International Journal on Advanced Science Engineering Information Technology

Vol.11 (2021) No. 6
ISSN: 2088-5334

The Effectiveness of Land Transportation Policy and the Dynamics of Travel Planned Behavior during the COVID-19 Pandemic in Indonesia

Miming Miharja [a,*], Mutharuddin [b], Lisna Rahayu [a] , Muhammad Farda [c]

[a] *Urban and Regional Infrastructure System Research Group, School of Architecture, Planning and Policy Development, Institut Teknologi Bandung, Bandung, 40132, Indonesia*
[b] *Research and Development Agency, Ministry of Transportation of Republic Indonesia, Jakarta Pusat, 10110, Indonesia*
[c] *National Center for Sustainable Transportation Technology, Institut Teknologi Bandung, Bandung, 40132, Indonesia*
*Corresponding author: *mimingm@pusat.itb.ac.id*

***Abstract*— Since 2020, Indonesia has become the country with the highest positive confirmed cases of COVID-19 in Southeast Asia. This situation has urged the Government to issue a series of policies in the transportation sector, namely the Large-Scale Social Restrictions and the new habitual adaptation period or the New Normal Period. This research aims to understand the effectiveness of both land transportation policy implementations during the COVID-19 pandemic and the dynamics of driving factors behind people's decision to travel during those periods. By taking a sample of 941 respondents in two phases of the survey, the data were processed by using Wilcoxon Signed Rank Test and Multiple Linear Regressions to be discussed in the Theory of Planned Behavior perspective. Serial data collection on two phases of travel restriction policies makes it possible to identify the dynamics of people's travel behavior. The results indicate that the policies were generally successful in reducing travel frequency. However, there were significant dynamics of intentional driving factors to travel. The upper-middle-income group has a more stable attitude between the two phases of the land transport restriction policy. On the contrary, the lower-middle-income group shows a more dynamic pattern of travel behavior with a higher intention to travel for work, particularly in the second phase. These results imply that the government's travel restriction policies during the pandemic should consider different strategies to cope with the different factors influencing the travel decision of each group.**

***Keywords*— Transport policy; COVID-19 pandemic; planned behavior.**

Manuscript received 2 Mar. 2021; revised 30 May 2021; accepted 5 Jul. 2021. Date of publication 31 Dec. 2021.

I. INTRODUCTION

The COVID-19 pandemic has significantly impacted the transportation sector worldwide [1]–[3]. Numbers of studies conclude that the transportation sector has great potential as a medium for spreading the virus. Wei *et al.* [4] has proven that areas with highly developed transportation have a higher risk for COVID-19. On the other hand, travel restrictions and lockdowns responding to the COVID-19 outbreak also have profoundly affected the world [5]–[8], although at some points, it also has a positive impact on energy savings and air quality [9], [10]. This pandemic has led to many studies regarding the COVID-19 pandemic's impact on various aspects of human life. There is an indication that most COVID-19 related research publications had a common interest, the pandemic spreading through human mobility [11]. Since no clear end is in sight in this matter, there is a notion that research in this field is important and needed [12]. Tirachini and Cats [13] also propose the same notion, emphasizing that some research needs urgent attention to address this pandemic-related transportation problem. This study is especially necessary for case studies in developing countries. The increasing number of studies regarding the impact of the pandemic is often analyzed from the developed countries point of view that leaves a gap in the understanding of how it affects developing countries [14]. Based on this urgency, this research aims to identify the impact of COVID-19 to the people movement, how effective the land transportation policies limiting people mobility and its relation with the dynamics of travel planned behavior during the COVID-19 pandemic by taking case study in Indonesia.

Indonesia has become a country with the highest positive confirmed cases of COVID-19 in Southeast Asia [15]. Responding to this situation, the Government established a travel restriction policy and implemented health protocols in the transportation sector. Transport restriction policy during the COVID-19 epidemic is classified into two phases. The

first phase is set as the direction of Large-Scale Social Restrictions (LSSR), which took effect between 15 March and 31 May 2020. Several transportation policies in this phase include the Regulation of the Minister of Transportation Nbr. 18/2020 regarding transportation control in order to prevent the spread of COVID-19 and the Regulation of the Minister of Transportation Nbr. 25/2020 regarding transportation control during the Eid homecoming 1441 H. Meanwhile, the second phase is set to issue the direction of the government to conduct the new habitual adaptation period (New Normal Period) which applies from 1 June 2020 up until now. Some of these policies include the Regulation of the Minister of Transportation Nbr. 41/ 2020 regarding Amendments to the Regulation of the Minister of Transportation Nbr. 18/ 2020 and Decree of the Minister of Transportation Nbr. 11 of 2020 concerning Guidelines and Technical Guidelines for Implementing Land Transportation during the adaptation of New Normal Period. In this period, travel restriction is relaxed but with tightening health protocol. Even though there are regulations restricting travel during the pandemic, some vital transportation functions are still running to support critical functions such as food supply, health services, financial services, etc.

Previous study by Irawan *et al.* [16] revealed that the virtual activities during the pandemic could not fully substitute physical activities. People still need to travel amid the pandemic, even though transportation is predicted as having a risk of spreading the disease [17]. Other research by Beck *et al.* [18] also provides solid evidence in Australia that even though governments comes with the regulation to shift the traveling pattern of workers from working from office to working from home, however, the last one is generally more feasible for people who live in urban areas and those with higher incomes and good access to internet facilities. Interestingly, different results appear in the study by Borkowski *et al.* [19], which indicated that the implementation of "Non-Pharmaceutical Interventions (NPI)" in Poland, e.g., recommendations for official housing, schools, and universities closings, tends to be effective in reducing the frequency of community movements during the pandemic. Huang *et al.* [20] highlight that the containment policy has a double-edged sword impact. While the restrictions on people's movement constraining the spread of the pandemic, it also may significantly change the people movement patterns. This academic debate gave rise to the need to identify the extent to which transportation regulations' current level of effectiveness in limiting people's mobility during the pandemic. By assessing the effectiveness of NPI, for example, government policymaking to mitigate the spread of COVID-19 is important for future response plans [21], [22].

This paper's objective is to identify the effectiveness of land transportation policies to prevent the spread of COVID-19 and its relation with the dynamics of people travel planned behavior in Indonesia. This goal is elaborated into two objectives: 1) Evaluating the effectiveness of land transportation policies by testing the significance difference of transportation activities during the COVID-19 pandemic in two phases of transportation policy, and 2) Identifying the intentional driving factors of people to travel during the pandemic, based on their socio-economic characteristics.

II. Materials and Method

A. Impact of COVID-19 on Transportation

The COVID-19 pandemic has had an impact on almost all aspects of human life worldwide. In the transportation sector, such a phenomenon has prompted emerging research to understand better the relation between transport activities and the spread of the pandemic [23]. De Vos [24] expects that there will be less travel, especially those who are using public transport during the pandemic. This then would be followed by the increase of remote activities such as e-learning, online shopping, online meetings, etc. Such prediction eventually materializes as Beck and Hensher [25] concluded based on a travel pattern survey in Australia. The survey result shows that the average trips dropped from 23.9 trips per week to 11 trips per week, with public transport having significantly lower trips than pre-pandemic levels.

In line with the study by Beck and Hensher [25], a study by Abdullah *et al.* [26] also analyzed travel behavior change during the pandemic in a number of countries. In addition to a considerable shift from public transport to private cars, the study shows that most travel during the pandemic is for shopping. Research by Barouki *et al.* [23] found that the social response to the pandemic has stimulated an array of behavioral as well as societal change, such as the increasing use of online transportation service platform of ordering food and other essentials delivery, workplace change toward working from home, and reduce business travel and shifting it to the online form. This implies a fundamental change in the way people live their lives caused by the pandemic. Abu-Rayash and Dincer [9] also summarize the change in trip frequency globally during the pandemic. Indonesia itself does not exempt from the travel disruption caused by the COVID-19 pandemic. Figure 1 and Figure 2 show a significant drop in trips in various locations, including retail, recreational area, offices etc, and the increase of staying duration in a residential area [27].

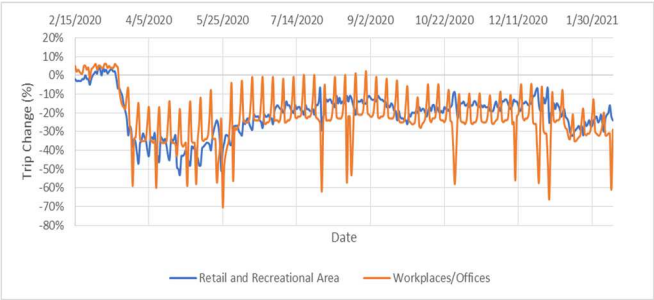

Fig. 1 Trip Change (%) in Retail and Recreational Area in Indonesia [27]

With the focus on perception or psychological aspects, research by Li *et al.* [28], analyzing post-pandemic planned travel behaviors, found that there is a dynamics of Chinese residents' perception between the intra-pandemic (i.e., during the pandemic) perceptions as well as post-pandemic planned behavior. Other research by Li *et al.* [29] concludes that there is a psychological distance caused by COVID-19 that can be classified into the temporal distance, spatial distance, and social distance, in which all of these distances have each perceived risk, for example, health risk, psychological risk, social risk, etc. The results of the data analysis by Barbieri *et*

al. [5] in several countries such as Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa, United States show the dynamic of modal shifts and people's cognitive-behavioral responses to the travel restrictions. Other studies show that threat severity and susceptibility create 'travel fear', which stimulates protection motivation and protective travel behavior [30].

Fig. 2 Duration of Stay Change (%) in Residential Area [27]

B. The Theory of Planned Behavior

To explore the dynamic of travel driving factors during the COVID-19 Pandemic in Indonesia, this research refers to the Theory of Planned Behavior (TPB) developed by Ajzen [31]. TPB itself develops the former Theory of Reasoned Action (TRA) by Fishbein and Ajzen [32]. What distinguishes TPB from TRA is that TPB lies on the idea that although some behaviors can meet the requirements of having volitional control in the form of motivation, the performance of most behaviors is also influenced by some non-motivational factors, i.e., the availability of opportunities and resources such as time, money, skills, and relation. These motivational and non-motivational factors would represent the actual control for an individual to perform a specific behavior.

Ajzen [31], in his TPB theory, postulates that three independent variables determine an intention. The first factor is "attitude" towards behavior that points to the extent to which an individual likes or dislikes performing a specific behavior. Attitude can also be described as our behavior assessment regarding whether the behavior has positive or negative consequences. Secondly, “subjective norm” refers to the perception of external pressure that affects whether or not to do things. Subjective Norm can also be defined as the perception of behavior influenced by the views, behavior, or expectations of people we consider important, such as family, friends, leaders, idols, etc. The third factor is "perceived behavioral control", which refers to the ability, easy or difficult, to do a thing and is assumed to reflect past behavior as well as a form of anticipation of an obstacle. Perceived Behavioral Control can be defined as the perception of obstacles or opportunities in realizing this behavior. This perception arises from the internal side (one’s own abilities, resources, etc.) and the external side (strict regulations, heavy penalties, etc.).

In its development, many researchers in field of transportation have referred to the Theory of Planned Behavior. For Instance, Kaye *et al.* [33] referred to the theory of planned behavior to analyze people’s intention in using automated vehicles. The study shows that attitude and subjective norms are significant drivers for using conditional or fully automated vehicles. Regarding public transport, a study by [34] identifies factors that influence car drivers to use the high-speed railway. The result shows that factors that fall into attitude, subjective norm, and perceived behavioral category positively influence car driver’s preference towards high-speed railway.

Moreover, Bordarie [35] utilize the theory to analyze the young driver to comply with speed limits, with the final aim to reduce road traffic accident and deaths. A study by Neto *et al.* [36] also analyzes the psychological determinants of walking intention in Brazil, and the results show that attitude and perceived behavioral control meaningfully influence walking intention. Li *et al.* [37], in their research also investigated the drivers' behaviors dimension and analyzed driving behavior competition in Beijing, and postulated that in addition to the three factors forming the behavior stated by Ajzen [31], they introduce a fourth factor which influences a person's intentional behavior, called the social environment factor.

C. Methodology

To meet the objectives described above, this study carried out primary data collection. The data collection methods are stated preference and revealed preference through online surveys with respondents taken from stakeholders and related agencies in the transportation sector. The data include information on people's travel behavior during the COVID-19 pandemic as follows: (1) Characteristic of the respondents comprises age, domicile, profession, income, and education level; (2) Behavioral patterns of people’s transportation, which are compared between before and after the implementation of the land transportation restriction policies responding to the COVID-19 pandemic, comprises: the frequency of trip per week before and after the pandemic, the mode used before and after the pandemic, and their motivation to travel during the pandemic. The population in this study is all Indonesian citizens who are in the productive age range, aged 15 - 69 years. Research confidence level and sampling errors are 95% and 5%, respectively. Considering that the sample of transportation users is very large and scattered, the sampling method used in this study is purposive sampling. A total of 941 respondents were successfully involved in the online questionnaire survey.

To evaluate the effectiveness of land transportation policies in these two phases, the analysis performs hypothesis testing based on the frequency of population movements in each phase of the land transportation policy implementation. The frequency is in the form of continuous, ordinal data. According to Chase and Bown [38], the suitable testing for this condition is the Wilcoxon Signed Rank Test. Transportation studies broadly use the Wilcoxon Signed Rank Test in its various topic of interest. However, the test in the field of transportation due to COVID-19 pandemic is still limited. The Wilcoxon signed-rank test is a hypothesis testing method that uses the median approach. The median in statistics is the middle value of a set of objects. If the data poses a normal distribution with the median of a population of Md, then the sample distributes symmetrically to the Md value. In the case of a one-sample group test, the Wilcoxon signed-rank test can be used to identify whether the predicted or hypothesized median value is really located in the middle or not. Whereas, in testing two dependent sample groups, the Wilcoxon signed-rank test facilitates testing the differences of

the median values between the two sample groups. In this research, this method tests the trip frequency median values of the two dependent sample groups, i.e. the sample group of before and after the COVID-19 pandemic occurred.

This method has been very useful in testing the hypothesis of the two dependent sample groups in many studies. In the context of COVID-19 pandemic, for example, Abdullah *et al.* [26] used this method to analyze the impacts of COVID-19 pandemic on travel behavior as well as mode preferences. In other research by [39], this method has also proven to be useful in comparing the spatial features of New York City and Chicago due to the COVID-19 pandemic. Caraka *et al.* [40] also use this method to identify the environmental and economic impact caused by a large-scale restriction in Indonesia. Meanwhile, [41] use this method to identify the impacts of the COVID-19 pandemic on traffic-related air pollution in a Northwester US city. In addition, this method also helps to analyze the impacts of COVID-19 on the global airline industry [42].

This research uses the multiple linear regression method and the theory of planned behavior (TPB) to elaborate the driving factors behind people's decision to travel during the pandemic. The multiple linear regression method is widely used to identify and measure the causal relationship between one dependent variable and several independent variables in various research fields. Previous researches include the use of multiple linear regression to understand such relationships based on the theory of planned behavior in the field of trips generation in Riga, Latvia [43], implementing new pharmaceutical services in Malaysia [44], and discussing statistical guidelines for studies in the field of psychology & health [45]. In this research, multiple linear regressions facilitate identifying the set of driving factors that influence travel frequency during the pandemic. As reviewed in section 2.2, TPB is a development of Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen [32]. The difference of TPB over the previous theory is the inclusion of non-motivational factors called perceived behavioral control as a driving force for an intention. Ajzen postulates that three independent factors determine people's intention in making an action: attitude, subjective norm, and perceived behavioral control [31]. In 2016, Li et al. [37] identified another factor driving people's intention to act, i.e., social environment. By combining the theory of planned behavior from Ajzen [31] and Li *et al.* [37], this research explains how to land transportation policies influence the dynamic of the factors that influence people's intention to travel during the COVID-19 pandemic in Indonesia.

III. Result and Discussion

A. The Difference of People Trip Frequency Before and After Policy Implementation

The trip frequency of people was compared between before the COVID-19 pandemic and during the pandemic (in two stages. The stages are after implementing the LSSR and New Normal Policy) to identify whether there is a difference between the trip frequency between those two periods. If the median value of the difference between the trip frequency before and after the policy implementation is 0. Then the frequency of people's trips tends to be the same before and after the pandemic. Conversely, if the value is not equal to 0, there is a significant difference in people's trips frequency between before and after the pandemic. The purpose of the land transportation policy was to reduce the people mobility in order to minimize the spread of the pandemic. Therefore, the transportation policy is considered to be successful if there is a significant difference between the frequency of people's trip before and after the pandemic. In other words the median value of the difference in the movement must not be equal to 0 (surely, the people's trip frequency after the pandemic must be lower than before).

To prove the allegation, then the following hypothesis was determined:

H0: MdD = 0, there is no significant difference between the frequency of movement before and after implementing the land transport restriction policy.

H1: MdD ≠ 0, there is a significant difference between the frequency of movement before and after implementing the land transport restriction policy.

In the Wilcoxon sign ranks test, the difference in frequency of trips between before and after the policy implementation is transformed into an absolute value so that it has positive value. We then rank the absolute value of this difference from lowest to highest. The ranks will be classified into positive rank and negative rank by returning the positive and negative signs in the initial phase of the process of determining the difference.

TABLE I
RANK OF TRIP FREQUENCY BETWEEN TWO PHASES OF REGULATION IMPLEMENTATION

		Rank of Phase I		
		N	Mean Rank	Sum of Ranks
Frequency_After_LSSR_Policy - Frequency_Before_the COVID-19_Pandemic	Negative Ranks	513[a]	264,70	13579.50
	Positive Ranks	9[b]	79,06	711.50
	Ties	87[c]		
	Total	609		

		Rank of Phase II		
		N	Mean Rank	Sum of Ranks
Frequency_After_New NormalPolicy - Frequency_Before_the COVID-19_Pandemic	Negative Ranks	248[a]	126.02	31253.50
	Positive Ranks	3[b]	124.17	372.50
	Ties	51[c]		
	Total	302		

a. Frequency_After_Regulation < Frequency_Before_Pandemic_COVID19
b. Frequency_After_Reguulation > Frequency_Before_Pandemic_COVID19
c. Frequency_After_Regulation = Frequency_Before_Pandemic_COVID19

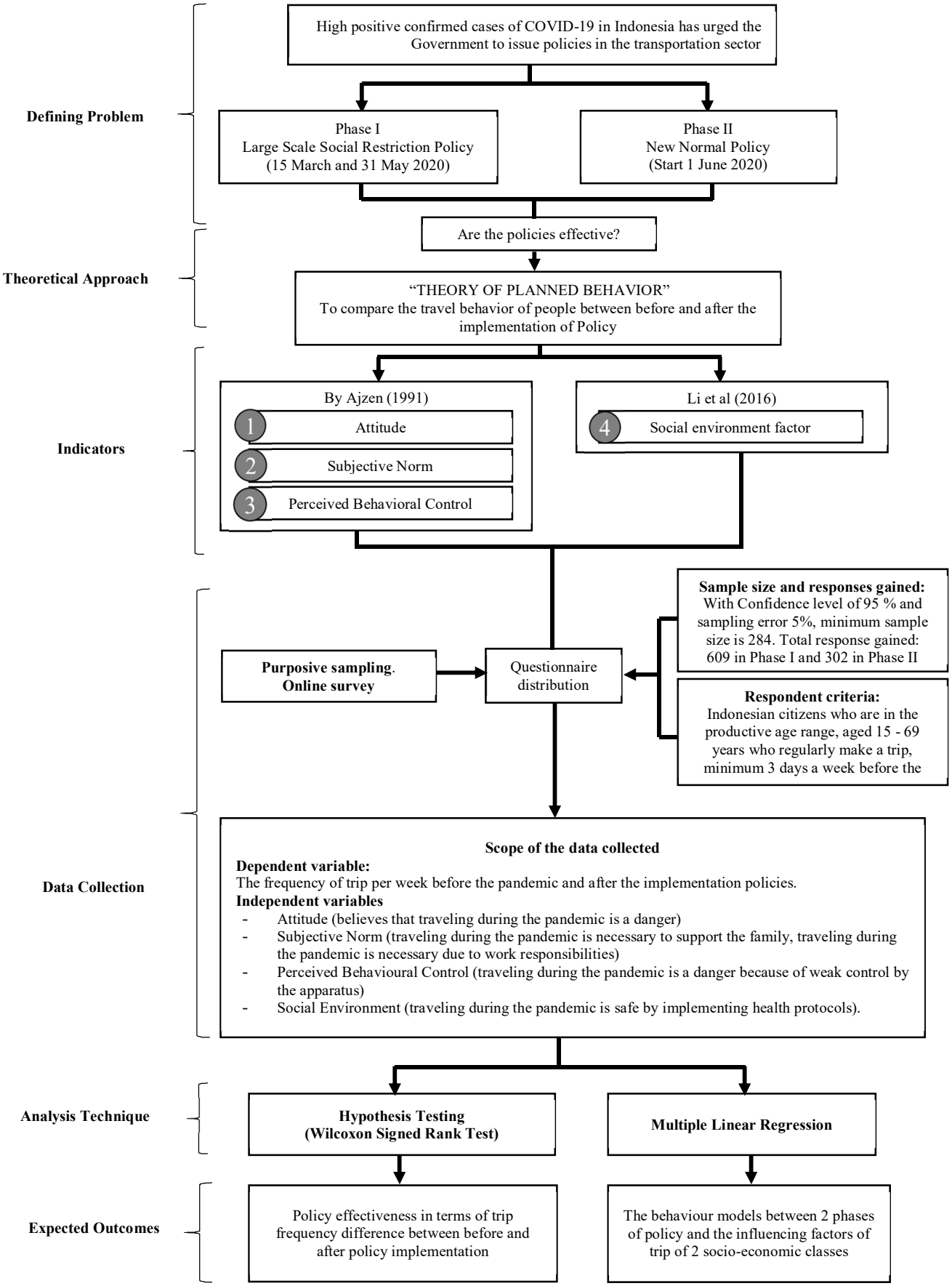

Fig. 3 The Conceptual and Methodological Framework

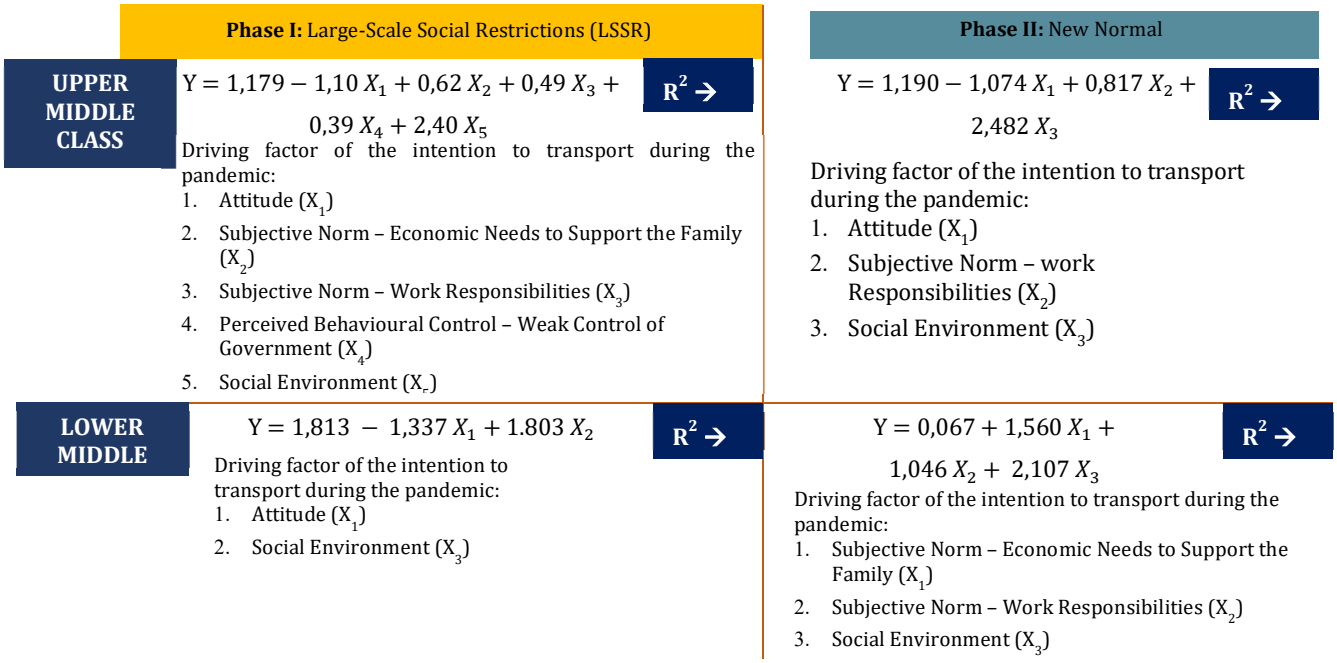

Fig. 4 The Dynamics of Driving Factor behind the Intention of People to Travel during the Pandemic

Table I indicates that the sum of negative ranks for LSSR and New Normal Policy implementation is bigger than the sum of positive ranks. This indicates a significant reduction of the frequency of people's trip between before the pandemic and after the implementation of the policies.

Table II shows that the Z value obtained for the two phases (-19.76 and -13.55) are much smaller than the Z table (0.05/2), which is -1.96 with a p value (Asymp. Sig 2 tailed) less than 0.05. Therefore, the hypothesis decision is to reject H0 and accept H1, which concludes that there is a significant difference between the people's trip frequency before and after implementing transportation policies responding to COVID-19. The results of this hypothesis testing conclude that the travel restriction policies issued by the Ministry of Transportation during the LSSR and new Normal Phase has succeeded in suppressing the frequency of community movement as a form to limit for the spread COVID-19.

TABLE II
WILCOXON SIGN RANK TEST RESULTS FOR TWO PHASES OF REGULATION IMPLEMENTATION

	Frequency_After_NewNormal - Frequency_Before_Pandemi_COVID19: (Phase I)
Z	-19.768[b]
Asymp. Sig. (2-tailed)	.000
	Frequency_After_NewNormal – Frequency_Before_Pandemi_COVID19: (Phase II)
Z	-13.555[b]
Asymp. Sig. (2-tailed)	.000

a. Wilcoxon Signed Ranks Test
b. Based on positive ranks.

B. The Dynamics of People Behavior during the Pandemic.

The dependent variable is the frequency of the people's trips during the Large Scale Social Restriction (LSSR) and New Normal Periods. The independent variable includes 5 variables with 4 related to the driving factors of travel intention in the Theory of Planned Behavior (attitude, subjective norm, and perceived behavioral control) developed by Ajzen [31]. The remaining variable is the social environment referring to the research by Li *et al.* [37]. In this research, the social environment variable illustrates people's perceptions that travel during a pandemic tends to be safe as long as they follow strict health protocols. Independent variables used in the regression model for the travel-planned behavior during the pandemic include:

- Attitude (believes that traveling during the pandemic is a danger)
- Subjective Norm (traveling during the pandemic is necessary to support the family)
- Subjective Norm (traveling during the pandemic is necessary due to work responsibilities)
- Perceived Behavioral Control (traveling during the pandemic is a danger because of weak control by the apparatus)
- Social Environment (traveling during the pandemic is safe by implementing health protocols).

Using multiple linear regression with a stepwise approach, it obtains four optimum models divided into two phases of policy implementation (LSSR and New Normal Policy) and two socio-economic classes of respondent (upper-middle class and lower-middle class) with the result displayed in Figure 3. There have been dynamics changes in the factors driving people's intention to travel during the pandemic. By classifying it into two socio-economic classes of society, the upper-middle class, and the lower-middle class, there are differences in the factors driving the travel intention between the two groups, and so do the inter-phases dynamics. In phase I of the LSSR policy implementation for the upper-middle class, many intentional factors stimulate their travel decision, ranging from attitude, subjective norms (economic needs to support the family, work responsibility), perceived behavioral control, and social environment. Entering phase II of the new

normal policy, attitude, subjective norms (derived by work responsibilities), and social environment stimulate the upper middle class to travel. It appears that the upper-middle class has a relatively stable attitude between the two phases. The upper-middle-class does not have the urgency to travel during the pandemic driven by the economic motive to maintain family's income, probably because of their saving.

Significantly different from the upper-middle class, the lower-middle-income class in the early pandemic tends to only be influenced by the attitude and social environment. In turn, in phase II (New Normal), the attitude factor no longer significantly correlates with the frequency of this class travel. The attitude level of the lower-middle class in facing the COVID-19 pandemic tends not to be as stable as the upper-middle class. In addition, a different trend is also shown in the subjective norm factor, in which in the second phase, the lower-middle-class tends to have a higher urge to fulfill economic needs than the upper-middle class. This study found that the driving factors influencing travel frequencies are different for each socioeconomic group.

These results imply that the government plans to develop travel restriction policies to control people's movement during the pandemic should consider different strategies for each socio-economic class. The interesting thing from the above findings is that in every phase of policy implementation and at every socio-economic segment, the social environment is the dominant factors driving the people's intention to travel during the pandemic. Whenever people perceive that the social environment is safe (e.g., they can travel safely by conducting a strict health protocol), there would be a strong tendency that they would decide to travel. However, this should consider the probable bias since people's perception of conducting health protocol might be different among them. Some people might perceive that using a mask is safe enough to make a trip during the pandemic, while others might perceive with a more tight procedure such as social distancing and the availability of hand sanitizer in public facilities. Due to this potential misleading perception, governments have to ensure that people have the same perception about the standard health protocol.

IV. Conclusion

Transportation is one of the potential means for the COVID-19 virus's spread. The more travel carried out during this pandemic, the easier the virus to be transmitted. Therefore, understanding how to control people's mobility is important to control the spread of the pandemic. Having concluded that the implementation of the two travel restriction policies has been effective in reducing the travel frequency in Indonesia, this research furthermore concludes that for the upper-middle-class, their trip frequency during the LSRR period is mostly influenced by social environment factor which strongly related with the implementation of health protocol. The second most significant factor is the attitude factor, which related to people consideration regarding the danger of traveling during the pandemic. The more danger people perceive, the less they would decide to travel. Three other factors, subjective norm – economic need to support the family, work responsibility as well as perceived behavioral control also play a role though with a lesser degree. In the New Normal Period, only three significant factors affect their decision to travel, i.e., social environment t- perceived danger, and the confidence to travel by implementing health protocols, followed by attitude and subjective norm – work responsibilities, respectively.

However, the influencing factor is different for the lower middle class. During the LSSR period, their travel decision is influenced only by two factors: i.e., attitude and social environment, with the latter having a higher influence on trip frequency. This, however, changes in the New Normal Period where the social environment becomes the most influencing factor, followed by the subjective norm – economic needs to support the family, and subjective norm – work responsibility, consecutively. Based on these results, we conclude that economic concern is becoming a major concern for them. This is most probably because their incomes are severely reduced during the LSRR and in the New Normal Period, they have no choice but to travel to maintain their sufficient income level.

These findings imply several policy implications. The government policies to control people's mobility should consider a different strategy for the different socio-economic class as they have different travel influencing factors. As Indonesia is currently in the New Normal Period, the factors influencing trip frequency during this phase should be considered for policy formulation. For the upper-middle class, the strategy to limit their travel frequency is through effective social campaigns that the current situation is still dangerous to travel. Meanwhile, controlling the low to middle class trip requires economic support to address their needs to reduce the urgency for them to travel.

Acknowledgment

This research is funded by the Research and Development Agency, Indonesian Ministry of Transportation through the partnership with the National Center for Sustainable Transportation Technology, Institut Teknologi Bandung, on managing the transport system in Indonesia during the COVID-19 pandemic.

References

[1] J. Zhang, Y. Hayashi, and L. D. Frank, "COVID-19 and transport: Findings from a world-wide expert survey," *Transp. Policy*, vol. 103, pp. 68–85, Mar. 2021, doi: 10.1016/j.tranpol.2021.01.011.

[2] M. Lenzen *et al.*, "Global socio-economic losses and environmental gains from the Coronavirus pandemic," *PLoS One*, vol. 15, no. 7, p. e0235654, 2020, doi: 10.1371/JOURNAL.PONE.0235654.

[3] P. Lal *et al.*, "The dark cloud with a silver lining: Assessing the impact of the SARS COVID-19 pandemic on the global environment," *Sci. Total Environ.*, vol. 732, Aug. 2020, doi: 10.1016/j.scitotenv.2020.139297.

[4] J. Te Wei *et al.*, "Impacts of transportation and meteorological factors on the transmission of COVID-19," *Int. J. Hyg. Environ. Health*, vol. 230, Sep. 2020, doi: 10.1016/j.ijheh.2020.113610.

[5] D. M. Barbieri *et al.*, "A survey dataset to evaluate the changes in mobility and transportation due to COVID-19 travel restrictions in Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa, United States," *Data Br.*, vol. 33, p. 106459, Dec. 2020, doi: 10.1016/j.dib.2020.106459.

[6] S. Luo and K. P. Tsang, "China and World Output Impact of The Hubei Lockdown During The Coronavirus Outbreak," *Contemp. Econ. Policy*, vol. 38, no. 4, pp. 583–592, Oct. 2020, doi: 10.1111/coep.12482.

[7] D. Ivanov, "Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 136, Apr. 2020, doi: 10.1016/j.tre.2020.101922.

[8] A. Cartenì, L. Di Francesco, and M. Martino, "The role of transport accessibility within the spread of the Coronavirus pandemic in Italy," *Saf. Sci.*, vol. 133, p. 104999, Jan. 2021, doi: 10.1016/j.ssci.2020.104999.

[9] A. Abu-Rayash and I. Dincer, "Analysis of mobility trends during the COVID-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities," *Energy Research and Social Science*, vol. 68. Elsevier Ltd, p. 101693, 01-Oct-2020, doi: 10.1016/j.erss.2020.101693.

[10] X. Tian, C. An, Z. Chen, and Z. Tian, "Assessing the impact of COVID-19 pandemic on urban transportation and air quality in Canada," *Sci. Total Environ.*, vol. 765, Apr. 2021, doi: 10.1016/j.scitotenv.2020.144270.

[11] B. Kutela, N. Novat, and N. Langa, "Exploring geographical distribution of transportation research themes related to COVID-19 using text network approach," *Sustain. Cities Soc.*, vol. 67, p. 102729, Apr. 2021, doi: 10.1016/j.scs.2021.102729.

[12] K. Kim, "Impacts of COVID-19 on transportation: Summary and synthesis of interdisciplinary research," *Transportation Research Interdisciplinary Perspectives*, vol. 9. Elsevier Ltd, 01-Mar-2021, doi: 10.1016/j.trip.2021.100305.

[13] A. Tirachini and O. Cats, "COVID-19 and public transportation: Current assessment, prospects, and research needs," *J. Public Transp.*, vol. 22, no. 1, pp. 1–34, Jan. 2020, doi: 10.5038/2375-0901.22.1.1.

[14] E. Mogaji, "Impact of COVID-19 on transportation in Lagos, Nigeria," *Transp. Res. Interdiscip. Perspect.*, vol. 6, p. 100154, Jul. 2020, doi: 10.1016/j.trip.2020.100154.

[15] R. Djalante *et al.*, "Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020," *Prog. Disaster Sci.*, vol. 6, p. 100091, Apr. 2020, doi: 10.1016/j.pdisas.2020.100091.

[16] M. Z. Irawan, M. Rizki, T. B. Joewono, and P. F. Belgiawan, "Exploring the intention of out-of-home activities participation during new normal conditions in Indonesian cities," *Transp. Res. Interdiscip. Perspect.*, vol. 8, p. 100237, Nov. 2020, doi: 10.1016/j.trip.2020.100237.

[17] Z. Du *et al.*, "Risk for transportation of coronavirus disease from Wuhan to other cities in China," *Emerging Infectious Diseases*, vol. 26, no. 5. Centers for Disease Control and Prevention (CDC), pp. 1049–1052, 01-May-2020, doi: 10.3201/eid2605.200146.

[18] M. J. Beck, D. A. Hensher, and E. Wei, "Slowly coming out of COVID-19 restrictions in Australia: Implications for working from home and commuting trips by car and public transport," *J. Transp. Geogr.*, vol. 88, Oct. 2020, doi: 10.1016/j.jtrangeo.2020.102846.

[19] P. Borkowski, M. Jażdżewska-Gutta, and A. Szmelter-Jarosz, "Lockdowned: Everyday mobility changes in response to COVID-19," *J. Transp. Geogr.*, vol. 90, p. 102906, Jan. 2021, doi: 10.1016/j.jtrangeo.2020.102906.

[20] J. Huang, H. Wang, M. Fan, A. Zhuo, Y. Sun, and Y. Li, "Understanding the Impact of the COVID-19 Pandemic on Transportation-related Behaviors with Human Mobility Data," in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2020, pp. 3443–3450, doi: 10.1145/3394486.3412856.

[21] N. Haug *et al.*, "Ranking the effectiveness of worldwide COVID-19 government interventions," *Nat. Hum. Behav.*, vol. 4, no. 12, pp. 1303–1312, Dec. 2020, doi: 10.1038/s41562-020-01009-0.

[22] J. Zhang, "Transport policymaking that accounts for COVID-19 and future public health threats: A PASS approach," *Transp. Policy*, vol. 99, pp. 405–418, Dec. 2020, doi: 10.1016/j.tranpol.2020.09.009.

[23] R. Barouki *et al.*, "The COVID-19 pandemic and global environmental change: Emerging research needs," *Environment International*, vol. 146. Elsevier Ltd, p. 106272, 01-Jan-2021, doi: 10.1016/j.envint.2020.106272.

[24] J. De Vos, "The effect of COVID-19 and subsequent social distancing on travel behavior," *Transp. Res. Interdiscip. Perspect.*, vol. 5, p. 100121, May 2020, doi: 10.1016/j.trip.2020.100121.

[25] M. J. Beck and D. A. Hensher, "Insights into the impact of COVID-19 on household travel and activities in Australia – The early days under restrictions," *Transp. Policy*, vol. 96, pp. 76–93, Sep. 2020, doi: 10.1016/j.tranpol.2020.07.001.

[26] M. Abdullah, C. Dias, D. Muley, and M. Shahin, "Exploring the impacts of COVID-19 on travel behavior and mode preferences," *Transp. Res. Interdiscip. Perspect.*, vol. 8, p. 100255, Nov. 2020, doi: 10.1016/j.trip.2020.100255.

[27] Google, "COVID-19 Community Mobility Reports: Indonesia," *Google*, 2021. [Online]. Available: https://www.google.com/COVID19/mobility/. [Accessed: 18-Jan-2021].

[28] J. Li, T. H. H. Nguyen, and J. A. Coca-Stefaniak, "Coronavirus impacts on post-pandemic planned travel behaviours," *Ann. Tour. Res.*, 2020, doi: 10.1016/j.annals.2020.102964.

[29] Z. Li, S. Zhang, X. Liu, M. Kozak, and J. Wen, "Seeing the invisible hand: Underlying effects of COVID-19 on tourists' behavioral patterns," *J. Destin. Mark. Manag.*, vol. 18, p. 100502, Dec. 2020, doi: 10.1016/j.jdmm.2020.100502.

[30] D. Zheng, Q. Luo, and B. W. Ritchie, "Afraid to travel after COVID-19? Self-protection, coping and resilience against pandemic 'travel fear,'" *Tour. Manag.*, vol. 83, p. 104261, Apr. 2021, doi: 10.1016/j.tourman.2020.104261.

[31] I. Ajzen, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, Dec. 1991, doi: 10.1016/0749-5978(91)90020-T.

[32] M. Fishbein and I. Ajzen, *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research Reading*. MA: Addison-Wesley, 1975.

[33] S. A. Kaye, I. Lewis, L. Buckley, and A. Rakotonirainy, "Assessing the feasibility of the theory of planned behaviour in predicting drivers' intentions to operate conditional and full automated vehicles," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 74, pp. 173–183, Oct. 2020, doi: 10.1016/j.trf.2020.08.015.

[34] M. N. Borhan, A. N. H. Ibrahim, and M. A. A. Miskeen, "Extending the theory of planned behaviour to predict the intention to take the new high-speed rail for intercity travel in Libya: Assessment of the influence of novelty seeking, trust and external influence," *Transp. Res. Part A Policy Pract.*, vol. 130, pp. 373–384, Dec. 2019, doi: 10.1016/j.tra.2019.09.058.

[35] J. Bordarie, "Predicting intentions to comply with speed limits using a 'decision tree' applied to an extended version of the theory of planned behaviour," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 63, pp. 174–185, May 2019, doi: 10.1016/j.trf.2019.04.005.

[36] I. L. Neto *et al.*, "Psychological determinants of walking in a Brazilian sample: An application of the Theory of Planned Behavior," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 73, pp. 391–398, Aug. 2020, doi: 10.1016/j.trf.2020.07.002.

[37] P. Li, J. Shi, X. Liu, and H. Wang, "The Theory of Planned Behavior and Competitive Driving in China," in *Procedia Engineering*, 2016, vol. 137, pp. 362–371, doi: 10.1016/j.proeng.2016.01.270.

[38] W. Chase and F. Bown, *General Statistics*, 4th ed. John Wiley & Sons, Ltd, 1999.

[39] A. R. Maroko, D. Nash, and B. T. Pavilonis, "COVID-19 and Inequity: a Comparative Spatial Analysis of New York City and Chicago Hot Spots," *J. Urban Heal.*, vol. 97, no. 4, pp. 461–470, Aug. 2020, doi: 10.1007/s11524-020-00468-0.

[40] R. E. Caraka *et al.*, "Impact of COVID-19 large scale restriction on environment and economy in Indonesia," *Glob. J. Environ. Sci. Manag.*, vol. 6, no. Special Issue, pp. 65–84, Aug. 2020, doi: 10.22034/GJESM.2019.06.SI.07.

[41] J. Xiang *et al.*, "Impacts of the COVID-19 responses on traffic-related air pollution in a Northwestern US city," *Sci. Total Environ.*, vol. 747, p. 141325, Dec. 2020, doi: 10.1016/j.scitotenv.2020.141325.

[42] S. Maneenop and S. Kotcharin, "The impacts of COVID-19 on the global airline industry: An event study approach," *J. Air Transp. Manag.*, vol. 89, p. 101920, Oct. 2020, doi: 10.1016/j.jairtraman.2020.101920.

[43] N. Zenina and A. Borisov, "Regression Analysis for Transport Trip Generation Evaluation," *Inf. Technol. Manag. Sci.*, vol. 16, no. 1, Jan. 2014, doi: 10.2478/itms-2013-0014.

[44] C. L. H. Tan, V. B. Y. Gan, F. Saleem, and M. A. A. Hassali, "Building intentions with the theory of planned behaviour: The mediating role of knowledge and expectations in implementing new pharmaceutical services in Malaysia," *Pharm. Pract. (Granada).*, vol. 14, no. 4, Oct. 2016, doi: 10.18549/PharmPract.2016.04.850.

[45] M. Hankins, D. French, and R. Horne, "Statistical guidelines for studies of the theory of reasoned action and the theory of planned behaviour," *Psychology and Health*, vol. 15, no. 2. Routledge, pp. 151–161, 2000, doi: 10.1080/08870440008400297.