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Investigating influencing factors for ICT adoption that changes travel behavior in response to the COVID-19 outbreak in Indonesia

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A R T I C L E I N F O

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A B S T R A C T

Mobility and out-of-home activities restrictions from the COVID-19 pandemic have forced people to maximize their in-home activities. Considering the increase in Information and Communication Technology (ICT) adoption during the outbreak, this paper tries to shed light on the factors that influence changing travel behavior. For these purposes, the study uses data collected through an online questionnaire during the outbreak in Indonesia, which was then analyzed using cluster and discriminant analyses. The study found that online adaptation during the outbreak was affected by income level, whereby high-income individuals are associated with high online adaptation. Residential location also influences ICT adaptation during the outbreak. Cities with higher access to the internet and ICT platforms as well as higher income per capita tend to have higher ICT adoption. People with more experience with online platforms or services also record higher online in-home activity adoption during the outbreak. Furthermore, while the lower-income group tends to reduce their travel, the higher-income group still continues to travel to fulfil their household needs during the outbreak, such as in-store shopping. Since the lower-income group and less accessible areas tend to have difficulty in accessing ICT as a substitute for travel, this study recommends that the government and ICT stakeholders ensure equal access to ICT to support physical distancing and to limit mobility in order to flatten the peak of the pandemic.

1. Background

The Coronavirus Disease 2019 (COVID-19) outbreak has shaken our planet, changing our daily lives and reshaping our economy. Human-to-human transmission facilitated by interconnected daily activities and hypermobility led to the inevitable significant increase of cases during the first half of 2020 (Musselwhite et al., 2020; Null & Smith, 2020). Countries across the world took measures to reduce the effects of the disease or slow them down to avoid overstretching their nations' public health resources. Limiting travel and out-of-home activities has been the primary means chosen by various countries to flatten the curve. This has resulted in enormous changes to how cities are functioning around the world, influencing how people perform their daily lives (De Vos, 2020; Zhang & Hayashi, 2020).

As the government banned most out-of-home activities, people had no choice other than to maximize their in-home activities to fulfill their needs and desires. Several investigations have reported that the travel and out-of-home activities restriction caused by the outbreak has indirectly influenced global and local economies (Woods et al., 2020) as well as the environment (Gautam & Hens, 2020; SanJuan-Reyes et al., 2021). Government agencies, global businesses, and educational institutions strived to transform their major practices to maintain target and performance, shifting from face-to-face interactions to online interactions. Moreover, mental health issues were predicted to worsen during the mobility restriction (Tarlton, 2020; Torales et al., 2020), and people looked for more activities to release their emotions as well as to enjoy during their time at home. Such mobility restriction has led to increasing demand for internet activities, such as online learning and video calls as

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well as movie streaming and online video games (Clement, 2020; Kunst, 2020).

These facts indicate major daily activity and travel behavior changes during the outbreak. It appears that information communication and technology (ICT) is facilitating those changes, with various new ICT facilities enabling people to perform activities without physical presence (Mokhtarian, 2004), consequently eliminating the need to travel (Ben-Elia, 2019). Some of the studies investigating the COVID-19 pandemic are focused on exploring the characteristics of the disease (Chen et al., 2020; Xu et al., 2020) and the mitigation to slow down the disease spread (Anderson et al., 2020; Chinazzi et al., 2020). Furthermore, studies on the disease's impact on travel behavior are mostly focused on public transportation and car traffic as well as logistics (De Vos, 2020; Parady et al., 2020; Zhang & Hayashi, 2020). Since ICT has proven to be an important platform during this pandemic times, some researches have found that the use of ICT platforms/ services (i.e., e-learning, online-shopping, teleworking) is influenced by ICT infrastructure and built environment (Mouratidis, 2021; Prasetyanto et al., 2022), socio-demography (Adibfar et al., 2022), and experience of the ICT services/platforms (Alaimo et al., 2020). While some studies have outlined several factors that influence the adoption of specific types of ICT platforms/services, studies investigating ICT adoption and its influencing factors during the outbreak remain limited. Mouratidis and Papagiannakis (2021) in Greece have explored the adoption of a wide range of online activities during COVID-19. While such investigation provides a fundamental understanding on how ICT helps people endure the outbreak, it is missing on the aspects that influence the adoption of ICT. This study aims to fill in the gap by investigating the factors that influence online activities and travel adaptation. This knowledge will be very beneficial for policymakers in navigating the current outbreak and in anticipating future implications, such as managing travel demands during emergencies, facilitating the need to take part in activities during a pandemic, and decreasing negative externalities caused by an outbreak.

On the other hand, while many studies have been done on the effect of ICT on travel behavior in developed countries (Ben-Elia, 2019; Gössling, 2018; Mokhtarian, 2009), fewer such studies have been found in developing countries (Irawan et al., 2019; Joewono et al., 2019; 2020). Meanwhile, there is a fundamental difference in terms of society, economy, infrastructure, and culture between developed and developing countries (Dharmowijoyo et al., 2016). In Indonesia's case, ICT development is characterized by low-quality internet and high smartphone ownership (Das et al., 2016). This study provides additional insight into understanding ICT behavior in Indonesia and other developing countries.

Indonesia reported the first COVID-19 case in early March 2020. In mid-March 2020, the National Government declared the outbreak a national disaster (Indonesia Cabinet Secretariat Office, 2020). The declaration was followed by various partial mobility restriction policies that forced most businesses, schools, universities, and tourism areas to close and imposed physical and social distancing (Djalante et al., 2020; Irawan et al., 2020; Rizki et al., 2022). As a lockdown similar to the one implemented in Wuhan, China, was not implemented in Indonesia, people could still travel (using public transport and inter-city travel) and conduct out-of-home activities for several reasons, such as work in certain permitted industries, healthcare purposes, and grocery shopping (Olivia et al., 2020). As such, the impact of these policies on daily activities and travel may differ from other countries.

The purpose of this paper is to better understand how ICT has facilitated daily activity and travel behavior changes during the COVID-19 outbreak. The investigation conducted focused on addressing three questions: how does ICT facilitate travel behavior changes, who are affected the most, and what factors affect them? To better investigate changes in travel behavior, we considered factors of socio-demographic, residential location, and ICT experience and usage characteristics. Using data collected from an online survey during the first half of the outbreak in Indonesia (March 2020), we performed a cluster analysis to classify travel behavior and in-home online activity changes during the outbreak. Afterward, we performed a discriminant analysis to explore the characteristics of the groups classified in the cluster analysis.

Following this introduction, we will provide an overview of the literatures on the impact of COVID-19 on travel and ICT use, the data collected, and descriptive statistics for key variables. We then present the cluster analysis for the travel response and in-home activity adaptation and the discriminant analysis. The findings will be presented in the discussion section, followed by concluding remarks.

2. Impact of COVID-19 on travel and ICT use

The substantial health risk from the global COVID-19 outbreak has forced national and local governments to restrict out-of-home activities (De Vos, 2020). In response to such government policy, companies and educational institutions moved their business and classrooms from offline to online. This resulted in changes in travel behavior and activities, which were manifested in two ways.

First, changes in travel and out-of-home activities resulted in the decline of public transport use and car traffic (Zhang & Hayashi, 2020). According to Moovit (2020), public transport use in cities worldwide, such as London, New York City, Berlin, Paris, and Sydney, experienced a significant drop. Paris recorded a decline of approximately 80 % from pre-pandemic levels. In the same vein, UITP (2020) reported that the pandemic caused 19 % of Indian bus operators to lose 90 % of its passengers and 91 % of them to be left with no ridership. Similar condition was seen in Indonesia. As passenger capacity was restricted and limited, passengers of most mass transits (i.e. MRT, BRT, and Commuter Rail) in Greater Jakarta decreased by more than 80 % from their usual levels (CNN Indonesia, 2020). Aside from the travel restriction imposed by the government, public transport was seen as a public facility where the virus can spread easily and as such, was mostly avoided by the people. Along with public transport, traffic also experienced a significant decrease in various cities. In March 2020, Madrid's traffic decreased by more than 80 % year-on-year, while New York's traffic decreased by 74 % (Wagner, 2020). In Indonesia, daily toll-road traffic in Greater Jakarta decreased by around 42–60 % in April 2020 (Murti, 2020). Most of the traffic recorded during the first half of the outbreak was contributed by the logistics sector, including essential services, medical devices, and healthcare services.

Second, the pandemic increased in-home activities facilitated by ICT platforms. For instance, changes occurred in shopping behavior to fulfill daily needs during quarantine. According to Clement (Clement, 2020), the number of visits to e-commerce websites worldwide jumped from around 12.81 billion in January 2020 to 14.34 billion in March 2020. A survey conducted by Kunst (2020) in three developed countries, namely Germany, United Kingdom, and the United States, reveals that approximately 4–27 % of respondents started buying different products online due to the COVID-19 pandemic. The same trend can be seen in Indonesia. Referring to Pusparisa (2020), the Indonesian e-commerce sector recorded a noticeable increase of monthly sales at 26 % from the previous year during the pandemic. Moreover, the number of daily transactions also increased from 3.1 million in the second quarter of 2019 to 4.8 million in April 2020. Pusparisa (2020) further stated that there is a significant increase in online shoppers during the pandemic with 12 million new users. Moreover, the use of teleworking application (i.e. online meeting platform) has been reported to surge substantially due to the rise of in-home activities (Baert et al., 2020) as most business and educational activities were conducted from home. This shift has also reduced office costs for employers and eliminated travel costs for employees (Knutson, 2020). Therefore, some companies are planning to retain such teleworking policy post-pandemic, at least for certain workers.

While various ICT platforms/services have emerged to facilitate online activities during the COVID-19 pandemic, Mokhtarian (2009) underlined that ICT adoption is not always possible, feasible, or desirable. Several scholars have investigated factors that influence the adoption of ICT platforms/services and found that individuals' characteristics, such as gender, income, age, and occupation, are among the factors that correlate with ICT adoption (Cao, 2009; Schwanen & Kwan, 2008; Varghese & Jana, 2019). Participation in activities on ICT platforms requires access to such ICT platform and the costs for such access are taken from the individual's income. High income was found to provide more flexibility in the adoption of online activities, such as teleworking (He & Hu, 2015) or online shopping (Cao, 2009). Younger age correlates with higher frequency of online shopping (Farag et al., 2003), telecommuting (Circella et al., 2016), and ride hailing (Clewlow & Mishra, 2017).

Furthermore, several scholars have investigated the role of accessibility in ICT use. For instance, while e-shopping is offered in various countries, some parts of the world still have difficulty in accessing these services (Murphy, 2007). ICT adaptation arguably relies heavily on broadband internet access and the necessary hardware. However, internet quality varies worldwide and some parts of the world do not have access to these services (Das et al., 2016; Doong & Ho, 2012). Hjorthol (2002) also highlights the influence of the accessibility and availability of devices to access ICT, such as laptops and computers, on teleworking adoption. The issue of inclusivity relating to access to mobile phones and ICT-related activities (e-learning) has been raised by Varghese and Jana (2019), as it appears to affect social inclusion of marginalized groups. ICT usage experience has also been found to correlate with online services adoption, in which more experience leads to higher tendency for adoption (Irawan et al., 2019; Joewono et al., 2020).

In the context of the outbreak, people rely heavily on ICT to fulfill their various obligations (such as work, school, and shopping); stay connected with family, friends, and relatives; and access entertainment (Molla, 2020). A reasonable hypothesis is that people maximized their in-home activities as the government enacted mobility and out-of-home activity restriction. Therefore, the barrier to ICT adoption to reduce travel was broken, making internet connection more important to the world than ever before. Some studies have shown an increase of teleworking (de Haas et al., 2020) even among workers who had no prior experience (Shamshiripour et al., 2020). However, earlier studies on teleworking during COVID-19 show that there is a gender gap in the adoption of teleworking adoption (Lyttelton et al., 2020) and that teleworking potentially decreases workers' productivity and well-being (Chang et al., 2020; Morikawa, 2020). Moreover, there might be different factors, such as socio-demographics, residential location/spatial characteristics, and ICT characteristics and experience, that influence ICT adoption during the COVID-19 outbreak. This study has the potential to fill in the information gap regarding the factors that influence ICT adoption during the COVID-19 pandemic in a developing nation.

3. Methodology

3.1. Data analysis

To explore how ICT has facilitated changes in daily activities and travel behavior during the COVID-19 outbreak, this study proposes the analysis framework illustrated in Fig. 1. The first part of this analysis focuses on online activity adoption while the second part focuses on travel behavior changes. While daily activities and travel behavior are related to each other, this study only focuses on virtual or online activities. With that separation, the analysis aims to reveal factors that influence online activity adoption during COVID-19. In order to explain

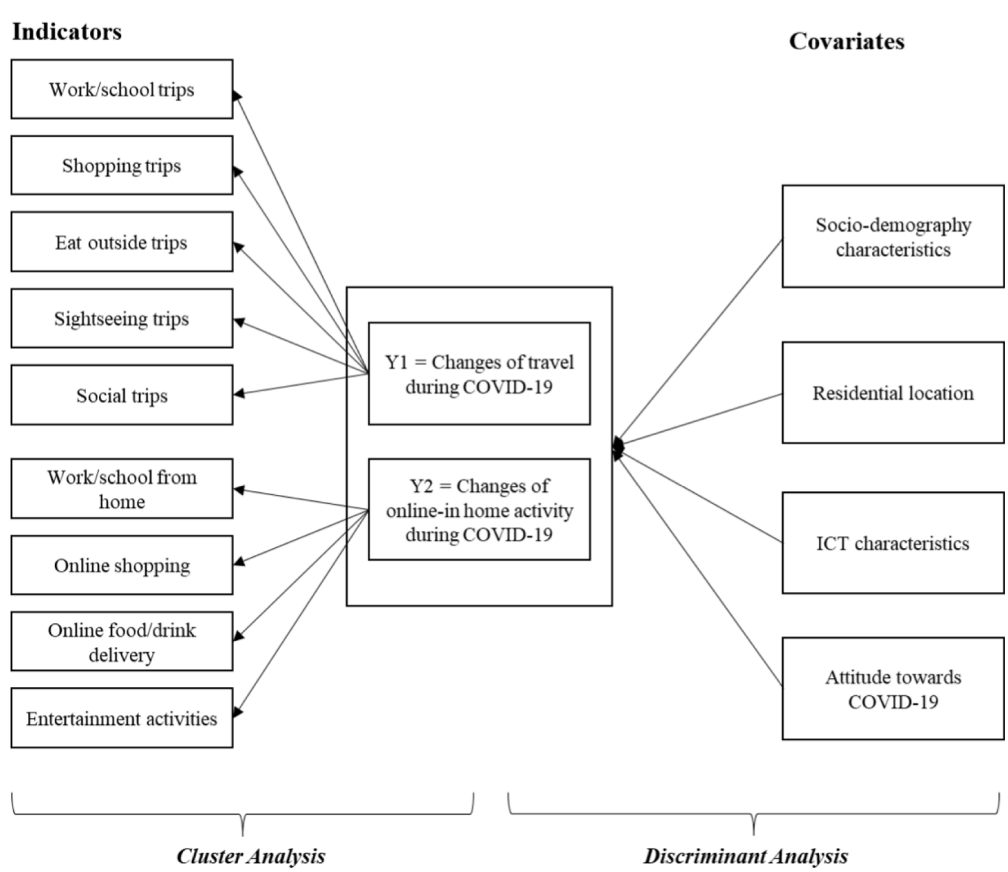

Fig. 1. Analysis framework.

travel behavior changes and online activity adoption, sociodemographic, residential location, ICT experience and usage characteristics, and attitude towards COVID-19 are used as explanatory variables.

The proposed model for the analysis is divided into two parts (Fig. 1). Since there are various types of travel and daily activity, the cluster analysis is used in the first part. Among the various clustering methods available (i.e. hierarchical and two-step clustering), k-means clustering was chosen based on its ability to handle continuous and large data as well as offer various insights on unsupervised clustering algorithm (Hair et al., 2010). The k-means clustering method performed to partition the observations into a number of clusters that account for the distinctiveness of observations (Chiang & Mirkin, 2010). Since (dis)similarity is a factor that influences the cluster group, the Euclidean distance was used for calculating the distance from cases to cluster centers. The analysis was run iteratively from the initial cluster centers until the convergence (Ahmad & Dey, 2007; Hair et al., 2010).

This classification group is then used in the subsequent analysis of daily activity and travel behavior changes during the COVID-19 outbreak using discriminant analysis. The method uses a different approach from the multinomial logistic regression model (Hair et al., 2010; Press & Wilson, 1978). It has been used in various analyses (Joewono et al., 2019, 2020; Lane, 2008; Peter & Anandkumar, 2016; Shi et al., 2018) and is very suitable where the samples are divided into groups of nonmetric dependent variables due to its ability to help understand the differences between groups (Hair et al., 2010). In discriminant analysis, the concept of variate is important. The method will discriminate the best between the cases based on the groups that are defined a priori. This is done when the maximum difference between groups has been defined and it calculates using the following discriminant function (Hair et al., 2010):

$$Z_{jk} = a + W_1X_{1k} + W_2X_{2k} + W_3X_{3k} + \cdots + W_nX_{nk} \tag{1}$$

Where: Z_{jk} is the discriminant Z score of j categories for object k; a is the intercept; W_i is the discriminant weight for independent variable i; and X_{ik} is independent variable i for object k. Therefore, the discriminant score for each object in the analysis is the summation of the values obtained by multiplying each independent variable by the discriminant loadings. The linear combination of explanatory variables above will discriminate between the categories of the dependent variable in a way that it can reveal the significant differences among the categories (Hair et al., 2010; Klecka et al., 1980). Since the linear discriminant function only separates two categories, more than one discriminant function may be present as a unique characteristic of discriminant analysis. As an example, only one discriminant function will be produced for two-category dependent variables, while two discriminant function will be produced for three-category dependent variabels (Hair et al., 2010; Lane, 2008). Further reading on discriminant analysis may refer to Hair et al. (2010).

3.2. Data collection

The locus of this research is Indonesia, a country with a population of more than 270 million in 2020 (Indonesian Bureau of Statistics, 2021) and a gross domestics product (GDP) of more than USD1 Trilion (World Bank, 2022). Similar with other developing countries (i.e., Thailand, Vietnam, Myanmar, etc.), Indonesian cities are facing urban development challenges such as urbanization, motorization, and low public transport quality. Most of Indonesians use motorcycle for their primary means of transportation, while paratransit is a common public transport mode in most Indonesian cities (Adriana et al., 2019; Joewono & Kubota, 2007). Paratransit in Indonesia mostly takes the form of minibuses that operate on fixed routes without fixed schedule. Complementing the paratransit, the government has been developing bus transit in various big and metropolitan cities (i.e., Bandung, Medan, Semarang, Yogyakarta, etc.) in the last few decades, through medium and big buses on fixed routes and specific locations for boarding and off-boarding (Adriana et al., 2019; Prayudyanto et al., 2016). Only Jakarta, which is the nation's capital and economic center, has Bus Rapid Transit (BRT) system and extensive rail network (Mass Rapid Transit (MRT) and commuter rail) serving the Jakarta Metropolitan Areas (JMA).[1] Moreover, similar with other cities worldwide, ride-sourcing has also been on the rise in Indonesia since 2015 and is currently available in more than 150 cities (Irawan et al., 2021; Rizki et al., 2020). Ride-sourcing apps have been expanding to facilitate not only passenger transport but also online shopping and delivery (Irawan & Belgiawan, 2022; Joewono et al., 2020), which are particularly popular during the COVID-19 outbreak.

In this study, we used the same data as the ones studied by Irawan et al. (2022) who distributed online questionnaires in web-based google forms in various Indonesian cities during the first months of the COVID-19 outbreak. This survey captures daily activities and travel behavior changes during and before the outbreak (2022) and the factors affecting them using the structural equation model (SEM). To investigate the influencing factors, Irawan et al. (2022) incorporated the effects of demographics and personal travel characteristics, descriptive norms, ICT use and experience, and attitude towards the COVID-19 disease as well as behavior towards preventing the spread of the disease after careful literature review of previous studies on travel behavior. Irawan et al. (2022) divided the questionnaire into eight sections.

The first section captures daily activity and travel changes during the outbreak through the general question, 'Does the outbreak significantly reduce your travel activities?'. The response is presented as a Likert scale with five options, ranging from 'completely staying at home' to 'making no changes at all'. More specific query on changes to travel behavior is covered in the second part. Here, the respondents are questioned about how often they travel outside of their homes each week for five distinct activities: working or studying, shopping, dining out, touring, and social activities like family visits. The third part of the questionnaire sources data on changes in the frequency of in-home ICT-based activities, including ride hailing, teleworking, and shopping, both during and before the outbreak. In the fourth section, questions cover the type of devices used to access ICT (smartphone/tabs and computer/laptop) and the online services used (e-shopping, ride-hailing, and same-day online food delivery). The survey also collected information on how long a person had been using ICT platforms/services to gauge their experience with ICT. This section also asks the respondents how many ICT devices they own and how much money they spend each month on internet plans. The fifth section probes on the respondents' general attitudes toward the COVID-19 virus through such questions as 'What do you think of the COVID-19 disease?'. A five-point Likert scale, from 'not at all harmful' to 'extremely dangerous', is used to represent the response. The sixth section also asks about the descriptive norms pertaining to the perceived action in halting the spread of COVID-19 with respect to five reference groups (the social environment within the family, neighborhood, city, province, and central government). Data on the respondents' eight different forms of behavior in relation to preventing COVID-19 infections is gathered in the seventh section. Frequent sunbathing, wearing a face mask when leaving the house, engaging in physical activity, maintaining physical distance, using disinfectants, washing hands with soap and sanitizer, getting enough sleep (8 h), and consuming a healthy diet are some of these behaviors. The questionnaire ends with the sociodemographic and geographic details of the respondents, including their gender, age, income, level of education, occupation, and residential location. Out of all the questions, only a few variables that are connected to the analysis' goals are used.

Convenience sampling was used to choose the respondents. The authors distributed the online survey to their contacts with assistance

[1] Further explanation of JMA can be found at Martinez & Masron, 2020.

from their students and other coworkers. Due to out-of-home restrictions, the study used a virtual platform to deliver the online questionnaire (i.e., WhatsApp, Facebook, Instagram, Twitter, and Line). This survey retains bias from the possibility that some community groups may not be able to access the questionnaire due to their limited access to smartphones, the internet, or social media. As such, community groups who are more accustomed to social media and have better access to computers and other ICT resources are more likely to participate in this online survey. As a result, the respondents in this study are those who possess a smartphone and have access to the internet and social media. Since the majority of Indonesians in 2020 owned smartphones (Statista, 2020), this limitation is belived to not be a substantial threat to the representativeness of data collecting and sampling.

As the survey focuses on travel behavior changes before and during the outbreak, it was conducted from the last week of March to April 2020. According to the definition of Irawan et al. (2022), the outbreak period begins when the first case was declared by the government in early March 2020. This definition of the period aligns with Currie (2020), who categorizes the phase of the outbreak into four periods (i.e., before, during outbreak, after lockdown, post the outbreak). Unlike in various developed countries (i.e., New Zealand, France, Italy), in Indonesia there were no full out-of-home activity and travel restrictions imposed by the government during that period. Nevertheless, several activities (such as tourism and leisure) were limited and all educational and certain office facilities were closed. Although the government strongly suggested that the public stay at home and practice social and physical distancing, some people still conducted out-of-home activities for economic reasons and due to various constraints. A total of 1,062 data sets were gathered in the final survey from respondents residing in various Indonesian provinces.

3.3. Respondents' characteristics

Table 1 presents the respondents' characteristics. Most of the respondents have a strong perception of the COVID-19 outbreak, viewing it as very and extremely dangerous (89.9 %). In the same vein, the majority of them (79.3 %) significantly restricts their travel and opts to stay at home fully. This means that most of the respondents conducted work or study at home and reduced out-of-home leisure and maintenance activities. In terms of residential location, most respondents (35.6 %) live in the Special Region of Yogyakarta, followed by Greater Jakarta (21.3 %). Most respondents are male (55.7 %) in their productive age of 26–40 and 18–25 years old, (44.5 % and 32.5 %, respectively). More than 55 % of the respondents are private employees and civil servants, while 32 % are students. In terms of income, the respondents are dominated by those that fall within the range of IDR1-5 million (equal to USD65–322) (40.0 %). Among the respondents there is a high level of motorcycle and car ownership at 2.2 units per person and 1.69 units per person, respectively.

We also looked at the respondents' experiences with online services and ICT platforms. Most of the respondents have vast experience with ICT platforms and online services, owning either smartphones/tabs or laptops/computers. The average smartphone and laptop/computer ownership amounts to 2.4 units per family and 2.2 units per family, respectively. Monthly spending for internet (cellular package, Wi-Fi payment, etc.) averages (31.3 %) at IDR100,000-IDR 200,000 (equal to USD6–12).

Table 2 provides a description of travel behavior, online in-home activities, and a computation of changes. A statistically significant increase in online in-home activities was seen during the COVID-19 epidemic, whereas out-of-home activity saw a steep decline. Based on travel frequency, work/school trips declined from an average of 5.87 trips/week before the outbreak to 2.16 trips/week during the outbreak. During the outbreak, the lowest travel frequency was recorded for social trips, which averages on 1.32 trips/week. Comparing trip frequencies during and before the outbreak shows a significant difference across all

Table 1
Data description (n = 1,062).

Variables		N	Proportion (%)	Mean	SD
Attitudes towards COVID-19 risk and travel behaviour changes					
The general implication of travel to trip and activity change during COVID-19	Not change	12	1.13	3.82	0.67
	Less significant change	39	3.67		
	Quite significant change	168	15.82		
	Very significant change	757	71.28		
	Fully stay at home	86	8.10		
Attitude towards COVID-19 risk	Not dangerous at all	2	0.18	4.26	0.83
	Less dangerous	76	7.16		
	Dangerous	29	2.73		
	Very dangerous	489	46.05		
	Extremely dangerous	466	43.88		
Personal characteristics					
Gender	Female	470	44.26		
	Male	592	55.74		
Age	<18 years old	12	1.13	–	–
	18–25 years old	345	32.49		
	26–40 years old	473	44.54		
	41–60 years old	216	20.34		
	>60 years old	16	1.51		
Occupation	Student	340	32.02	–	–
	Civil Servant/ Police/Army	296	27.87		
	Private Employee	290	27.31		
	Entrepreneur	84	7.91		
	Housewives	40	3.77		
	Retired	12	1.13		
Income‡	<1 million IDR	235	22.12	–	–
	1–2.5 million IDR	163	15.35		
	2.6–5 million IDR	264	24.86		
	5.1–7.5 million IDR	145	13.65		
	7.5–10 million IDR	100	9.42		
	>10 million IDR	155	14.6		
Education	High school or lower	99	9.32	–	–
	Bachelor or professional courses	544	51.22		
	Master or PhD	419	39.45		
Car ownership				1.69	0.84
Motorcycle ownership				2.20	0.85
ICT characteristics					
Number of smartphones/tabs				2.40	0.63
Number of laptop/computer				2.22	0.6
Monthly internet cost‡	<IDR 100.000	231	21.75	–	–
	IDR 100.000–IDR 200.000	333	31.36		
	IDR 200.000–IDR 300.000	227	21.37		
	IDR 300.000–IDR 500.000	192	18.08		
	>IDR 500.000	79	7.44		
Smartphone/tab experience	<6 months	26	2.45	–	–
	6–12 months	28	2.64		
	1–2 years	147	13.84		
	2–4 years	134	12.62		
	4–6 years	114	10.73		

(*continued on next page*)

Table 1 (*continued*)

Variables		N	Proportion (%)	Mean	SD
	>6 years	613	57.72		
Laptop/computer experience	<6 months	65	6.12	–	–
	6–12 months	36	3.39		
	1–2 years	135	12.71		
	2–4 years	129	12.15		
	4–6 years	88	8.29		
	>6 years	609	57.34		
Online shopping experience	<6 months	191	17.98	–	–
	6–12 months	103	9.70		
	1–2 years	220	20.72		
	2–4 years	286	26.93		
	4–6 years	130	12.24		
	>6 years	132	12.43		
Ride-hailing/online transport experience	< 6 months	171	16.10	–	–
	6–12 months	94	8.85		
	1–2 years	278	26.18		
	2–4 years	387	36.44		
	4–6 years	94	8.85		
	>6 years	38	3.58		
Online food/ beverages delivery experience	<6 months	198	18.64	–	–
	6–12 months	105	9.89		
	1–2 years	323	30.41		
	2–4 years	340	32.02		
	4–6 years	67	6.31		
	>6 years	29	2.73		
Resident Location					
Resident location	The Greater Jakarta	226	21.28	–	–
	Special Region of Yogyakarta	378	35.59		
	West Java	92	8.66		
	East Java	59	5.56		
	Center Java	119	11.21		
	Other provinces	188	17.70		

‡ USD1 = IDR15,500 in April 2020; -: not available.

types of out-of-home activities. Furthermore, the frequency of online in-home activities also changed during the outbreak. Work/school from home or telecommuting reached an average of 5.07 times/week compared to only 2.08 times/week before the outbreak. Average entertainment (movie streaming, online/e-game) and online shopping frequencies were also found to increase during the outbreak. Surprisingly, there was a decline in the average online food delivery frequency from 2.8 times/week before the outbreak to 2.59 times/week during the outbreak. This might be related to considerations of safety and hygiene of the services during the first half of the outbreak. It is predicted that the respondents had the tendenc to avoid using food delivery services since no health protocol for food delivery was available at the time of the survey.

4. Model estimation

This section presents the estimation results of the investigation of the factors that influence ICT adoption for online in-home activities as well as travel for out-of-home activities during the COVID-19 outbreak. We divided the analysis into two parts. The first part investigates the changes in online in-home activities. The analysis was started by classifying the respondents based on changes in their online in-home activities using k-mean cluster analysis. The k-means clustering method was used to partition the observations into a number of clusters that account for the distinctiveness of observations (Chiang & Mirkin, 2010). The characteristics of each of the clusters produced from the cluster analysis were analyzed using the discriminant analysis. The second part of the analysis investigates changes to travel behavior to participate in out-of-home activities during the outbreak. The analysis was started by clustering the respondents' travel frequency changes using k-mean cluster analysis. To explore every group's characteristics and determinants, the discriminant analysis was performed on the resulting clusters as the dependent variable. The explanatory variables were personal characteristics (such as gender, income, occupation), trip or online in-home activity frequency changes, attitude towards COVID-19, behavior towards self-protection from COVID-19, ICT characteristics, and experience with online services.

4.1. Adaptation to online In-home activities model

Using k-means clustering, clusters of online in-home activities adoption were formed based on the similarities in four online in-home activity frequency changes. The first cluster, 'work/school-related online activities adapter', represents respondents who are most likely to shift their work-school activities to online. Respondents who showed a significant increase in online in-home activities are grouped into the second cluster of 'high online activities adapter.' In contrast, respondents who had lower adoption of online in-home activities are presented in the last cluster of 'low online activities adapter'. These clusters were built using four dependent variables, namely difference in work/school from home (WFH/SFH) frequency, difference in online shopping frequency, difference in online food/drinks delivery frequency, and difference in entertainment activity frequency. Based on the average silhouette width (AWS) (Chiang & Mirkin, 2010), the optimal number of clusters based on these attributes was two clusters. However,

Table 2
Travel Behavior and Online In-home Activities Frequency Changes.

Type of trips	*Weekly travel frequency during COVID-19*		*Weekly travel frequency before COVID-19*		*Difference between during and before COVID-19*		
	Mean	SD	Mean	SD	Mean	SD	*t*-stat
Work/school	2.16	1.95	5.87	1.50	−3.71	2.27	−49.10**
Shopping	2.49	1.30	3.67	1.67	−1.18	1.65	−18.17**
Eating out	1.58	1.30	3.76	1.95	−2.18	2.00	−30.24**
Sightseeing	1.56	1.11	3.07	1.65	−1.50	1.64	−24.57**
Social	1.32	0.84	2.79	1.45	−1.48	1.48	−28.59**
Online In-home Activity	*Weekly frequency of online in-home activities during COVID-19*		*Weekly frequency of online in-home activities before COVID-19*		*Difference frequency of online in-home activities during and before COVID-19*		
	Mean	SD	Mean	SD	Mean	SD	*t*-stat
Work/School from home	5.07	2.03	2.08	1.75	2.99	2.66	36.34**
Online shopping	2.16	1.57	1.99	1.16	0.18	1.92	2.89**
Online food/drinks delivery	2.59	1.88	2.80	1.72	−0.21	2.51	−2.69**
Entertainment activities	5.00	2.21	3.49	1.99	1.51	2.93	16.56**

**significant at 5%.

this study increased the number of clusters to three to accommodate the behavior groups and exploration of such behaviors. The name of each cluster was determined after evaluating the estimate value in the upper half of Table 3, in which a higher number means higher online activity adoption during the outbreak.

Table 3 shows the composition of the clusters, and 'high online activities adapter' is the biggest cluster among the three at 36.8 % of all samples. The smallest cluster 'low online activities adapter' at 27.3 %, while the 'work/school online activities adapter' cluster makes up 35.9 %. Table 3 shows the Euclidean distances between the final cluster centers. The second and third clusters show the biggest difference, while the first cluster is roughly similar to the second and third clusters. The samples are almost equally distributed across the clusters, indicating that the cluster groups are suitable to be used in further analysis.

Furthermore, the formed groups are used as the dependent variables in the discriminant analysis, as shown in Appendix A. The outcome of the Box's M test demonstrates that the null hypothesis of equal population covariance matrices is rejected. The ratio of cases to independent variables is more than 5:1, with more than 1,000 respondents in the sample and 19 independent variables, thus increasing the model's generalizability and representativeness as suggested by Hair et al. (Hair et al., 2010). If the variance and covariance matrices are equal, a non-significant value of M is anticipated when performing Box's M test; nevertheless, with a large sample, a significant result is not viewed as a concern (Burns & Burns, 2020). The function in this model is highly significant according to Wilks' lambda. According to the classification result, 48.2 % of respondents were correctly classified, which is higher than the threshold number required by the proportional chance criterion (42.3 %). On the basis of statistical significance and practical relevance, it can be determined that the overall model findings are satisfactory.

The structural matrix is only used in this study's interpretation for attributes in a structure matrix with loadings greater than 0.30. The structural matrix, which is interpreted similarly to factor loadings, displays the correlations between each variable and each discriminating function (Burns & Burns, 2020). Function 1 separates the high online activities adapter (0.414) from the low online activities adapter (-0.340). Function 2 separates the group of low online activities adapter (0.215) from the group that only adapts for work/school (-0.212).

According to the structural matrix values, the predictor variables strongly associated with the first discriminant function are individuals' socio-demographic characteristics, residential location, ICT experience, and individuals' attitude to COVID-19. High-income individuals (monthly income of more than IDR10 million or equal to USD645) are more likely to fall under the 'high online activities adapter' group. Respondents residing in Greater Jakarta are most likely to fall under the 'high online activities adapter' group. In comparison, respondents residing outside of Java are associated with lower online activities adoption. Respondents who have more experience using laptops/computers tend to fall within the 'high online activities adapter' group. This is supported by the finding that those who spend more on monthly Internet package are associated with high online in-home activities adoption during the outbreak.

Similarly, the more experience respondents have with online services (i.e., food delivery, online shopping, and ride hailing), the more likely they are to increase the use of online platforms during the outbreak. Furthermore, individuals who think that COVID-19 is not dangerous tend to have lower adoption of online in-home activities.

The second function shows a significant correlation with ICT characteristics and experience. Smartphone ownership does not influence online activities adoption. In fact, smartphone ownership relates more to the 'low online activities adaptation' group than with the 'work- or school-related online adapter' group. Furthermore, individuals who are highly experienced with laptops or computers relate more to the 'work- or school-related online activities adapter'.

4.2. Response to travel model

The k-means clustering was performed for five types of travel frequency changes: a difference in the number of work/school trips; a difference in shopping trips; a difference in dine-in activities; a difference in sightseeing trips; and a difference in social trips. The AWS recommends two clusters. However, the number of clusters was increased to three to extend to accommodate the behavior groups and exploration of such behaviors. Based on the similarities among those travel frequency changes, the three clusters were formed. By evaluating the value in the upper half of Table 4, each of the cluster was named. The lower value in the upper half of the table represents significant changes in decreased travel/out-of-home activities during the outbreak. Therefore, the first cluster, 'high reduced in travel response', represents respondents who significantly reduced their travel frequency. The respondents who had a significant decline in work/school trips are grouped into the second cluster 'work/school-related reduced travel response'. The last cluster, 'low reduced travel response', represents the group of respondents who made no significant reduction of their trip.

The result of the k-means cluster analysis is shown in Table 4. The 'work- or school-related reduced travel response' makes up the biggest proportion at 45.75 %, followed by the 'high reduced travel response' cluster at 35.9 %. In contrast, among the three clusters, the Euclidean distances between the final cluster centres show that the first and third clusters have the biggest difference while the second cluster is roughly equal to the second and third clusters. Identical to the previous cluster analysis, the samples are almost equally distributed across the clusters, indicating that the cluster groups are suitable to be used in further analysis.

The result of the discriminant analysis over three sets of travel responses from the prior cluster analysis is shown in Appendix B. Similar to the earlier model, the outcome of the Box's M test demonstrates that the null hypothesis of equal population covariance matrices is rejected. Since the sample size is sufficient and the ratio of cases to independent variables is greater than 5:1, no issue was found (Burns & Burns, 2020;

Table 3
Cluster Estimation for online in-home activities adoption.

Online activities frequency changes*	Cluster group		
	work/school related online activities adapter	High online activities adapter	Low online activities adapter
Difference of work/school from home (WFH/SFH) frequencies	4.221	4.123	-0.166
Difference of online shopping frequencies	-0.539	1.267	-0.356
Difference of online delivery food/drinks frequencies	−1.834	1.736	-0.685
Difference of entertainment activities frequencies	1.126	3.662	-0.872
Proportion of the sample (%)	35.9 %	36.8 %	27.3 %

Distances between Final Cluster Centers

Cluster group	Work/school related online activities adapter	High online activities adapter	Low online activities adapter
Work/School Related Online Activities Adapter		4.738	4.959
High Online Activities Adapter	4.738		6.888
Low Online Activities Adapter	4.959	6.888	

*number of activities/week during the outbreak (around last week of March 2020) – before the outbreak.

Table 4
Cluster estimation for travel response.

Travel frequency changes*	Cluster group		
	High reduced travel response	Work- or school-related reduced travel response	Low reduced travel response
Difference of work/ school trips	−4.813	−4.862	-0.321
Difference of shopping trips	−2.290	-0.860	-0.472
Difference of dine-in activities	−4.490	−1.471	-0.785
Difference of sightseeing trip	−2.961	−1.056	-0.619
Difference of social trips	−2.632	−1.157	-0.709
Proportion of the sample (%)	29.3 %	45.7 %	25.0 %

Distances between Final Cluster Centers

Cluster Group	High Reduced Travel Response	Work- or School-related Reduced Travel Response	Low Reduced Travel Response
High Reduced Travel Response		4.120	6.812
Work- or School-related Reduced Travel Response	4.120		4.651
Low Reduced Travel Response	6.812	4.651	

*number of trips/week during the outbreak (around last week of March 2020) – before the outbreak.

Hair et al., 2010). The discriminant functions of the model are highly significant based on Wilks' lambda parameter. The group classification from the model (52.4 %) shows higher values than the threshold value of the proportional chance criterion (44.6 %).

The interpretation of the model was based on the group's centroid function, which separates the two choices by observing the most positive value and the most negative value of each function. Two functions were obtained as there were three choices available. The first function separates the 'high reduced travel response' group (0.537) from the 'low reduced travel response group (-0.596)'. The second function seperates the group that only reduces travel for work/school trips (0.337) from the group with lower travel reduction (-0.301).

According to loading as expressed by the structure matrix value, the predictor variables strongly associated with discriminant function 1 are socio-demographic characteristics, experience with online platform/ services, and attitude towards COVID-19 disease. Respondents in productive age (25–40 years old) tend to have lower travel frequency during the outbreak, while students significantly reduced their out-of-home activities during the outbreak. Supporting the previous model, we found that lower attitude towards the risk of COVID-19 is associated with lower out-of-home activities reduction. Moreover, experience with online services tend to lead to higher travel reduction during the outbreak.

The second function shows significant correlation with socio-demographic characteristics and the individual's effort to mitigate the transmission of COVID-19. While high-income respondents tend to reduce work- or school-related travel, respondents with income of less than IDR1 million (equal to USD68) are more likely to be associated with low out-of-home activities reduction. Government officials are more likely to reduce their work trips. Postgraduate respondents are more likely to reduce their out-of-home activities, especially their work trips. Supporting the first function, experience with ICT platforms tend to lead to more travel reduction during the outbreak, especially for working/ school trips.

5. Discussion

The presented result shows changes in daily activities and travel behavior facilitated by ICT platforms and services that are influenced by various factors during the outbreak. The online in-home activity changes model shows the difference in behavior among the 'high online adapter', 'low online adapter', and 'work- or school-related online adapter' groups. High-income individuals have more flexibility for online in-home activity adoption during the outbreak. The reason behind this finding is provided by He and Hu (2015), who underline the high accessibility possessed by high-income individuals to various online platforms and services, such as telecommuting, which is supported by their education and household characteristics. In contrast, low-income workers are faced with a different set of social, financial, and mobility challenges within their daily lives and therefore have less opportunity to adapt to online platforms. Accessibility in ICT adoption was also found to be based on spatial characteristics. While Greater Jakarta residents are most likely to fall within the 'high online activities adapter' group, residents outside of Java tend to fall within the 'low online adapter' group. This finding is not surprising since ICT infrastructure and availability are currently higher in Indonesia's capital city and its surrounding areas. In contrast, ICT penetration outside of Java remains limited (Das et al., 2016). In fact, Greater Jakarta remains the nation's business center that records a higher gross domestic product (GDP) per capita (Roberts et al., 2019). All of these contribute to ICT accessibility and individual's capacity to perform online-related activities, as suggested by Mokhtarian (2009), Murphy (2007) and Schwanen and Kwan (2008). The availability of high-quality and accessible ICT infrastructure as well as greater financial capacity will lead to more opportunities for online activities adoption. Another concern that needs to be addressed is ICT's capability to help deal with the risk of contamination (Lin et al., 2020). As contamination rate and cases rise, megacities worldwide (i.e., Singapore, Jakarta, Hongkong, etc.) have used ICT to contain the COVID-19 outbreak. Digital healthcare, online learning, online shopping, remote working, and other ICT platforms have been used and optimized by the government and private sector to facilitate the peoples' daily needs as well as to help track the infection (Irawan & Belgiawan, 2022; Prasetyanto et al., 2022; Siriwardhana et al., 2021; Yap & Yong, 2021). On the other hand, with a lower number of cases, rural areas that have lower ICT infrastructure quality have to implement different strategies to curb COVID-19 infection. Moreover, disobedience with pandemic measures was a also a challenge that needed to be addressed and a few areas still relied on face-to-face interaction or printed information to distribute COVID-19 information (Callaghan et al., 2021; Ministry of Villages, Development of Disadvantaged Regions and Transmigration, 2021).

The 'high online adapter' group was also found to be correlated with experience with ICT platforms/services (i.e., food delivery, e-shopping, and ride-hailing). Previous studies (Joewono et al., 2020; Mokhtarian, 2004) show that online services retain several risks, such as poor item quality, order loss, or delays. An individual having more experience with these services may indicate that the individual has a positive feeling towards the process (Farag et al., 2003). Such individual has been able to manage the risks and be satisfied with the service, which leads to repeat online orders. Such positive feelings and, consequently, trust, result in higher online in-home activity adoption. Interestingly, work- or school-related in-home online activities adoption was found to be more closely associated with experience using a laptop rather than a smartphone, as work or school obligations are more accessible with a laptop than a smartphone. Therefore, experience with a laptop lends more flexibility in work- or school-related in-home online activities adoption during the outbreak. Moreover, higher spending on monthly internet cost is more closely associated with higher online activity adoption, which is reasonable concidering the bandwith needed and the increased Internet cost that will occur for an increase in online activities. It is also worth noting that online adoption during the outbreak is also affected by individuals' attitude towards the risk of COVID-19. Individuals who do not perceive COVID-19 to be dangerous for their health record less online adoption during the outbreak.

The cluster analysis for travel behavior changes imply that while significant changes in travel behavior occurred during the outbreak, a group of people did not record any change in their travel frequency. The different characteristics among the travel responses groups were analyzed using a discriminant analysis. Socio-demographic characteristics were found to influence travel frequency changes. Students or younger people are more likely to reduce their travel frequency during the outbreak, which might be related to the fact that a number of universities in Indonesia implemented e-learning, therefore reducing the need for travel. Productive-age respondents, government officials, and highly educated persons are more likely to fall within the group of people who did not reduce their travel or only reduced their work/school trips. This might be related to fulfilling the household needs during the outbreak. Several segments of the population still had to do weekly or monthly in-store shopping to fulfill their needs during the outbreak.

Surprisingly, the lower-income group tends to reduce their overall trips while the higher-income group tends to reduce only their work/school trips. While higher-income works have been characterized as more technological/online friendly, low-income works most likely rely on physical activities (Prabandari et al., 2020; World Bank, 2019). A previous study indicates that the impact of COVID-19 was more felt by lower-income individuals who had no alternative to participating in offline activities (Prabandari et al., 2020). Moreover, people still had to fulfill their primary needs such as food and drink during the outbreak. In-store shopping was an option as it was one of the out-of-home activities not restricted by the government. As a result, people in the higher-income group was able to fulfill their primary needs by taking the trip for in-store shopping. On the other hand, people in the lower-income group decreased their overall trips, including shopping trips, which might be a result of the outbreak affecting their income level.

In line with previous findings, more experience with online services mostly leads to a more substantial travel reduction during the outbreak. Experience with ICT platforms was also found to reduce the need for travel, especially work- or school-related travel. When ICT platforms are available to enable the replacement of activities that previously required physical presence, a reduction in travel occurred. The decrease in travel was also found to be influenced by the participants' attitude towards the risk of COVID-19. Lower perception of COVID-19 risks by individuals leads to less travel reduction. When people think COVID-19 is less risky to their health, they may feel safe in participating in out-of-home activities and engage in travel.

6. Conclusion

This study examines the factors that influence ICT activities adoption during the COVID-19 outbreak in Indonesia. While this study aims to shed light on the impact of the COVID-19 outbreak on travel behavior, which has been rarely investigated (at least during this study period), it also contributes to enriching knowledge on ICT and travel behavior. A significant reduction in travel and increase in online activities adoption occurred during the outbreak. Such response was influenced by the participants' experience with ICT, their socio-demographic, and their spatial characteristics. While some people significantly increased their online in-home activities and therefore reduced their travel during the outbreak, a section of the population recorded lower online activity adoption and lower reduction in travel. Income plays a great role in this, whereby high-income individuals tended to adapt more easily to online in-home activities. In contrast, marginalized people tended to show lower adoption of online platforms. Surprisingly, travel reduction occurred more among marginalized people than in higher-income groups, which mostly reduced their work trips and not other trips. Furthermore, spatial characteristics were found to influence online adoption as participants had different levels of accessibility to ICT platforms and online services as well as different economic characteristics (such as GDP per capita). A resident of Greater Jakarta, the nation's business center is more likely to adapt to online activities than a resident outside of Java. This study also underlines the effect of experience with online platforms or services on online in-home activity adoption as well as travel reduction during the outbreak. In addition, attitude towards COVID-19 also influences online adoption and travel behavior changes, whereby individuals that do not perceive COVID-19 as a risk are less likely to reduce their out-of-home activities and adopt online in-home activities.

These study findings derive two main policy recommendations for maximizing the reduction of out-of-home activities during this outbreak as well as for preparing for and managing future pandemics. First, as this study acknowledges the magnificent power of the internet and ICT platform during this outbreak, it also notes that the lack of equality in the accessibility of ICT platforms and online services lessens the effectiveness of online adaptation. Therefore, this study suggests increasing the accessibility, inclusiveness, and quality of the Internet, ICT platform, and online services. Government, telecommunication providers, as well as online service operators (i.e., e-learning, e-shopping, e-working, e-meeting services) must maximize their efforts to attract communities through inclusive accessibility and quality improvement. Moreover, as more people use online services for businesses, government, and social purposes, security must also be ensured. At the end, the Government must focus on improving and expanding ICT infrastructure for various occupations to enable remote work for more people so that infection rate can be curbed within the capacity of the healthcare system amid the uncertainty surrounding the COVID-19 variances. ICT provides a platform for not only mandatory obligations (i.e., work or study) but also leisure and social activities. Considering that mental health issues are predicted to rise during the outbreak (Musselwhite et al., 2020; Van Hoof, 2020), more accessibility to these activities might also give people the opportunity to release their emotions and fulfill their needs to connect with friends, family, and relatives.

Second, as reducing out-of-home activities is key to slowing down the spread of COVID-19, the Government, businesses, and educational institutions must continue to maximize their efforts in restricting mobility and face-to-face activities, especially for daily activities such as work or school. Moreover, the issue of ICT accessibility for low-income and marginalized communities indicated by our research findings must be addressed by the Government. Most middle-class, low-income, and marginalized groups in Indonesia rely on their informal sector jobs where they struggle to fulfill their daily needs (Cahyani & Widaningsih, 2019). It appears that when the mobility restriction was implemented, their income automatically decreased, which significantly reduced their travel. The mobility restriction policy must be accompanied by a fiscal incentive for these groups. In contrast, high-income groups continued to travel for in-store shopping trips to fulfill their needs in the effort to improve their in-home experience. As some travel is essential to ensure their ability to perform in-home activities, policies to ensure the safety and security of both the providers and consumers (i.e., management, protocol and code of conduct for out-of-home activities and travel during the outbreak) are paramount. In addition, our study found that perception on the risk of COVID-19 influences the decision to reduce out-of-home activities. This means that education on the risk of COVID-19 by all stakeholders is key to reducing out-of-home activities during this outbreak.

This study's limitation must be taken into consideration even if it adds to our knowledge of ICT adaptation and its influencing factors during an outbreak. This analysis uses data from the first week of the outbreak and the week prior to the outbreak. Future researches that incorporate more disaggregated daily travel and activity data could enhance the discussion on the research findings considering the variety in individuals' travel and activities. Moreover, we have not elaborated on the effect of individuals' occupation and office role on online adaptation. Since some roles have more flexibility for virtual performance, further research that focuses on the impact of occupational role on online adaptation has the potential to extend the knowledge on online working adoption. This study also focuses more on travel behavior during the COVID-19 pandemic. How such behavior will change post-pandemic remains unclear. The significant daily activity and travel changes that occurred during the outbreak raise various questions on their implication post-outbreak. Therefore, further investigations on this issue could provide valuable recommendation for both existing policies and future policies for the next global pandemic.

CRediT authorship contribution statement

MR: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Software, Writing - Original Draft. **TBJ:** Conceptualization, Investigation, Validation, Writing - Review & Editing, Supervision. **MZI:** Conceptualization, Investigation, Funding Acquisition, Writing - Review & Editing, Validation. **PFB:** Conceptualization, Investigation, Validation, Writing - Review & Editing. **FFB:** Investigation, Writing - Review & Editing. **DP:** Investigation, Writing - Review & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A. . Discriminant analysis of online In-home activities changes

Variables	Dependent Variable Group Means			F	Sig.	Structural Matrix	
	Work/School Related Online Activities Adapter	High Online Activities Adapter	Low Online Activities Adapter			F1	F2
Socio-demography characteristics							
>10,000,000 IDR income/month [D]	0.121	0.195	0.107	6.530	0.002	0.342*	0.047
<18 years old [D]	0.011	0.008	0.014	0.305	0.737	−0.070*	0.048
18–25 years old [D]	0.311	0.356	0.304	1.332	0.264	0.154*	0.033
Civil servant/Police/Army [D]	0.313	0.251	0.266	1.963	0.141	−0.022	0.259*
Private employee [D]	0.250	0.274	0.301	1.080	0.340	−0.109	−0.289*
Motorcycle ownership	2.187	2.133	2.325	4.370	0.013	−0.236	0.285*
Resident location							
Greater Jakarta Resident [D]	0.174	0.279	0.173	8.395	0.000	0.381*	0.151
Central Java Resident [D]	0.129	0.115	0.087	1.510	0.221	0.057	−0.292*
East Java Resident [D]	0.050	0.038	0.087	3.842	0.022	−0.215	0.286*
Outer Java Resident [D]	0.211	0.110	0.221	9.549	0.000	-0.412*	-0.100
Attitudes towards COVID-19							
COVID-19 is common disease [D]	0.118	0.062	0.128	5.215	0.006	−0.306*	−0.049
ICT Characteristics							
Smartphone/Tab ownership	2.334	2.469	2.401	4.400	0.013	0.217	0.338*
Laptop ownership	2.205	2.274	2.149	3.737	0.024	0.252*	-0.118
Internet packet cost per month	2.426	2.785	2.516	9.031	0.000	0.366*	0.322
Experience in Online Platform/ Services							
Experience using laptop/computer	4.853	5.097	4.516	11.609	0.000	0.421*	−0.335
Experience using smartphone/tab	5.011	5.133	4.785	5.399	0.005	0.276*	−0.272
Experience in online shopping	3.342	3.777	3.076	17.658	0.000	0.557*	−0.172
Experience in online transport/ride-hailing	3.118	3.546	2.976	18.710	0.000	0.581*	−0.022
Experience in online food delivery	2.874	3.408	2.813	24.456	0.000	0.659*	0.157

Goodness of Fit Parameters		**Function at Group Centroid**	**Function 1**	**2**
Box's M [F;df1;df2;*p-value*]	[1.709; 380; 2540632.758; 0.000]			
Eigen Values [Canonical Correlation]	0.105; 0.30 [0.308; 0.170]	Work/School Related Online Activities Adapter	−0.166	−0.212
Wilks' Lambda F1 through F2; F2 [p-value]	0.879; 0.971 [0.000; 0.032]	High Online Activities Adapter	0.414	0.048
Percent Correct	48.20 %	Low Online Activities Adapter	−0.340	0.215

[D]: dummy variable, 1 = if yes; 0 = otherwise; *largest absolute correlation between each variable and any discriminant function.

Appendix B. . Discriminant analysis of travel frequency changes

Variables	Dependent Variable Group Mean			F	Sig.	Structural Matrix	
	High Reduce Travel Response	Work/School Related Reduce Travel Response	Low Reduce Travel Response			F1	F2
Socio-demography characteristics							
< IDR. 1.000.000 income/month [D]	0.497	0.283	0.400	19.534	0.000	0.196	−0.563*
> IDR. 10,000,000 income/month [D]	0.123	0.188	0.091	7.513	0.001	0.070	0.374*
25–40 years old [D]	0.461	0.723	0.732	36.021	0.000	−0.530*	0.450
Student [D]	0.510	0.269	0.196	40.621	0.000	0.623*	−0.313
Civil servant/Police/Army [D]	0.171	0.349	0.272	15.386	0.000	−0.215	0.470*
Private employee [D]	0.235	0.267	0.328	3.203	0.041	−0.183*	−0.052
Post graduates [D]	0.284	0.519	0.294	30.733	0.000	−0.042	0.778*
Car ownership	1.577	1.760	1.683	4.521	0.011	−0.119	0.253*
Motorcycle ownership	2.177	2.171	2.298	2.122	0.120	−0.122	−0.123*
Resident location							
Greater Jakarta Resident [D]	0.190	0.236	0.196	1.433	0.239	−0.018	0.167*
Outer Java Resident [D]	0.148	0.180	0.204	1.538	0.215	−0.129*	0.018
Attitudes towards COVID-19							
Common disease [D]	0.045	0.110	0.147	8.810	0.000	−0.304*	0.078
Extremely dangerous [D]	0.442	0.448	0.415	0.397	0.673	0.046	0.063*
ICT Characteristics							
Smartphone/Tab ownership	2.435	2.413	2.343	1.645	0.194	0.127*	0.058
Laptop/computer ownership	2.271	2.238	2.109	5.846	0.003	0.235*	0.123
Internet packet cost per month	2.639	2.595	2.494	1.046	0.352	0.103*	0.036
Experience in Online Platform/ Services							
Experience using laptop/computer	5.016	5.058	4.279	24.488	0.000	0.411	0.422*
Experience using smartphone/tab	5.032	5.147	4.672	10.574	0.000	0.224	0.344*
Experience in online shopping	3.668	3.504	3.015	13.395	0.000	0.363*	0.160
Experience in online transport/ride-hailing	3.426	3.335	2.838	17.339	0.000	0.394*	0.245
Experience in online food delivery	3.303	3.091	2.694	16.775	0.000	0.420*	0.109
Goodness of Fit Parameters			**Function at Group Centroid**			**Function**	
Box's M [F;df1;df2;*p-value*]	[2.084; 462; 1994368.350; 0.000]					**1**	**2**
Eigen Values [Canonical Correlation]	0.174; 0.96 [0.385; 0.296]		High Reduce Travel Response			0.537	−0.268
Wilks' Lambda F1 through F2; F2 [p-value]	0.777; 0.913 [0.000; 0.000]		Work/School Related Reduce Travel Response			−0.018	0.337
Percent Correct	52.40 %		Low Reduce Travel Response			−0.596	−0.301

[D]: dummy variable, 1 = if yes; 0 = otherwise; *largest absolute correlation between each variable and any discriminant function.

References

Adibfar, A., Gulhare, S., Srinivasan, S., Costin, A., 2022. Analysis and modeling of changes in online shopping behavior due to Covid-19 pandemic: a Florida case study. Transp. Policy 126, 162–176. https://doi.org/10.1016/j.tranpol.2022.07.003.

Adriana, M.C., Rizki, M., Joewono, T.B., 2019. Investigating satisfaction and its determinants of BRT-lite services in Indonesian cities. J. East. Asia Soc. Transp. Stud. 13, 1447–1468. https://doi.org/10.11175/easts.13.1447.

Ahmad, A., Dey, L., 2007. A k-mean clustering algorithm for mixed numeric and categorical data. Data Knowl. Eng. 63 (2), 503–527. https://doi.org/10.1016/j.datak.2007.03.016.

Alaimo, L.S., Fiore, M., Galati, A., 2020. How the Covid-19 pandemic is changing online food shopping human behaviour in Italy. Sustainability 12 (22), Article 22. https://doi.org/10.3390/su12229594.

Anderson, R.M., Heesterbeek, H., Klinkenberg, D., Hollingsworth, T.D., 2020. How will country-based mitigation measures influence the course of the COVID-19 epidemic? Lancet 395 (10228), 931–934. https://doi.org/10.1016/S0140-6736(20)30567-5.

Baert, S., Lippens, L., Moens, E., Weytjens, J., Sterkens, P., 2020. *The covid-19 crisis and telework: a research survey on experiences, expectations and hopes* (SSRN Scholarly Paper ID 3596696). Soc. Sci. Res. Netw. https://papers.ssrn.com/abstract=3596696.

Ben-Elia, E., 2019. The Evolving Impacts of ICT on Activities and Travel Behavior. Academic Press.

Burns, R., Burns, R.P. (2020). *Business Research Methods and Statistics Using SPSS*. SAGE. https://uk.sagepub.com/en-gb/eur/business-research-methods-and-statistics-using-spss/book231518.

Cahyani, D., Widaningsih, L., 2019. Identification of the marginalized urban communities characteristics and preferences. *KnE Soc. Sci.* 178–192. https://doi.org/10.18502/kss.v3i21.4967.

Callaghan, T., Lueck, J.A., Trujillo, K.L., Ferdinand, A.O., 2021. Rural and urban differences in COVID-19 prevention behaviors. J. Rural Health 37 (2), 287–295. https://doi.org/10.1111/jrh.12556.

Cao, X. (Jason), 2009. E-Shopping, spatial attributes, and personal travel: a review of empirical studies. Transp. Res. Rec. 2135 (1), 160–169. https://doi.org/10.3141/2135-19.

Chang, Y., Chien, C., Shen, L.-F., 2020. Telecommuting during the coronavirus pandemic: future time orientation as a mediator between proactive coping and perceived work productivity in two cultural samples. Pers. Individ. Differ. 171, 110508.

Chen, H., Guo, J., Wang, C., Luo, F., Yu, X., Zhang, W., Li, J., Zhao, D., Xu, D., Gong, Q., Liao, J., Yang, H., Hou, W., Zhang, Y., 2020. Clinical characteristics and intrauterine vertical transmission potential of COVID-19 infection in nine pregnant women: a retrospective review of medical records. Lancet 395 (10226), 809–815. https://doi.org/10.1016/S0140-6736(20)30360-3.

Chiang, M.-M.-T., Mirkin, B., 2010. Intelligent choice of the number of clusters in K-means clustering: an experimental study with different cluster spreads. J. Classif. 27 (1), 3–40. https://doi.org/10.1007/s00357-010-9049-5.

Chinazzi, M., Davis, J.T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Pastore y Piontti, A., Mu, K., Rossi, L., Sun, K., Viboud, C., Xiong, X., Yu, H., Halloran, M.E., Longini, I.M., Vespignani, A., 2020. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science 368 (6489), 395–400.

Circella, G., Tiedeman, K., Handy, S., Alemi, F., Mokhtarian, P. (2016). *What Affects Millennials' Mobility? Part I: Investigating the Environmental Concerns, Lifestyles, Mobility-Related Attitudes and Adoption of Technology of Young Adults in California*. https://escholarship.org/uc/item/6wm51523.

Clement, J. (2020, June 3). *COVID-19 impact retail e-commerce site traffic 2020*. Statista. https://www.statista.com/statistics/1112595/covid-19-impact-retail-e-commerce-site-traffic-global/.

Clewlow, R.R., Mishra, G.S. (2017). *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. https://escholarship.org/uc/item/82w2z91j.

CNN Indonesia. (2020, April 20). *Corona Bikin Transjakarta, KRL, MRT, dan LRT Sepi Penumpang*. Ekonomi. https://www.cnnindonesia.com/ekonomi/20200420111334-92-495176/corona-bikin-transjakarta-krl-mrt-dan-lrt-sepi-penumpang.

Currie, G. (2020, May 20). *Long term post-pandemic impacts of the COVID-19 crisis on travel*. Presentation in The Smart Public Transport Lab Webinar. http://smartptlab.tudelft.nl/sptl-seminar-by-graham-currie-long-term-post-pandemic-impacts-of-the-covid-19-crisis-on-travel.

Das, K., Gryseels, M., Sudhir, P., Tan, K.T. (2016). *Unlocking Indonesia's digital opportunity*. McKinsey & Company. https://www.mckinsey.com/featured-insights/asia-pacific/unlocking-indonesias-digital-opportunity.

de Haas, M., Faber, R., Hamersma, M., 2020. How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: evidence from longitudinal data in the Netherlands. Transp. Res. Interdiscip. Perspect. 6, 100150 https://doi.org/10.1016/j.trip.2020.100150.

De Vos, J., 2020. The effect of COVID-19 and subsequent social distancing on travel behavior. Transp. Res. Interdiscip. Perspect. 5, 100121 https://doi.org/10.1016/j.trip.2020.100121.

Dharmowijoyo, D.B.E., Susilo, Y.O., Karlström, A., 2016. Day-to-day variability in travellers' activity-travel patterns in the Jakarta metropolitan area. Transportation 43 (4), 601–621. https://doi.org/10.1007/s11116-015-9591-4.

Djalante, R., Lassa, J., Setiamarga, D., Sudjatma, A., Indrawan, M., Haryanto, B., Mahfud, C., Sinapoy, M.S., Djalante, S., Rafliana, I., Gunawan, L.A., Surtiari, G.A.K., Warsilah, H., 2020. Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020. Prog. Disaster Sci. 6, 100091 https://doi.org/10.1016/j.pdisas.2020.100091.

Doong, S.H., Ho, S.-C., 2012. The impact of ICT development on the global digital divide. Electron. Commer. Res. Appl. 11 (5), 518–533. https://doi.org/10.1016/j.elerap.2012.02.002.

Farag, S., Dijst, M., Lanzendorf, M., 2003. Exploring the use of E-Shopping and its impact on personal travel behavior in the Netherlands. Transp. Res. Rec. 1858 (1), 47–54. https://doi.org/10.3141/1858-07.

Gautam, S., Hens, L., 2020. COVID-19: Impact by and on the environment, health and economy. Environ. Dev. Sustain. 22 (6), 4953–4954. https://doi.org/10.1007/s10668-020-00818-7.

Gössling, S., 2018. ICT and transport behavior: a conceptual review. Int. J. Sustain. Transp. 12 (3), 153–164. https://doi.org/10.1080/15568318.2017.1338318.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. (2010). *Multivariate Data Analysis*. Pearson. https://www.pearson.com/uk/educators/higher-education-educators/program/Hair-Multivariate-Data-Analysis-Global-Edition-7th-Edition/PGM916641.html.

He, S.Y., Hu, L., 2015. Telecommuting, income, and out-of-home activities. Travel Behav. Soc. 2 (3), 131–147. https://doi.org/10.1016/j.tbs.2014.12.003.

Hjorthol, R.J., 2002. The relation between daily travel and use of the home computer. Transp. Res. A Policy Pract. 36 (5), 437–452. https://doi.org/10.1016/S0965-8564(01)00012-X.

Indonesia Cabinet Secretariat Office. (2020, March 31). *Presiden Putuskan Pembatasan Sosial Berskala Besar Opsi Atasi Dampak Covid-19- Sekretariat Kabinet Republik Indonesia*. https://setkab.go.id/presiden-putuskan-pembatasan-sosial-berskala-besar-opsi-atasi-dampak-covid-19/.

Indonesian Bureau of Statistics. (2021). *Hasil Sensus Penduduk 2020*. https://www.bps.go.id/pressrelease/2021/01/21/1854/hasil-sensus-penduduk-2020.html.

Irawan, M.Z., Bastarianto, F.F., Dewanti, Sugiarto, S., Rizka Fahmi Amrozi, M., 2021. Measuring the perceived need for motorcycle-based ride-hailing services on trip characteristics among university students in Yogyakarta, Indonesia. Travel Behav. Soc. 24, 303–312. https://doi.org/10.1016/j.tbs.2021.05.005.

Irawan, M.Z., Belgiawan, P.F., 2022. Ride-hailing app use for same-day delivery services of foods and groceries during the implementation of social activity restrictions in Indonesia. Int. J. Transp. Sci. Technol. https://doi.org/10.1016/j.ijtst.2022.03.004.

Irawan, M.Z., Belgiawan, P.F., Tarigan, A.K.M., Wijanarko, F., 2019. To compete or not compete: exploring the relationships between motorcycle-based ride-sourcing, motorcycle taxis, and public transport in the Jakarta metropolitan area. Transportation 47 (5), 2367–2389.

Irawan, M.Z., Rizki, M., Joewono, T.B., Belgiawan, P.F., 2020. Exploring the intention of out-of-home activities participation during new normal conditions in Indonesian cities. Transp. Res. Interdiscip. Perspect. 8, 100237 https://doi.org/10.1016/j.trip.2020.100237.

Irawan, M.Z., Belgiawan, P.F., Joewono, T.B., Bastarianto, F.F., Rizki, M., Ilahi, A., 2022. Exploring activity-travel behavior changes during the beginning of COVID-19 pandemic in Indonesia. Transportation 49 (2), 529–553. https://doi.org/10.1007/s11116-021-10185-5.

Joewono, T.B., Kubota, H., 2007. User satisfaction with paratransit in competition with motorization in indonesia: anticipation of future implications. Transportation 34 (3), 337–354. https://doi.org/10.1007/s11116-007-9119-7.

Joewono, T.B., Tarigan, A.K.M., Rizki, M., 2019. Segmentation, classification, and determinants of in-store shopping activity and travel behaviour in the digitalisation era: the context of a developing country. Sustainability 11 (6), Article 6. https://doi.org/10.3390/su11061591.

Joewono, T.B., Rizki, M., Belgiawan, P.F., Irawan, M.Z., 2020. Why do shoppers keep making online shopping trips? Learning from evidence in Bandung, Indonesia. *Asian Transp. Stud.* 6, 100016 https://doi.org/10.1016/j.eastsj.2020.100016.

Klecka, W.R., Iversen, G.R., Klecka, W.R., 1980. Discriminant Analysis. SAGE.

Knutson, T. (2020, April 8). *Telecommuting Surge Likely To Last Past COVID-19 Crisis, Predicts Brookings Report*. Forbes. https://www.forbes.com/sites/tedknutson/2020/04/08/telecommuting-surge-likely-to-last-past-covid-19-crisis-says-brookings-report/.

Kunst, A. (2020, June 2). *Online shopping due to the COVID-19 pandemic 2020*. Statista. https://www.statista.com/statistics/1107859/shifting-to-online-purchases-because-of-the-covid-19-pandemic-by-category/.

Lane, B.W., 2008. Significant characteristics of the urban rail renaissance in the United States: a discriminant analysis. Transp. Res. A Policy Pract. 42 (2), 279–295. https://doi.org/10.1016/j.tra.2007.10.001.

Lin, C., Braund, W.E., Auerbach, J., Chou, J.-H., Teng, J.-H., Tu, P., Mullen, J., 2020. Policy decisions and use of information technology to fight Coronavirus disease, Taiwan. *Emerg. Infect. Dis.* 26 (7), 1506–1512. https://doi.org/10.3201/eid2607.200574.

Lyttelton, T., Zang, E., Musick, K., 2020. *Gender Differences in Telecommuting and Implications for Inequality at Home and Work* (SSRN Scholarly Paper ID 3645561). Soc. Sci. Res. Netw. https://doi.org/10.2139/ssrn.3645561.

Martinez, R., Masron, I.N., 2020. Jakarta: a city of cities. Cities 106, 102868. https://doi.org/10.1016/j.cities.2020.102868.

Ministry of Villages, Development of Disadvantaged Regions and Transmigration. (2021). *Mendes PDTT: Penanganan Covid-19 Di Desa Lebih Sederhana Dan Efektif*. https://kemendesa.go.id/berita/view/detil/4101/mendes-pdtt-penanganan-covid-19-di-desa-lebih-sederhana-dan-efektif.

Mokhtarian, P.L., 2004. A conceptual analysis of the transportation impacts of B2C e-commerce. Transportation 31 (3), 257–284. https://doi.org/10.1023/B:PORT.0000025428.64128.d3.

Mokhtarian, P., 2009. If telecommunication is such a good substitute for travel, why does congestion continue to get worse? Transp. Lett. 1 (1), 1–17.

Molla, R. (2020, March 11). *Microsoft, Google, and Zoom are trying to keep up with demand for their now free work-from-home software*. Vox. https://www.vox.com/recode/2020/3/11/21173449/microsoft-google-zoom-slack-increased-demand-free-work-from-home-software.

Moovit. (2020, May). *Moovit Public Transit Index*. https://moovitapp.com/insights/en/Moovit_Insights_Public_Transit_Index-countries.

Morikawa, M. (2020, April 10). COVID-19, teleworking, and productivity. *VoxEU.Org*. https://voxeu.org/article/covid-19-teleworking-and-productivity.

Mouratidis, K., 2021. How COVID-19 reshaped quality of life in cities: a synthesis and implications for urban planning. Land Use Policy 111, 105772. https://doi.org/10.1016/j.landusepol.2021.105772.

Mouratidis, K., Papagiannakis, A., 2021. COVID-19, internet, and mobility: the rise of telework, telehealth, e-learning, and e-shopping. Sustain. Cities Soc. 74, 103182 https://doi.org/10.1016/j.scs.2021.103182.

Murphy, A.J., 2007. Grounding the virtual: the material effects of electronic grocery shopping. Geoforum 38 (5), 941–953. https://doi.org/10.1016/j.geoforum.2006.12.012.

Murti, T. (2020). Toll road traffic in Jakarta, West Java, and Banten plummets by 42-60%: Toll road business starting to be hindered by coronavirus. PwC. https://www.pwc.com/id/en/media-centre/infrastructure-news/april-2020/toll-road-traffic-in-jakarta-west-java-and-banten-plummets-by-42-60-percent.html.

Musselwhite, C., Avineri, E., Susilo, Y., 2020. Editorial JTH 16 –The Coronavirus disease COVID-19 and implications for transport and health. J. Transp. Health 16, 100853. https://doi.org/10.1016/j.jth.2020.100853.

Null, S., Smith, H. (2020, March 26). *COVID-19 Could Affect Cities for Years. Here Are 4 Ways They're Coping Now*. https://wri-indonesia.org/en/blog/how-cities-coping-with-covid-19.

Olivia, S., Gibson, J., Nasrudin, R., 2020. Indonesia in the time of Covid-19. Bull. Indones. Econ. Stud. 56 (2), 143–174. https://doi.org/10.1080/00074918.2020.1798581.

Parady, G., Taniguchi, A., Takami, K., 2020. Travel behavior changes during the COVID-19 pandemic in Japan: analyzing the effects of risk perception and social influence on going-out self-restriction. Transp. Res. Interdiscip. Perspect. 7, 100181 https://doi.org/10.1016/j.trip.2020.100181.

Peter, S., Anandkumar, V., 2016. Travel motivation-based typology of tourists who visit a shopping festival: an empirical study on the Dubai shopping festival. J. Vacat. Mark. 22 (2), 142–153. https://doi.org/10.1177/1356766715607587.

Prabandari, A., Itriyati, F., Sutarsa, I.N. (2020). *No work, no money: How self-isolation due to COVID-19 pandemic punishes the poor in Indonesia*. The Conversation. http://theconversation.com/no-work-no-money-how-self-isolation-due-to-covid-19-pandemic-punishes-the-poor-in-indonesia-134141.

Prasetyanto, D., Rizki, M., Sunitiyoso, Y., 2022. Online learning participation intention after COVID-19 pandemic in Indonesia: do students still make trips for online class? Sustainability 14 (4), 1982.

Prayudyanto, M.N., Rizki, M., Ningtyas, D.U. (2016). *Report of Public Transport Service Analysis of Greater Bandung Area* [Part of Sustainable Urban Transport Improvement Project]. Ministry of National Development Planning.

Press, S.J., Wilson, S., 1978. Choosing between logistic regression and discriminant analysis. J. Am. Stat. Assoc. 73 (364), 699–705. https://doi.org/10.1080/01621459.1978.10480080.

Pusparisa, Y. (2020, May 20). *E-Commerce Tumbuh di Tengah Pandemi Covid-19*. https://katadata.co.id/infografik/2020/05/20/e-commerce-tumbuh-di-tengah-pandemi-covid-19.

Rizki, M., Joewono, T.B., Belgiawan, P.F., Irawan, M.Z., 2020. The travel behaviour of ride-sourcing users, and their perception of the usefulness of ride-sourcing based on the users' previous modes of transport: a case study in Bandung City, Indonesia. IATSS Res. 45 (2), 267–276.

Rizki, M., Syahputri, J., Joewono, T.B., Belgiawan, P.F., Irawan, M.Z., 2022. Mobility restriction policy effect to travel-activity participation after the policy lifted: evidence from the COVID-19 outbreak in Indonesia. J. East. Asia Soc. Transp. Stud. 14, 179–198. https://doi.org/10.11175/easts.14.179.

Roberts, M., Gil Sander, F., Tiwari, S. (2019). *Augment, Connect, Target: Realizing Indonesia's Urban Potential* [Text/HTML]. World Bank. https://www.worldbank.org/en/country/indonesia/publication/augment-connect-target-realizing-indonesias-urban-potential.

SanJuan-Reyes, S., Gómez-Oliván, L.M., Islas-Flores, H., 2021. COVID-19 in the environment. Chemosphere 263, 127973. https://doi.org/10.1016/j.chemosphere.2020.127973.

Schwanen, T., Kwan, M.-P., 2008. The Internet, mobile phone and space-time constraints. Geoforum 39 (3), 1362–1377. https://doi.org/10.1016/j.geoforum.2007.11.005.

Shamshiripour, A., Rahimi, E., Shabanpour, R., Mohammadian, A.(Kouros), 2020. How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. Transp. Res. Interdiscip. Perspect. 7, 100216 https://doi.org/10.1016/j.trip.2020.100216.

Shi, T., Liu, X., Li, J., 2018. Market segmentation by travel motivations under a transforming economy: evidence from the Monte Carlo of the orient. Sustainability 10 (10), 3395.

Siriwardhana, Y., Gür, G., Ylianttila, M., Liyanage, M., 2021. The role of 5G for digital healthcare against COVID-19 pandemic: opportunities and challenges. ICT Express 7 (2), 244–252. https://doi.org/10.1016/j.icte.2020.10.002.

Statista. (2020, October 14). *Smartphone Marketin Indonesia—Statistics and Facts*. Statista. https://www.statista.com/topics/5020/smartphones-in-indonesia/.

Tarlton, D. (2020, May 22). *Addressing mental health during COVID-19*. UNDP. https://www.undp.org/content/undp/en/home/blog/2020/addressing-mental-health-during-covid-19.html.

Torales, J., O'Higgins, M., Castaldelli-Maia, J.M., Ventriglio, A., 2020. The outbreak of COVID-19 coronavirus and its impact on global mental health. Int. J. Soc. Psychiatry 66 (4), 317–320.

UITP. (2020, May 27). *Bus operations in India: What has been the impact of COVID-19?* UITP. https://www.uitp.org/news/bus-operations-india-what-has-been-impact-covid-19.

Van Hoof, E. (2020, April 9). *Lockdown is the world's biggest psychological experiment—And we will pay the price*. World Economic Forum. https://www.weforum.org/agenda/2020/04/this-is-the-psychological-side-of-the-covid-19-pandemic-that-were-ignoring/.

Varghese, V., Jana, A., 2019. Interrelationships between ICT, social disadvantage, and activity participation behaviour: a case of Mumbai, India. Transp. Res. A Policy Pract. 125, 248–267. https://doi.org/10.1016/j.tra.2018.06.009.

Wagner, I. (2020). *COVID-19: Traffic reduction in selected cities worldwide*. Statista. https://www.statista.com/statistics/1106135/change-in-daily-traffic-volume-amid-coronavirus-crisis-key-countries/.

Woods, N., Alter, R., Muggah, R., Bishop, J., Roberts, A., Saran, S., Lamy, P., Pedrosa, E., Burrow, S., Byanyima, W., Kousky, C., Koh, C. G., Lee, L., Lo, C., Wong, C., Yap, J. (2020). *Challenges and Opportunities in the Post-COVID-19 World* (ISBN-13: 978-2-940631-02-5). https://www.weforum.org/reports/post-covid-19-challenges-and-opportunities/.

World Bank. (2019). *Aspiring Indonesia: Expanding the Middle Class* [Text/HTML]. World Bank. https://www.worldbank.org/en/country/indonesia/publication/aspiring-indonesia-expanding-the-middle-class.

World Bank. (2022). *GDP (current US$)—Indonesia | Data*. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=ID.

Xu, Z., Shi, L., Wang, Y., Zhang, J., Huang, L., Zhang, C., Liu, S., Zhao, P., Liu, H., Zhu, L., Tai, Y., Bai, C., Gao, T., Song, J., Xia, P., Dong, J., Zhao, J., Wang, F.-S., 2020. Pathological findings of COVID-19 associated with acute respiratory distress syndrome. Lancet Respir. Med. 8 (4), 420–422. https://doi.org/10.1016/S2213-2600(20)30076-X.

Yap, F.F., Yong, M., 2021. Implementation of a real-time, data-driven online Epidemic Calculator for tracking the spread of COVID-19 in Singapore and other countries. Infect. Dis. Model. 6, 1159–1172. https://doi.org/10.1016/j.idm.2021.10.002.

Zhang, J., Hayashi, Y., 2020. *Impacts of COVID-19 on the Transport Sector and Measures as Well as Recommendations of Policies and Future Research: Analyses Based on a World-Wide Expert Survey* (SSRN Scholarly Paper ID 3611806). Soc. Sci. Res. Netw. https://papers.ssrn.com/abstract=3611806.