state variables S, R, R. Let 0.1% of the population be infected at the start of the epidemic so, I = 0.1%, S = 0.999, and R = 0.
6. The *ode()* function of the *deSolve* package in R is utilized to solve the system of differential equations. For this purpose the following arguments are entered into the *ode()* function: start (the starting state values of S, I, and R), times, the gradient function, and the parameters.
7. Plot the values of S, I, R, against time as shown in Figure 1(a).
8. Plot R_0 on the horizontal axis, and the corresponding proportion of the population that will ultimately become infected if no preventive measures are taken to stop the spread of the infectious disease. This is shown in Figure 1(b).
9. The following R script was utilized to obtain the results of this study.

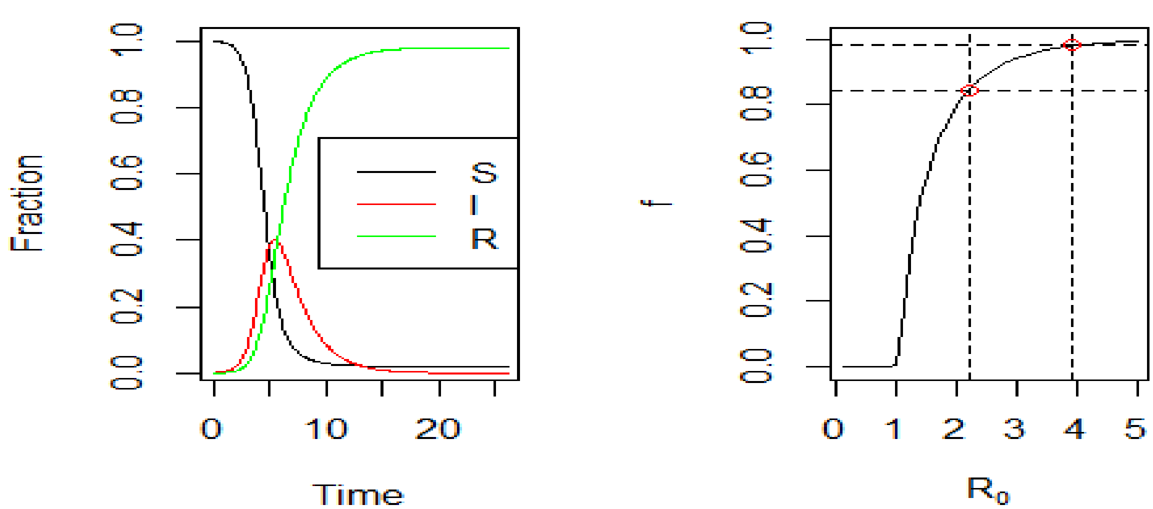
```
# Adapted from Bjornstad, O. N. (2018) Epidemics: Models and Data Using R, Springer.
# Here a # represents a comment and ## represents results generated by R code.

# Closed SIR model, mu = 0
```

```r
# Load the required package in R
require(deSolve)

## Loading required package: deSolve

# Define the gradient function
sir_mod <- function(t, y, parms){
  S = y[1]; I = y[2]; R = y[3]
  beta = parms["beta"]; mu = parms["mu"]; gamma = parms["gamma"]; N = parms["N"]

  dS = mu * (N-S) - beta * S * I/N
  dI = beta * S * I/N - (mu+gamma) * I
  dR = gamma * I - mu * R
  res = c(dS, dI, dR)
  list(res)
}

times = seq(0, 26, by = 1/10)
parms = c(mu=0, N=1, beta=2, gamma=1/2)
start = c(S=0.999, I=0.001, R=0)

out=ode(y=start, times=times, func=sir_mod, parms=parms)
out=as.data.frame(out)

par(mfrow=c(1,2))
plot(x=out$time, y=out$S, ylab="Fraction", xlab = "Time", type="l")
lines(x=out$time, y=out$I, col="red")
lines(x=out$time, y=out$R, col="green")
legend("right", legend = c("S", "I", "R"), lty = c(1,1,1), col = c("black", "red",
"green"))

# Calculate R0
(R0 <- parms["beta"]/(parms["gamma"] + parms["mu"])) # So R0 = 4.

## beta
##    4

# Calculate the threshold for vaccine-induced herd immunity.
(pc <- 1 - 1/R0) # So 0.75% vaccine cover is required to eliminate the disease.

## beta
## 0.75

# Final epidemic size. Load the rootSolve pacakge in R.
require(rootSolve)

## Loading required package: rootSolve

equil=runsteady(y=c(S= 1-1E-5, I=1E-5, R=0),
                times=c(0, 1E5), func=sir_mod, parms=parms)

# Final epidemic size - rough method
(f <- exp(-R0))
```

```
##      beta
## 0.018316

# For R0 = 4, what fraction of S escape infection?
round(equil$y, 3)

##    S    I    R
## 0.02 0.00 0.98

# The fraction of S that escape infection = 1-f
R0 = seq(0.1, 5, length=50)
betas = R0 * 1/2
f=rep(NA, 50)
for(i in seq(from=1, to=50, by=1)){
  equil=runsteady(y=c(S=1-1E-5, I=1E-5,R=0), times=c(0,1E5), func=sir_mod,
                  parms=c(mu=0, N=1, beta=betas[i], gamma=1/2))
  f[i]=equil$y["R"]
}

# Plot f, the fraction of S that become infected.
plot(R0, f, type="l", xlab = expression(R[0]))
abline(v=2.2, lty=2); abline(v=3.9, lty=2);
abline(h=.845, lty=2); abline(h=.98, lty=2)
points(x=2.2, y = .845, pch = 21, col = "red")
points(x=3.9, y = .98, pch = 21, col = "red")
```

RESULTS AND CONCLUSION

Figure 1 (a): The S, I, and R over time. Figure 1(b): The fraction infected (f) versus R_0



- Figure 1 displays the fraction of susceptibles, infected, and recovered individuals over time in the left panel, and the relationship between the proportion of the pupation that becomes infected with the disease and the basic reproductive rate. It is apparent that a higher proportion of the pupation will become infected as R_0 increases. So, the basic message here is to reduce R_e as much as possible to bring the spread of disease under control. So, every effort must be made to reduce the effective R_e to reduce the fraction of infected individuals in the population.

Esterman (2022) provides R_0 = 3.3 (for the ancestral strain in Wuhan, China); R_0 = 5.1 for Delta that appeared in India; R_0 = 9.5 for Omicron BA.1 in Botswana and South Africa; and R_0 = 13.3 Omicron BA.2. For this study we set the range of $R_0 = 2.2 - 3.9$. Figure 1(b) displays these R_0 values on the horizontal axis and the corresponding proportion of the population that would become infected if no measures are taken to reduce the spread of Covid-19 disease:

1. If $R_0 = 2.2$, at equilibrium only 15.50% of the population escapes infection while 84.50% of the population becomes infected and recovers that includes individual who are impaired health or those who die due to this disease.
2. If $R_0 = 3.9$, at equilibrium only 2% of the population escapes infection while 98% of the population becomes infected and recovers that includes individual who are impaired health or those who die due to this disease.

Clearly these infection numbers are very high and intolerable and call for taking steps to reduce the effect reproductive rate, R_E, that will bring this epidemic under control. Traditional methods of disease surveillance often do not measure cases that are asymptomatic, not diagnosed, or not reported. So, the traditional methods should be supplemented by studies of population-level incidence of Covid-19 based on a national blood sample containing infection-induced SARS-CoV-2 antibodies. One such recent study, published by the CDC, shows that by December 2021, 33.5% (95% CI = 33.1–34.0) of the US population was infected with Covid-19 and by February 2022, 57.7% (95% CI = 57.1–58.3) of the US adults, and about 75% of the US children, were infected by Covid-19 (Clarke, et al., 2022).

Vaccine-Induced Herd Immunity

The threshold for vaccine-induced herd immunity, p_c, can be calculated by p_c = 1 - 1/R_0. So, if $R_0 = 2.2 - 3.9$ then p_c = 54.55% - 74.36% vaccine cover is required to eliminate the disease. This percentage will need to be adjusted for the effectiveness of a vaccine (say it is 50% - 90% effective) and what proportion of the population will take the vaccine.

Taking Steps to Control the Spread of Covid-19

The final research question is addressed here.

- RQ #5. What steps should individuals and organizations take to control the spread of this disease?

The Covid-19 has had a very severally negative impact on the lives of many Americans as they have had to adapt to the new reality of this epidemic. Both non-pharmaceutical and pharmaceutical measurers should be undertaken to control the spread of Covid-19. WHO, CDC, Federal and state governments, The Association of American Medical Colleges, the Center for Health Security, and organizational administrators issues guidelines to guide the behavior of individuals. Table 1 presents some guidelines that were issued in early 2020 and most of them are still valid as a reference for future.

Table 1: Guideline to Reset the US Response to Covid-19	
A Road Map to Reset the Nation's Approach to the Pandemic	Resetting Our Response: Changes Needed in the US Approach to Covid-19
Source: Association of American Medical Colleges. Retrieved from https://www.aamc.org/Covidroadmap/roadmap	Source: The Center for Health Security. Retrieved from https://www.centerforhealthsecurity.org/our-work/pubs_archive/pubs-pdfs/2020/200729-resetting-our-response.pdf
Immediate Actions 1. Remedy critical supply and drug shortages. 2. Increase availability and accessibility of testing. 3. Establish national standards on face coverings. 4. Establish and enforce national criteria for local stay-at-home orders and reopening protocols. 5. Establish national criteria for K-12 school reopenings and convene a working group to study different approaches by mid-August. 6. Immediately expand health insurance through COBRA. 7. Begin planning now to prioritize distribution of the SARS-CoV-2 vaccine. 8. Address and resolve health care inequities. 9. Inform, educate, and engage the public. Longer-Term Actions 1. Broaden health insurance. 2. Strengthen the nation's public health infrastructure.	1. Encourage and, where appropriate, mandate nonpharmaceutical interventions. 2. Close higher risk activities and settings in jurisdictions where the epidemic is worsening and reinstitute stay-at-home orders where healthcare systems are in crisis. 3. Bolster PPE supply chains and stockpiles and make information about the PPE manufacturing base and supply chain publicly available, with the goal of expanding PPE availability. 4. Bolster test supply chains, plan for shortages, and collaborate with states and commercial laboratories to expand capacity and improve test turnaround times. 5. Conduct and make public detailed analyses of epidemiologic data collected during case investigations and contact tracing. 6. Curate and fund a rapid research agenda to cope with major challenges that have arisen. 7. Scale up contact tracing and continue to improve performance. 8. Identify and disseminate best practices for improving the public health response. 9. Plan for a vaccine, including production, allocation, distribution, and community engagement, to ensure a successful rollout. 10. Develop policies and best practices to better protect group institutions.

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APPENDIX: A BREIF INTRODUCTION TO R LANGUAGE AND ENVIRONMENT

R is an open-source and free software language and environment for statistical analysis, model building, and visualization. R can produce elegant graphs with ease. Ross Ihaka and Robert Gentleman, University of Auckland, developed R in 1991 by utilizing two programming languages -- Scheme and S. Scheme emphasizes simplicity and elegance, and it is a dialect of Lisp language. S language was developed at Bell Telephone Laboratories (Bell Labs) during 1970s and 1980s; it focused on data analysis and emphasized ease of use (Peng, 2022).

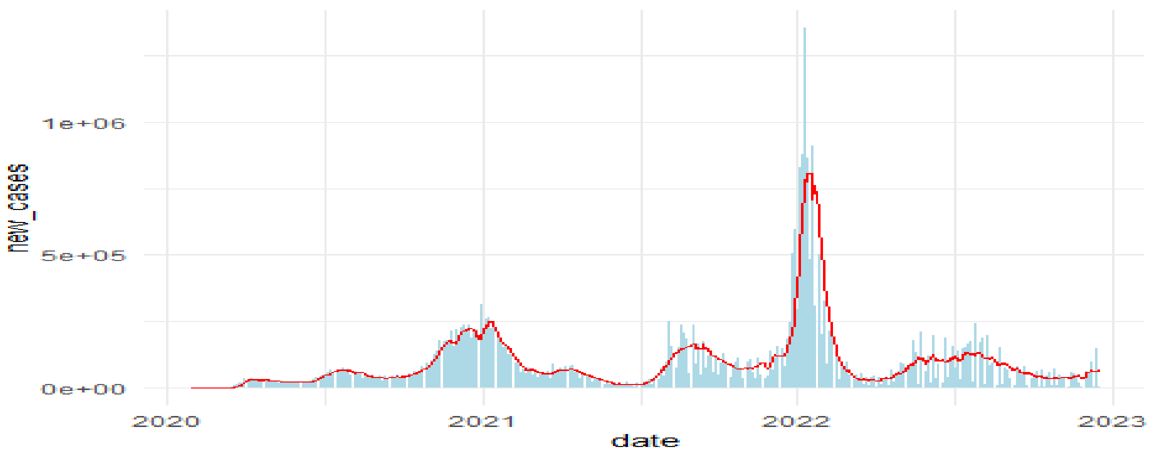
Managers and policy makers interested in exploring and understanding the dynamics of an infectious disease like Covid-19 can do so by using R that they can download and install from https://cran.r-project.org/. Posit (or RStudio) is a popular Integrated Development Environment (IDE) that makes it easier to utilize R and produce high quality output in various formats

(DOCX, HTML, PDF, etc.). Posit is also free and can be download and installed from https://posit.co/. Both R and Posit run on a variety of operating systems including most Unix platforms, Mac OS, and Windows. Many YouTube videos guide beginners to download and install R and Posit (or RStudio) and run R programs (for example, R Programming 101, 2018).

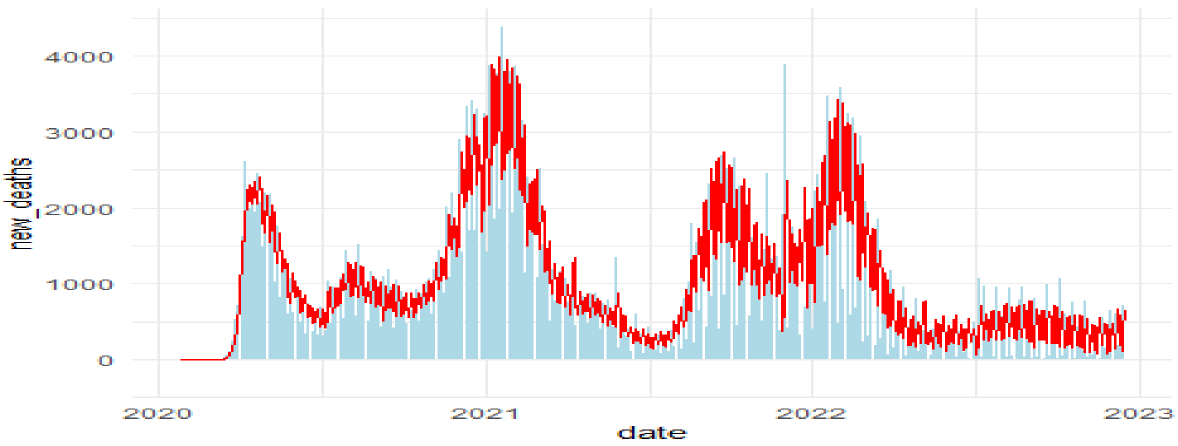
While R is an impressive language and environment for modeling, data analysis, and visualization, its capabilities have been extended by thousands of packages. There are over a hundred R packages for Covid-19 modeling and data analysis (Soetewey, 2020). The following illustrates how to utilize tidycovid19 package in R along with other R packages, to collect and analyze Covid-19 data. The tidycovid19 package provides many functions for downloading, analyzing, and displaying Covid-19 information (Gassen, n.d., Gassen, 2022). Readers can work in the R console or in Posit (or RStudio) to create an R script containing the following R code. China and the US took two different approaches to Covid-19 control, so the following code highlights infections and deaths in these two countries along with analyses about geographic spread of this disease in different regions. The reader will appreciate the ease with which latest Covid-19 data can be accessed, analyzed, and displayed.

```
# R code to obtain, analyze, and display the latest Covid-19 data
# Here a # represents a comment and ## represents results generated by R code.

# set RStudio as the CRAN mirror to download and install R packages
options(repos = c(CRAN = "http://cran.rstudio.com"))

# install an R package called remotes
# install tidycovid19 package: remotes::install_github("joachim-gassen/tidycovid19")

# install an R package called pacman
# load several packages with p_load() function in pacman package
pacman::p_load(tidyverse, tidycovid19, zoo)

# download data with download_merged_data() function in tidycovid19
df <- download_merged_data(cached = TRUE, silent = TRUE)

str(df) # look at the structure of df data file

# print regions
unique(df$region)

## [1] "Latin America & Caribbean " "South Asia"
## [3] "Sub-Saharan Africa "        NA
## [5] "Europe & Central Asia"      "Middle East & North Africa"
## [7] "East Asia & Pacific"        "North America"

# print 3-letter country code
unique(df$iso3c)

# print country names
unique(df$country)

#------------ USA -----------
# new cases aveaged weekly
```

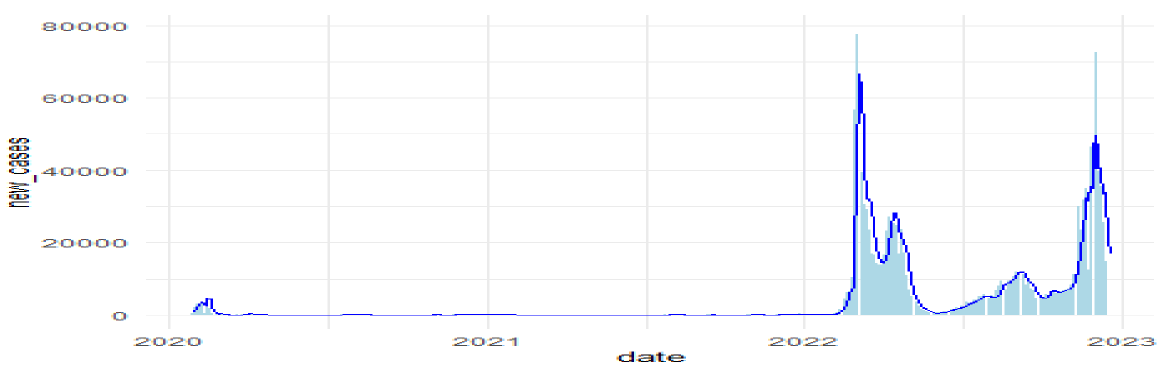
```
df %>% filter(iso3c == "USA") %>%
  mutate(
    new_cases = confirmed - lag(confirmed),
    ave_new_cases = rollmean(new_cases, 7, na.pad=TRUE, align="right")
  ) %>%
  filter(!is.na(new_cases), !is.na(ave_new_cases)) %>%
  ggplot(aes(x = date)) +
  geom_bar(aes(y = new_cases), stat = "identity", fill = "lightblue") +
  geom_line(aes(y = ave_new_cases), color ="red") +
  theme_minimal()
```



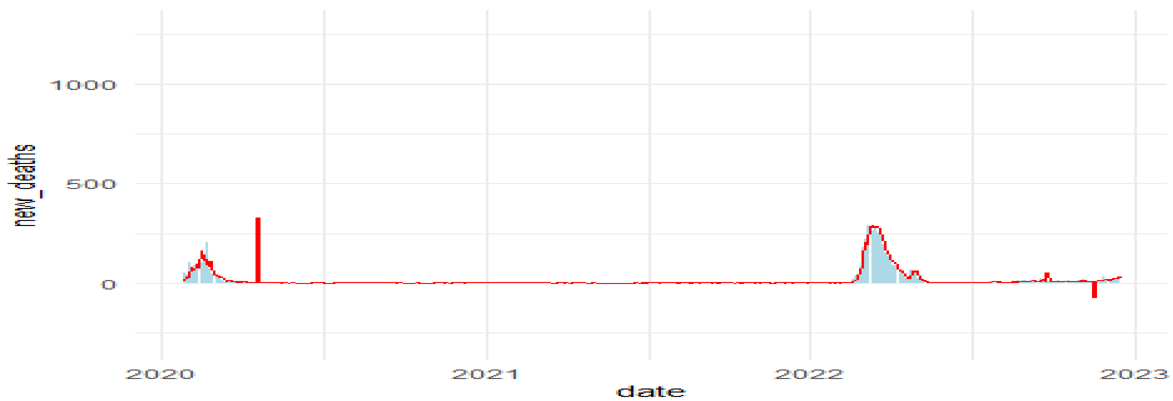

```
# new weekly deaths averaged over a month
df %>% filter(iso3c == "USA") %>%
  mutate(
    new_deaths = deaths - lag(deaths),
    ave_new_deaths = rollmean(new_deaths, 4, na.pad=TRUE, align="right")
  ) %>%
  filter(!is.na(new_deaths), !is.na(ave_new_deaths)) %>%
  ggplot(aes(x = date)) +
  geom_bar(aes(y = new_deaths), stat = "identity", fill = "lightblue") +
  geom_line(aes(y = ave_new_deaths), color ="red") +
  theme_minimal()
```



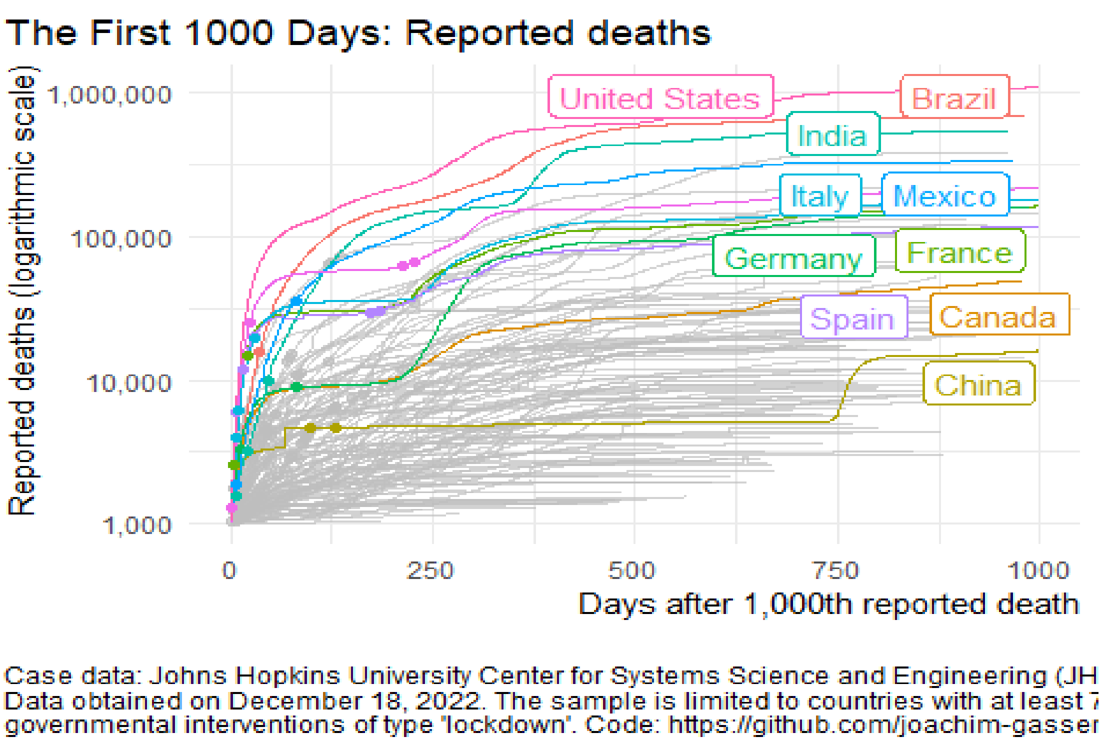

```r
#--------- China -----------------
df %>%
  filter(iso3c == "CHN") %>%
  mutate(
    new_cases = confirmed - lag(confirmed),
    ave_new_cases = rollmean(new_cases, 7, na.pad=TRUE, align="right")
  ) %>%
  filter(!is.na(new_cases), !is.na(ave_new_cases)) %>%
  ggplot(aes(x = date)) +
  geom_bar(aes(y = new_cases), stat = "identity", fill = "lightblue") +
  geom_line(aes(y = ave_new_cases), color = "blue") +
  theme_minimal()
```

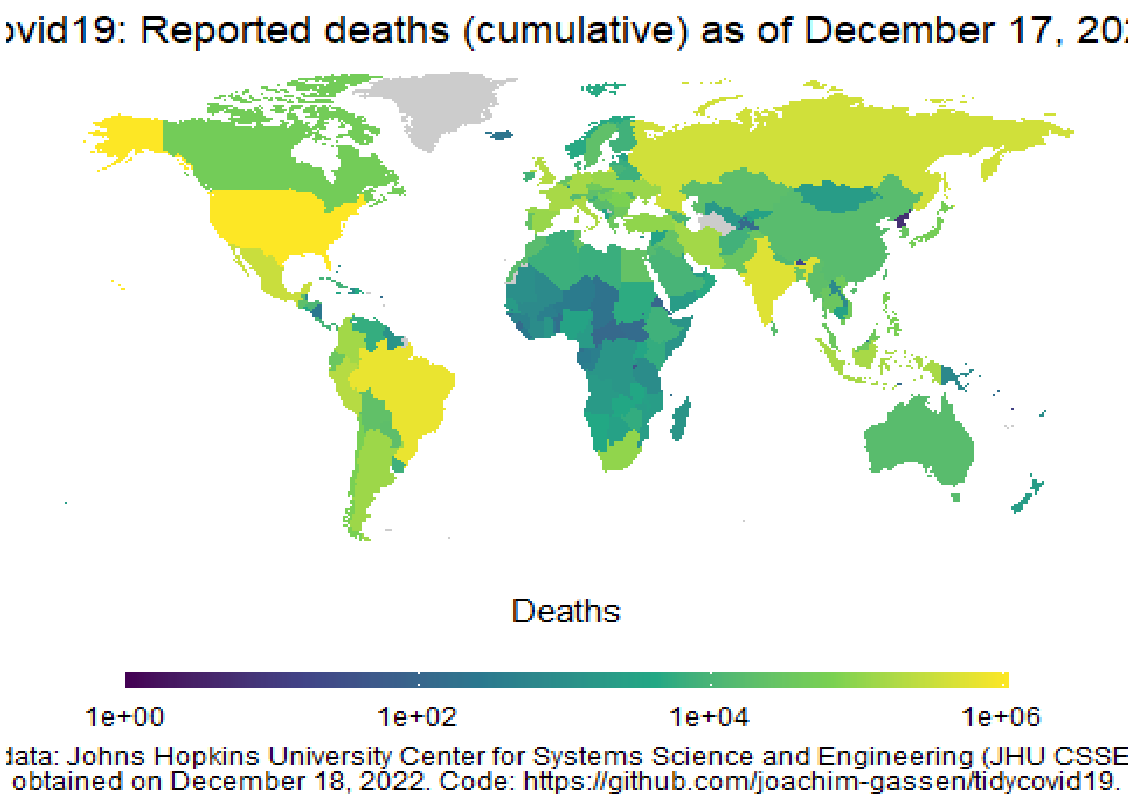



```r
# new weekly deaths averaged over a month
df %>% filter(iso3c == "CHN") %>%
  mutate(
    new_deaths = deaths - lag(deaths),
    ave_new_deaths = rollmean(new_deaths, 4, na.pad=TRUE, align="right")
  ) %>%
  filter(!is.na(new_deaths), !is.na(ave_new_deaths)) %>%
  ggplot(aes(x = date)) +
  geom_bar(aes(y = new_deaths), stat = "identity", fill = "lightblue") +
  geom_line(aes(y = ave_new_deaths), color ="red") +
  theme_minimal()
```



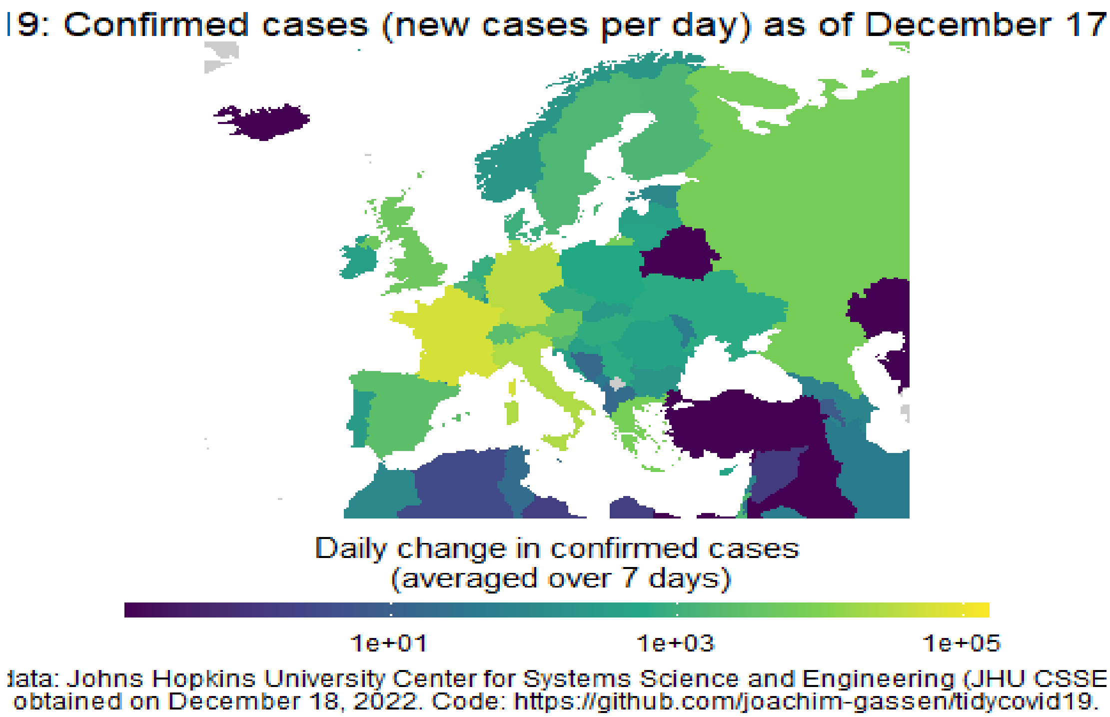

```
#------ many countries ------------------
merged <- download_merged_data(cached = TRUE, silent = TRUE)
plot_covid19_spread(
  merged, highlight = c("BRA", "CAN", "CHN", "DEU", "ESP", "FRA", "GBR", "IND",
"ITA", "MEX", "USA"),
  intervention = "lockdown", edate_cutoff = 1000
)

## Warning: ggrepel: 1 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



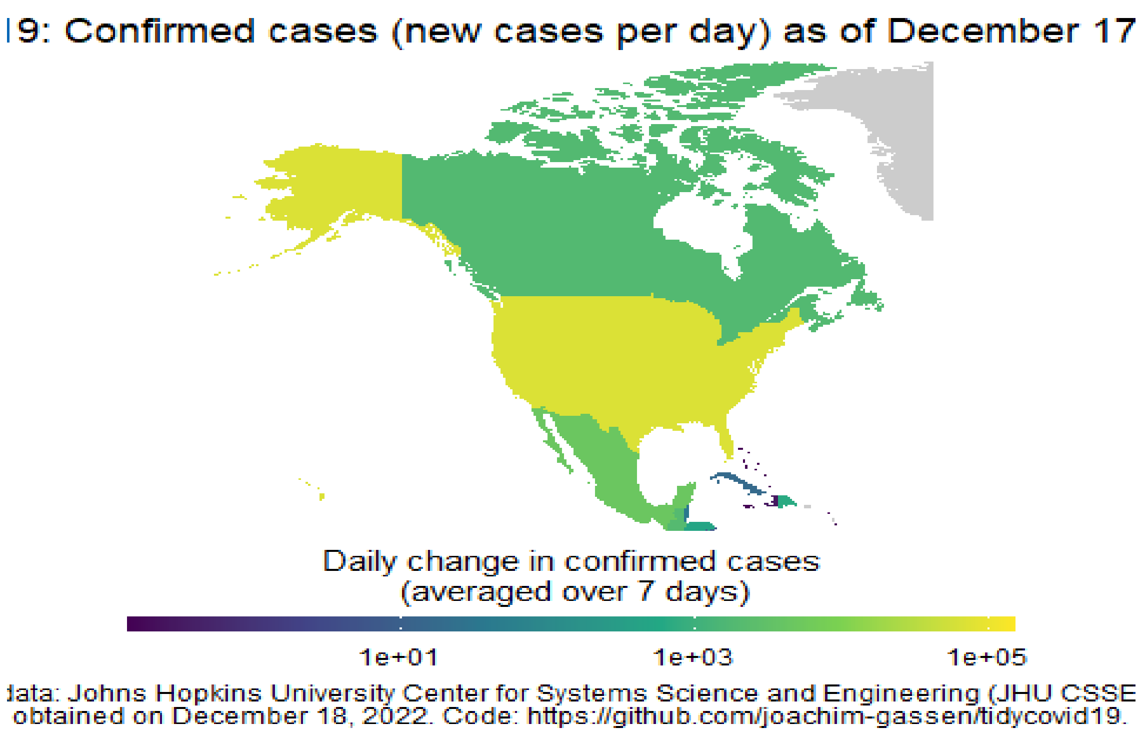


Covid19: Confirmed cases (new cases per day) as of December 17, 2022

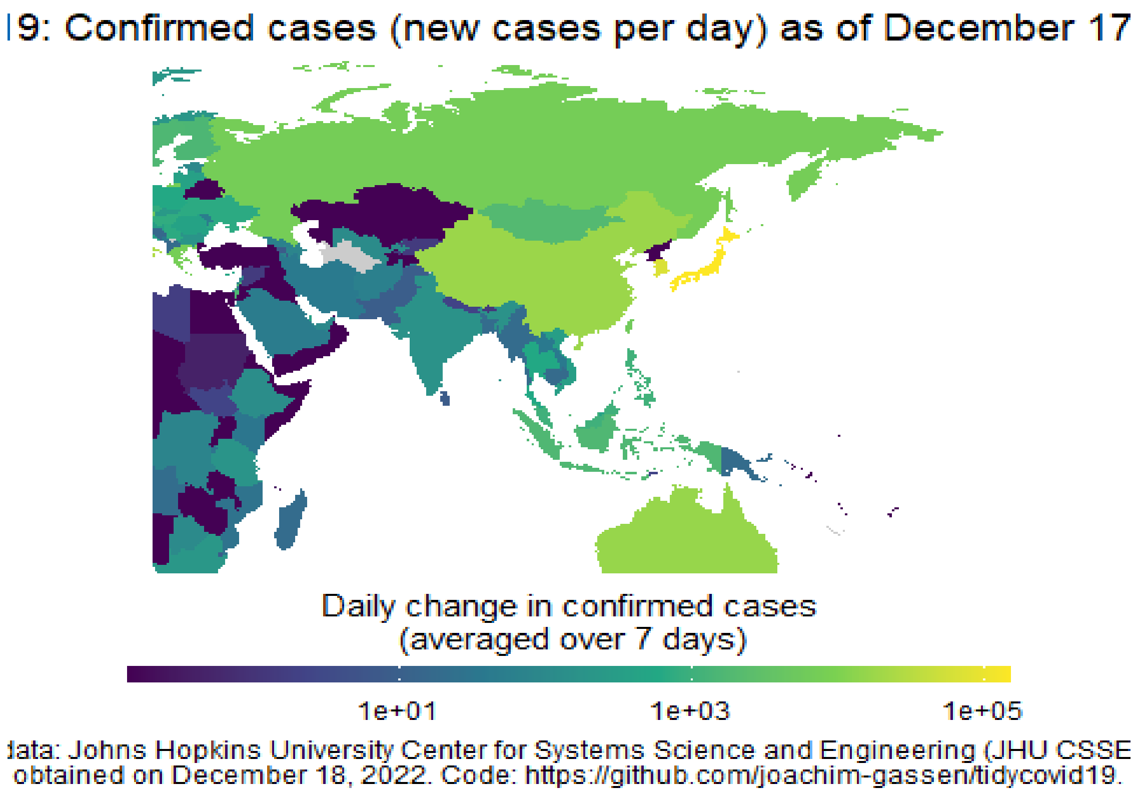
```
# Covid19: Confirmed cases (new cases per day) as of December 17, 2022
map_covid19(merged, type = "confirmed", region = "Europe")
```




```
# Covid19: Confirmed cases (new cases per day) as of December 17, 2022
map_covid19(merged, type = "confirmed", region = "North America")
```




```
# Covid19: Confirmed cases (new cases per day) as of December 17, 2022
map_covid19(merged, type = "confirmed", region = "Asia")
```


9: Confirmed cases (new cases per day) as of December 17
Daily change in confirmed cases
(averaged over 7 days)
1e+01
1e+03
1e+05
lata: Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE
obtained on December 18, 2022. Code: https://github.com/joachim-gassen/tidycovid19.

UNDERGRADUATE BUSINESS STUDENT ONLINE ATTITUDE AND BEHAVIOR: AN EMPIRICAL EXAMINATION OF THE COVID-19 PANDEMIC EFFECTS

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ABSTRACT

Phishing has been an ongoing challenge for both individuals and organizations. Of particular concern to information systems educators are the attitudes and online behavior of the next corporate users, our current business students. This study was therefore conducted to empirically examine the aspects of spyware, phishing, and identity theft and, in particular, if there are COVID-19 pandemic effects. Results suggest that online minutes have greatly increased, concern about spyware has decreased, and concern about identity theft has increased since the beginning of the pandemic. However, no statistically significant correlation between online minutes and behavior was found.

Keywords*: phishing, identity theft, undergraduate students, empirical study*

INTRODUCTION

Spyware is one of the oldest and most widespread online threats in which the computer is secretly infected to initiate a variety of illegal activities including identity theft or a data breach (Malwarebytes.com, 2022). Techniques include phishing, spoofing, using Trojan horses, exploiting security vulnerabilities such as back doors, and so on.

In terms of identity theft, the Aite-Novarica Group found that 47% of Americans experienced financial identity theft in 2020. And, the Federal Trade Commission's (FTC) Consumer Sentinel Network analysis of over 5.7 million complaints in 2021 found that 25% were for identity theft (Insurance Information Institute, 2022). The most common types of identity theft were for government benefits applied for/received (31%) and credit card fraud for new accounts (29%).

Data threats can be manifested in several forms such as ransomware, targeted hacking, vendor or customer impersonation, IP address hacking, extortion, and so on (Neustar, 2018). The most recent noteworthy data breaches include: the 2021 LinkedIn data breach exposing the personal information of 700 million users (93% of all LinkedIn members), the March 2021 attack on Microsoft that affected more than 30,000 U.S. businesses and government agencies, the 2021 infiltration of the Colonial Pipeline Company with ransomware that caused fuel shortages across the U.S., and the ransomware attack of the meat processing company JBS that shut down beef and poultry processing plants on four different continents (Sobers, 2022).

The IBM Security (2021) Data Breach Report estimates the average cost of a data breach is $4.24 million. Data breaches that take longer than 200 days to identify and contain cost on average $4.87 million as compared to $3.61 million for breaches that take less than 200 days. Overall, the report found it takes an average of 287 days to identify and contain a data breach. Ransomware attacks, for example, cost an average of $4.62 million which includes escalation, notification, lost business, and response costs, not including the cost of the ransom.

According to Verizon's Data Breach Investigative Report 2022 analysis of over 23,000 cybersecurity incidents and 5,200 confirmed breaches from around the world, 25% of all data breaches involve phishing and 85% of data breaches involve a human element (Verizon.com 2022). Moreover, the FBI's Internet Crime Complaint Center (IC3) found that phishing, including vishing, SMiShing and pharming, was the most prevalent threat in the U.S. in 2020, with 241,342 victims (Jones, 2022). This was followed by non-payment/non-delivery (108,869 victims), extortion (76,741 victims), personal data breach (45,330 victims) and identity theft (43,330 victims). This is problematic given that Terranova Security's 2020 Gone Phishing Tournament found nearly 20% of all employees are likely to click on phishing email links and, of those, 67.5% go on to enter their credentials on a phishing website.

Phishing mechanisms continue to evolve. A new form is through the use of Quick Response (QR) codes (Bergal, 2022). In January of 2022, the FBI issued an alert about cybercriminals tampering with posted QR codes to steal login and financial information. Pay-to-park kiosks, for example, have been targeted with criminals slapping stickers with fake QR codes on pay stations. Fake codes are then used to redirect payments and embed malware in the unsuspecting victim's mobile device.

According to Check Point, in the fourth quarter of 2020, Microsoft was the most impersonated brand globally when it comes to brand phishing attempts, accounting for 43% of the attempts (checkpoint.com, 2020). Attackers are likely exploiting Microsoft's name given the increase in organizations relying on Microsoft's suite of cloud applications since the start of the pandemic. Other brands impersonated include DHL (18% of attempts), LinkedIn (6% of attempts), and Amazon (5% of attempts). Unfortunately, email security provider Ironscales' State of Cybersecurity Survey poll of more than 400 U.S. IT professionals found that 81% of respondents experienced an increase in email phishing attacks since the start of the pandemic, from March 2020 to September 2021 (Thomas, 2021). And, only 19% of organizations provide cybersecurity awareness training on an annual basis.

Given the increasing incidences of phishing, data breaches, and identity theft, the study was conducted to examine the attitude, incidence, and trends relative to undergraduate business students. This empirical study examines several questions. Are students concerned about spyware and identity theft? What are student online activity minutes? Are students protected with a second firewall? Have students responded to phishing email and/or have been a victim of identity theft? And, has the March 11, 2020 World Health Organization declaration of the novel coronavirus (COVID-19) as a global pandemic changed attitudes and activity (Cucinotta & Vanelli, 2020)? Results are important in better understanding the state of student online behavior and if modifications to student education are needed to minimize vulnerability.

PREVIOUS RESEARCH

An initial study by the authors conducted in 2006-2007 found that only 26% of undergraduate students indicated receiving phishing email with 16 phishes received per month per student (Case and King, 2008). A subsequent study conducted 2007-2010 examined email quantity (King & Case, 2012). Results demonstrated that students received 212 emails per month with the largest category, 35%, being unsolicited or spam emails. Class-related (26%), personal/non-class (13%), and other email (26%) were less common. A third study by the authors conducted 2011-2015 examined types of phishing (Case & King, 2016). Responses illustrate that for every year of the study, credit card phishing emails were the most common type of attack with 18-23% of students per year indicating receiving them. Amazon.com (14-19%), eBay (8-12%), Nigerian Scam (6-10%), and other (4-5%) phishes were also received.

To predict user susceptibility to phishing websites, Abbasi, et.al (2021) proposed and tested the phishing funnel model (PFM). PFM incorporates user, threat, and tool-related factors to predict actions during four key stages of the phishing process: visit, browse, consider legitimate, and intention to transact. Experiments demonstrated PFM significantly outperformed competing models/methods by correctly predicting visits to high-severity threats 96% of the time. In addition, a follow-up field study revealed that employees using PFM were significantly less likely to interact with phishing threats relative to comparison models and baseline warnings.

Furthermore, because scammers may use a step by step approach to gain a potential victim's trust, Abroshan, et.al (2021) investigated the extent risk-taking and decision-making styles influence the likelihood of phishing victimization in such instances. Results suggest that the attitude to risk-taking and gender can predict users' phishability in the different steps selected.

In terms of spyware, Sideri et al. (2019) used a case study to investigate the privacy literacy of university students in relation to the usage of social media. Researchers held a thirteen-week course on social media with the goal of strengthening privacy literacy. Although the students at the outset did not have the necessary knowledge in this field, after completing the course participants exercised more caution with regard to their profile visibility, paid more attention to the privacy settings of Facebook, and had increased awareness of the usefulness of anti-spyware software.

Relative to identity theft, Ogbanufe & Pavur (2022) explored why and how individuals adaptively and maladaptively respond to the threat. The researches provided empirical evidence of conditions under which fear and regret motivate personal security protection measures, thus enabling practitioners to promote identity theft protection more efficiently. Results suggest that fear is only effective when the threat is high and anticipated regret is effective in both high and low threat conditions. Also, anticipated regret has the most potent effect on increasing adaptive coping responses in a low threat model. Thus, anticipated regret rather than fear could be used in situations where the threat is low.

Finally, Salam, et.al (2021) proposed an empirical assessment of the construct of user control over identity theft. Findings suggest that when users have the perception of more control over the identity theft threat, they are likely to find solutions, feel it is their responsibility, and have more intentions for identity theft prevention actions to prevent identity theft.

RESEARCH DESIGN

This study employs a survey research design. The research was conducted at a private, northeastern U.S. university. A Student Phishing instrument was developed by the authors and administered each semester during a five-year period (from spring 2018 through spring 2022) to undergraduate students enrolled in a School of Business course. However, because of the university unanticipated face-to-face instruction discontinuance midway through the spring of 2020, no data were collected during that semester. The courses included a variety of subjects such as Business Information Systems, Introduction to Financial Accounting, Introduction to Managerial Accounting, Macroeconomics, and Business Policy. A convenience sample of class sections and faculty members was selected to minimize the probability of a student receiving the survey in more than one class and to ensure consistency, the same questions were asked during each of the semesters. Because of the sensitivity of the subject and to encourage honesty, no personally-identifiable data were collected and respondents were informed that surveys were anonymous, participation was voluntary, and responses would have no effect on his/her course grade. In addition, students were asked to complete the survey only one time per semester. Prior to the pandemic, the surveys were completed via paper in an academic classroom. Subsequent to the beginning of the pandemic, the surveys were completed via an online link.

The survey instrument was utilized to collect student demographic data such as gender and academic class. In addition, the survey examined student Internet behavior regarding shopping, non-school related surfing, phishing, spyware, firewalls, and identity theft. Results were summarized by activity and correlations were calculated to determine potential relationships between online minutes and behaviors. To examine potential trends, the data was segmented by calendar year. However, because of the anonymity of respondents, it could not be determined if a given student participated during multiple semesters so repeated measures were not examined.

RESULTS

A sample of 952 usable surveys was obtained. As indicated in Table 1, 60% of the respondents were male and 40 were female. These percentages were fairly consistent with the study university's School of Business student population.

Table 1
Gender Response Rate by Year

	2018	2019	2020	2021	2022	Total
Male	59%	60%	67%	58%	65%	60%
Female	41%	40%	33%	42%	35%	40%
Count	311	344	80	155	62	952

The response rate by academic class was relatively equally distributed. As indicated in Table 2, 18% of respondents were freshmen, 36% were sophomores, 30% were juniors, and 16% were seniors.

Table 2
Academic Class Response Rate by Year

	2018	2019	2020	2021	2022	Total
Freshmen	21%	28%	0%	4%	10%	18%
Sophomore	36%	32%	23%	41%	55%	36%
Junior	28%	17%	70%	46%	26%	30%
Senior	15%	8%	8%	9%	10%	16%

Responses were first examined with regard to the student's level of concern about spyware. As indicated in Table 3, in 2018, 16% strongly disagreed, 22% disagreed, 28% were neutral, 20% agreed, and 10% strongly agreed with respect to being concerned about spyware. At the onset of the pandemic in 2020, 24% strongly disagreed, 33% disagreed, 19% were neutral, 23% agreed, and 6% strongly agreed about his/her concern. By 2022, 19% strongly disagreed, 31% disagreed, 21% were neutral, 21% agreed, and 8% strongly agreed about his/her concern. Results demonstrate that the percent of students concerned about spyware was relatively consistent from 2018 to 2022 with 30%, 28%, 29%, 30%, and 29%, respectively, of students indicating concern. On the other hand, the percentage not concerned varied from 2018 to 2022 to 38%, 37%, 57%, 39%, and 50%, respectively, of students.

Table 3
Concerned About Spyware by Year

Level of Agreement	2018	2019	2020	2021	2022
Strongly Disagree	16%	13%	24%	14%	19%
Disagree	22%	24%	33%	25%	31%
Neutral	28%	30%	19%	32%	21%
Agree	20%	19%	23%	21%	21%
Strongly Agree	10%	9%	6%	9%	8%

Next, responses were examined with regard to the student's level of concern about identity theft. As indicated in Table 4, in 2018, 8% strongly disagreed, 31% disagreed, 47% were neutral, 13% agreed, and 3% strongly agreed with respect to being concerned about identity theft. At the onset of the pandemic in 2020, 18% strongly disagreed, 34% disagreed, 20% were neutral, 28% agreed, and 5% strongly agreed about his/her concern. In terms of identity theft, from 2018 to 2022, 16%, 15%, 33%, 34%, and 26%, respectively, of students indicated concern. The percentage not concerned varied from 2018 to 2022 to 39%, 27%, 52%, 39%, and 46%, respectively, of students.

Table 4
Concerned About Identity Theft by Year

Level of Agreement	**2018**	**2019**	**2020**	**2021**	**2022**
Strongly Disagree	8%	3%	18%	16%	15%
Disagree	31%	24%	34%	23%	31%
Neutral	47%	58%	20%	30%	29%
Agree	13%	15%	28%	21%	21%
Strongly Agree	3%	0%	5%	13%	5%

Activity minutes per day are presented in Table 5. Results illustrate that in 2018, respondents indicated spending 1 minute per day shopping online while spending 112 minutes per day engaged in non-school surfing. At the onset of the pandemic in 2020, respondents spent 3 minutes shopping and 221 minutes engaged in non-school surfing per day. By 2022, respondents spent 1 minutes shopping and 177 minutes engaged in non-school surfing per day. While shopping online minutes per day remained consistent at one minute per day from 2018 to 2022, non-school surfing varied from 112 minutes, 110 minutes, 221 minutes, 157 minutes, and 177 minutes per day, respectively, during the study years. Overall, total minutes per student increased from 107 minutes (1.8 hours) in 2018 to 165 minutes (2.8 hours) in 2022.

Table 5
Activity Minutes Per Day by Year

Activity	**2018**	**2019**	**2020**	**2021**	**2022**
Shopping Online	1	1	3	1	1
Non-School Surfing	112	110	221	157	177
Total	107	105	219	154	165

Respondent behavior was further examined and presented in Table 6. In 2018, 6% indicated responding to a phishing email in the past year, 27% indicated using a second firewall, 4% indicated being a victim of identity theft, and 26% indicated personally knowing a victim of identity theft. At the onset of the pandemic in 2020, 7% indicated responding to a phishing email in the past year, 17% indicated using a second firewall, 7% indicated being a victim of identity theft, and 37% indicated personally knowing a victim of identity theft. By 2022, 2% indicated responding to a phishing email in the past year, 11% indicated using a second firewall, 5%

indicated being a victim of identity theft, and 53% indicated personally knowing a victim of identity theft. With respect to behavior, in general, the majority of students did not exhibit any of the behaviors during each of the five years. For example, from 2018 to 2022, only 6%, 6%, 7%, 8%, and 2%, respectively per year, of students responded to a phishing email during the past year. Moreover, only 4%, 11%, 7%, 7%, and 5%, respectively per year, of students have been a victim of identity theft. Second firewall usage was more common each year, respectively, with 27%, 35%, 17%, 14%, and 11%, respectively per year, of students indicating this behavior. Personal knowledge of an ID theft victim was also more common with 26%, 24%, 37%, 38%, and 53%, respectively per year, of students indicating this knowledge.

Table 6
Behaviors by Year

Behavior	**2018**	**2019**	**2020**	**2021**	**2022**
Responded to Phishing Email in Past Year	6%	6%	7%	8%	2%
Use a Second Firewall	27%	35%	17%	14%	11%
Have Been Victim of Identity Theft	4%	11%	7%	7%	5%
Personally Know an ID Theft Victim	26%	24%	37%	38%	53%

Finally, potential correlations between the quantity of surfing minutes and various behaviors were examined in Table 7. Statistically significant Spearman Rho correlations were not found with respect to any behavior including responding to a phishing email in the past year, using a second firewall, or being a victim of identity theft.

Table 7
Spearman Rho Correlations between Surfing Minutes and Behavior

Behavior	Correlation Coefficient
Responded to Phishing Email in Past Year	-.188
Use a Second Firewall	.132
Have Been Victim of Identity Theft	.082

* Correlation is significant at .05 level (2-tailed).
** Correlation is significant at .01 level (2-tailed).

The limitations of these results are primarily a function of the sample, sample distribution, and type of research. The use of additional universities, a more equal distribution among gender, and increased freshman participation would increase the robustness of results. Another limitation relates to the self-reported nature of the survey.

IMPLICATIONS

There are three important implications from the study. One implication relates to student attitude. Prior to the pandemic, a minority, 36-37%, of students per year were not concerned about spyware. However, at the onset of the pandemic, the majority, 57%, of students indicated a lack of concern. This lack of concern remained at 50% of students by the end of the pandemic. It is possible the social isolation and life traumas associated with the pandemic resulted in an increased sense that online privacy is not as important as the other life and death challenges associated with a pandemic. Another aspect of the pandemic relates to concerns about identity theft. Prior to the pandemic, 15-16% of students indicated concern. However, at the onset of the pandemic, this percentage more than doubled to 33%. At the end of the pandemic, the percentage decreased to 26%, but remains much larger than the pre-pandemic years. It is possible that the increased dependence on and use of the Internet because of face-to-face COVID-19 exposure concerns and/or travel lock-downs during the pandemic has triggered the identity theft concern. These changes suggest that the pandemic has affected attitude related to both personal privacy and security threats.

A second implication is evident when examining behavior. While two behaviors, responding to a phishing email and being a victim of identity theft, have remained relatively small and consistent in occurrence during each of the five years, other behaviors have changed since the onset of the pandemic. Non-school surfing increased by 100% to 221 minutes per day during the first year of the pandemic and remained 54% higher at the end of the pandemic as compared to four years earlier. It likely that surfing increased because of the social isolation and/or increased discretionary time as a result of unemployment and tele-commuting. Another behavior, using a second firewall for intrusion detection/prevention, decreased by 50% to 17% at the onset of the pandemic and continued to decrease through the study years. This may also be a result of the feeling of social isolation and perception that one is not being spied upon.

Finally, the third implication relates to the difference in the level of identity theft victimization between students and others. While respondents indicated a dramatic increase in the knowledge of others being victimized (24% prior to pandemic, 37% at the onset, and 53% at the end of the pandemic), student victimization has varied slightly, from 4% to 11% per year, during the study. It is possible that either students are more aware of other's victimization or are more vigilant because of education. This suggests that continued proactive education has been and may continue to be helpful in combating the scourge of identity theft. Future research will need to determine if the pandemic effects have permanently changed undergraduate student attitudes and behavior.

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