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Insights into the long-term effects of COVID-19 responses on transportation facilities

Boniphace Kutela\textsuperscript{a,}\textsuperscript{*}, Tabitha Combs\textsuperscript{b}, Rafael John Mwek’iga\textsuperscript{c}, Neema Langa\textsuperscript{d}

\textsuperscript{a} Roadway Safety Program, Texas A&M Transportation Institute, 1111 RELLIS Parkway, Bryan, TX 77807, United States
\textsuperscript{b} Dept. of City & Regional Planning, University of North Carolina at Chapel Hill, United States
\textsuperscript{c} Ibra Contractors Limited, P.O.Box 20881, Dar es Salaam, Tanzania
\textsuperscript{d} Department of Sociology/African American Studies, University of Houston, 3553 Cullen Boulevard, United States

A R T I C L E  I N F O

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A B S T R A C T

The impacts of COVID-19 on transportation sector have received a substantial research attention, however, less is known about localized COVID-19 responses that provided safe space for mobility and other daily activities. We applied logistic regression and text mining approaches on the Shifting Streets COVID-19 Mobility Dataset to explore the long-term outcomes of the localized responses. We explored the purpose, affected space, function, and implementation approach. We found that responses instituted for economic recovery and public health are less likely to be long-term, while responses meant to improve safety or bicycle/pedestrian mobility are more likely to be long-term. Further, operational or regulatory responses are less likely to be long-term. Additionally, responses affecting curb space are more likely to be long-term than those affecting other right-of-way areas. Text-mining of responses’ narratives revealed key patterns for both short-term and long-term outcomes. Study findings showcase the possible design and operations changes during post-COVID-19 era.

1. Background

To date, over 320 million cases of COVID-19 have been reported worldwide since the first case reported in Wuhan, China on December 8, 2019 (BBC, 2022; Ritchie et al., 2022; WHO, 2020). The United States, India, Brazil, the United Kingdom, and France are the leading countries in cumulative total cases and total deaths (BBC, 2022; Ritchie et al., 2022). Transportation is among the sectors most heavily affected by COVID-19. The impact of COVID-19 on transportation comes in different ways, including large-scale mobility restrictions (e.g., internal travel restrictions, cross-border travel restrictions, national and regional lockdowns) and localized responses.

There is a rapidly growing body of literature examining the impacts of these responses on global and local travel demand (Van Wee and Witlox, 2021; Suau-Sanchez et al., 2020), active mobility patterns (Hunter et al., 2021), individual decision-making (such as residential relocation and vehicle ownership; Habib and Anik, 2021), energy use, and air quality (Abu-Rayash and Dincer, 2020). Research is also emerging on the wide-ranging impacts of street-level interventions meant to lower local transmission of COVID-19 and provide safe, physically distanced space to walk, bike, and conduct business outdoors by altering the allocation, use, and regulation of space in the roadway right-of-way (Firth et al., 2021; Fischer and Winters, 2021; Mayo, 2021; Vecchio et al., 2021; Wright and Reardon, 2021). Others have explored factors enabling street-level responses (e.g., Combs and Pardo, 2021), cities’ motivations and

\* Corresponding author.
E-mail addresses: b-kutela@tti.tamu.edu (B. Kutela), tab@unc.edu (T. Combs), nmлагaa@central.uh.edu (N. Langa).

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objectives for street-level responses (e.g., Fischer and Winters, 2021), the distribution of benefits of the responses (e.g., Wright and Reardon, 2021), and overall public perceptions about the responses (e.g., Shirgaokar et al., 2021).

Limited literature is available on the long-term impact of COVID-19 in transportation (Advani et al., 2021; Habib and Anik, 2021; Marra et al., 2022; Truong, 2021; Zhang and Zhang, 2021). A study by Truong (2021) examined the medium and long-term impact of COVID-19 on air transportation using neural network and Monte Carlo simulation. The study found weekly economic index and travel distance as the key to air travel in the post-pandemic period, concluding that it would take several years before the air travel recovers to pre-pandemic levels. Another study by Marra et al. (2022) focused on changes in public transport use in Switzerland. They reported that the key difference was the perception of costs of transfers and of travel time in train. A study by Habib and Anik (2021) in Nova Scotia, Canada investigated the long-term impact of COVID-19 on transport and land use. The study predicted an increase of vehicle ownership for suburban areas by up to 74% by 2030. Other studies by Advani et al. (2021) and Zhang and Zhang (2021) focused on non-motorists and decarbonization of the transport sector, respectively.

Little is known yet about the long-term outcomes of the street-level responses. For instance, it is unknown whether and which responses will outlast the pandemic, or the factors associated with their longevity and durability. Given long-standing calls around the world for massive overhauling of the transportation sector in order to address on-going crises of climate change and deepening inequality, understanding whether and how the pandemic might lead to enduring changes to how roadway space is allocated, used, and regulated is critical (Combs and Pardo, 2021).

Using the “Shifting Streets COVID-19 Mobility Dataset,” we seek to identify factors that predict the likelihood of street-level responses outlasting the pandemic. The Shifting Streets dataset documents, describes, and catalogs these street-level responses based on information gathered from 534 cities in over fifty countries around the world (Combs and Pardo, 2021), providing a unique opportunity to assess the short-term and long-term impacts of COVID-19 on the transportation industry at the local level. We use a mixed methods approach to this research, combining logistic regression of key variables in the Shifting Streets dataset with text mining of the dataset’s narrative description of each response.

2. Methods

2.1. Data

The Shifting Streets COVID19 Mobility Dataset contains over 1400 unique responses to changing demands on public space in 550 cities in 60 countries (as of January 2022). Most of the observations were collected from North America (56%), Europe & Central Asia (30%), Latin America and Caribbean (5.6%), East Asia & Pacific (5.2%), while Sub-Saharan Africa had the least proportion of observations (0.8%). Data have been collected and curated continuously since March 11, 2020, and includes information about local, state/regional, and national-level responses to changing demands for mobility and on public space that were initiated between March and September 2020. The dataset is open source and available for public download at pedbikeinfo.org/shiftingstreets. This paper uses data downloaded from the September 2021 version of the data.

The Shifting Streets data document and describe the wide range of mobility-related actions cities around the world took to in response to the pandemic. The dataset was created to highlight innovation and flexibility in the transport sector, uncover lessons cities learned from their pandemic responses, and support and inspire research into how the transport sector is evolving based on its experience during the COVID19 pandemic (Combs and Pardo, 2021). Further details about the data collection methods and intended uses are available on the Shifting Street website (http://pedbikeinfo.org/shiftingstreets) and in Combs and Pardo (2021).

The variables in the Shifting Streets dataset of interest for this study include:

i. Description: a brief narrative describing the response, written by the individual reporting on the response or gleaned from the news or press releases about the response.

ii. Longevity: the anticipated duration of the response, including one-time implementation (e.g., the response is in place for a single weekend or special event), temporary (the response is intended to be removed at some point in the future), indefinite (no clearly defined whether long or short term plans have been established for the response), permanent, and temp-to-perm (the response was originally intended to be temporary but has or will be converted to a permanent installation). We collapsed the longevity variable in our analyses “long-term” (including permanent and temp-to-perm), “short term” (one-time implementation or temporary), and indefinite, and unknown.

iii. Time: the days and/or times of day the response is in effect, which we collapse in this analysis to a binary variable indicating whether or not the response is in place 24/7

iv. Space: the portion of the roadway directly affected by the response, including the entire roadway, entire travel lane(s), parking lanes, curb space, sidewalks and other off-street space, and intersections

v. Purpose: the main purpose behind the response, which includes economic recovery, equity, moving goods, moving people, public engagement, safety, and public health

vi. Function: the manner in which the response is intended to affect users, including creating street space for active mobility, other active mobility supports, creating street space for commerce, and miscellaneous other actions. Given that the focus of the analysis was on changes to the physical design, use, or regulation of street space, we used the ‘function’ variable to filter out responses that dealt with changes to transit service, funding streams, access to bicycles, and temporary mobility restrictions.

vii. Category: implementation approach or general nature of how the response is implemented, including operational, physical, regulatory, and financial.
2.2. Analytical approach

To understand the long-term impact of COVID-19-related street changes, this study employed two approaches: text mining and logistic regression. Text mining was used to explore the key patterns of short-term and long-term COVID-19 mobility responses. We used logistic regression to evaluate the likelihood of responses outlasting the pandemic, i.e., being transformed into permanent installations. The next section presents the details of each approach.

2.2.1. Text network

Text mining, while well-established in social science research, is a relatively new method for data analysis in transportation research. Among text mining methodologies, the text network is a relatively compact approach that enables visual representation of the language structures in text-based narratives. Text networks use nodes and links (Fig. 1) to present the topology of the narratives.

In the network, nodes represent keywords, while links represent the co-occurrence of the keywords (Kim and Jang, 2018; Boniphace et al., 2021; Paranyushkin, 2011). The size of the node represents the frequency of the keyword in the network, while the thickness of the link represents the frequency of co-occurrence of the keywords. The closer the nodes in the network, the closer the keywords are in the sentence. Further, keywords of similar themes form a community of keywords.

To create a text network, the text data/narratives need to be normalized, transformed from unstructured to structured and mapped on the network (Kim and Jang, 2018; Kutela et al., 2021; Paranyushkin, 2011; Yoon and Park, 2004). All the texts are converted to lower case and stop words (connecting words) are removed during normalization. The transformation from unstructured to structured involves the creation of a matrix of keywords. Mapping of keywords involves assigning each keyword to the network. In this step, the algorithm maps the keyword from the matrix to the network as a node. If the pair of the keywords appears for the first time, the frequency associated with that node and the frequency of the edge between the two keywords are mapped. If the next pair contains one of the keywords from the previous pair, an additional frequency of the existing keyword is mapped, followed by the new keyword and the link (Boniphace Kutela, Das, et al., 2021; Boniphace Kutela and Teng, 2021; Paranyushkin, 2011).

Upon completion of the network, the interpretation depends on various metrics, including the keyword frequency, document frequency, co-occurrence frequency, collocation frequency, and betweenness centrality (Kim and Jang, 2018; Paranyushkin, 2011). In this study, the topology of the network, keyword frequency, document frequency, co-occurred keywords, and collocated keywords (Blaheta and Johnson 2011), are used for interpretation. Keyword frequency represents the number of times the keyword appears in the entire dataset. On the other hand, document frequency represents the number of times the entire narrative/description contains a keyword of interest in the dataset. Collocated and co-occurred keywords differ by the location of the keywords. They both represent the keywords appearing in the same sentence, but the collocated keywords are next to each. For instance, in the statement “Arlington has implemented automatic pedestrian signal phases at all signalized intersections in its densely populated corridors”, the keywords pedestrian and signal are collocated while pedestrian and phases are co-occurred keywords. Thus, collocated keywords provide more insights than co-occurred keywords. Furthermore, in addition to the frequency, the strength of the association and statistical significance of collocated keywords can be measured using lambda and z-value. The large magnitude of lambda the strong is the association, and the z-value greater than 1.96 indicates a statistical significance at a 95% confidence interval (Blaheta and Johnson, 2011; Boniphace Kutela, Langa, et al., 2021). The analysis was performed in R 4.1.1-environment (R Core Team, 2021), with the help of quanteda and igraph packages (Benoit et al., 2018; Csárdi, 2020). For the simplicity of the network, only the top 50 keywords were considered.
2.2.2. Logistic regression

The likelihood of the response being long-term can be represented as the binary outcome, i.e., either yes (long-term) or no (short-term). With the two possible outcomes, binary regression models such as logit and probit are the best candidate for this type of data. Previous studies suggest that logit models are preferred due to the ease of interpretation of the parameters in terms of odds ratios (Boniphace Kutela and Teng, 2020; Woodridge, 2012).

Logistic regression can be expressed using the Bernoulli probability function. Given that the dependent variable \( Y_i \) has two possible outcomes (1 for long-term response, or 0 for short-term response), the \( \theta_i \), which is the probability that the event is long-term, can be expressed as an inverse logistic function of a vector of explanatory variables \( X_i \) as:

\[
\theta_i = \frac{1}{1 + e^{-\beta X_i}}
\]  

(1)

After linearizing Eq. (1), the \( \theta_i \) can be written as

\[
\text{logit}(\theta_i) = \ln \left( \frac{\theta_i}{1 - \theta_i} \right) = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \ldots + \hat{\beta}_n X_n
\]  

(2)

The \( \hat{\beta}_i \)'s represent coefficients of variable that are to be estimated, while \( \hat{\beta}_0 \) is a constant term.

Further, to apply logistic regression, several assumptions were checked. These include the independence of the observations, multicollinearity among independent variables, linearity of independent variables, and sample size.

3. Results and discussion

This section presents the results and discussion of the study. It is divided into three sections: descriptive statistics, text networks results and discussion, and logistic regression results and discussions. The text network part of the results explores the content of both short-term and long-term responses using the narrative description of the response. The logistic regression presents the likelihood of the response becoming a long-term implementation. The implications of the results on roadway operations are also presented.

3.1. Descriptive statistics

The September 2021 version of the data used in this analysis contains 1,407 observations; however, a number of observations had missing or unverified data on some of our variables of interest. After removing these records, a total of 487 observations with complete, verified data on our variables of interest were available for analysis. Table 1 presents the descriptive statistics of the variables used in our analyses. It can be observed that the majority (75%) of the responses recorded in the final dataset were short-term (“temporary” or “one-time implementation”), while 11.5% were listed as long-term (“permanent” or “temp-to-perm”). Twelve and a half percent were described as “indefinite,” meaning that at the time of recording, no decisions had been announced as to their ultimate resolution (i.e., whether they would become short-term or long-term). Thus, while developing the statistical model, the “indefinite” observations will be assessed on either side. That is, one model will categorize the indefinite responses as a potential long-term outcome, and another will categorize them as short-term outcomes. The intention of inclusion of the indefinite observation was to perform a sensitivity

| Variable | Variable category | Count | Percent |
|----------|-------------------|-------|---------|
| Longevity| Permanent/ Temp-to-perm | 56 | 11.5% |
|          | Indefinite        | 74 | 15.2% |
|          | One-time/temporary | 366 | 75.3% |
| Time (all day everyday) | All day, everyday | 399 | 82.1% |
|          | Not all day, everyday | 87 | 17.9% |
| Space affected | Entire roadway | 234 | 48.1% |
|          | Intersection      | 24 | 4.9% |
|          | Curb              | 38 | 7.8% |
|          | Travel lanes      | 116 | 23.9% |
|          | Parking lane      | 42 | 8.6% |
|          | Parks/plazas/sidewalk | 32 | 6.6% |
| Purpose  | Moving people     | 217 | 44.7% |
|          | Economic recovery | 109 | 22.4% |
|          | Public health     | 136 | 28.0% |
|          | Safety            | 24 | 4.9% |
| Function | Space for bike/ped | 294 | 60.5% |
|          | Space for commerce | 96 | 19.8% |
|          | Other bike/ped    | 38 | 7.8% |
|          | Others            | 58 | 11.9% |
| Category | Physical          | 366 | 75.3% |
|          | Operational       | 83 | 17.1% |
|          | Regulatory        | 37 | 7.6% |
analysis, allowing us to examine whether the extent to which the results are dependent on indefinite actions being removed or converted to permanent interventions. The remaining distributions of observations is self-explanatory, as presented in Table 1.

3.2. Text network results and discussion

This section presents results and discussion of the text network analysis. It covers three aspects—short-term response, long-term response, and indefinite response text networks—and associated metrics. The networks were developed using the description variable and based on the longevity variable.

Fig. 2 and Table 2 present the text network for long-term responses and the associated metrics, respectively. The network is centered on the keywords streets, bicycle, lane, city, and space. Street appears most frequently in the narrative descriptions for permanent/long-term responses.

Table 2 also presents the co-occurrence and collocation statistics. It can be observed that all the collocated keywords presented in the table are statistically significant at a 95% confidence interval (z-value > 1.96). Further, the statistical association of the keywords is strongest for physical distancing collocated keywords with lambda value of 8.37. Table 2 also shows that bike lane was most likely to be a long-term response. Further, social distancing was the major focus for long-term responses that added new bicycle lanes. New bike lanes are clearly expected to be a long-term effect of the COVID-19 responses. In addition, the responses related to health care workers and public transportation as indicated in the text network are expected to be long-term.

Fig. 3 and Table 3 present the text network and top keyword co-occurred and collocated keywords for short-term responses of COVID-19. Most keywords that were in the long-term responses network are also available in the short-term responses network. Such keywords include street, city, bicycle, space, park, and lane. This observation implies that regardless of the longevity of the response, the same infrastructure/attribute are affected. All the collocated keywords are statistically significant at a 95% confidence interval. The collocated keywords motor vehicle have the strongest association with the lambda value of 8.11.

Fig. 4 presents the text network for indefinite observations. The content of the text networks is similar to the two previous networks. The keywords street, social, and distancing are the major keywords in this network as they were in the previous two networks. Other common keywords include bus, pedestrians, transport, shared, riders, and drivers, among others. The network, however, does not have the keyword temporary, which was in the short-term network. The remembrance of the indefinite network signifies that the observation can be either short-term or long-term.

3.3. Logistic regression results and discussion

Table 4 presents logistic regression results. Two logistic regression models were developed considering the “indefinite” observations. It should be noted that, as discussed earlier, the indefinite longevity outcome might end up being either permanent or temporary. Thus, the first model considered indefinite longevity as the long-term, while the second considered them as short-term.

The discussion of the result uses the Odds Ratios (OR) and associated p-values. The ORs are computed by exponentiating the estimated coefficients. The OR greater than 1 implies that the variable category is associated with the increased likelihood of long-term effects, on the other hand, OR less than one implies that the variable is not associated with the increased likelihood of long-term effects (Boniphace Kutela and Teng, 2019; Woodridge, 2012).

![Text network for Permanent/Long-term Responses.](image-url)
According to the results in Table 4, the odds of the COVID-19 response causing a permanent change of the transportation facilities varies significantly per space, purpose, function, category, and time that the response covers. Furthermore, the logistic regression results provide the association between various responses and the likelihood of being long-term or short-term. However, the analysis could not portray the exact content of such responses. Therefore, the text mining of selected responses of interest was performed to understand the content of various responses. The section also presents the text mining results for the following types of responses: responses taking place in travel lanes, responses with function “other bike/ped,” and responses whose implementation approach was categorized as “regulatory.” The selection was based on the fact that these values were the only ones that were statistically significant at a 90% confidence level. The text mining results provide more information on the content of the variables of interest than the traditional logistic regression model results.

The logistic regression results show a few dissimilarities when the indefinite observations are considered as long-term compared to short-term. Such dissimilarities involve the changes in the magnitudes and directions of the estimates as well as changes in the statistical significance level. The next section presents the discussion of the results focusing on the five variables of interest.

### Table 2

| Keyword Frequency | Co-occurrence Frequency | Collocation Association |
|-------------------|-------------------------|-------------------------|
| **Keyword**       | **Count** | **Docfreq** | **Keywords** | **Count** | **bicycle lane** | **Count** | **Lambda** | **Z-value** |
| street            | 145      | 66         | bicycle lane | 71        | bicycle lane    | 51        | 6.16       | 20.81       |
| city              | 96       | 60         | physical distancing | 36 | physical distancing | 35 | 8.37 | 13.85 |
| bicycle           | 103      | 53         | street traffic | 20 | social distancing | 17 | 7.86 | 9.07 |
| distancing        | 68       | 50         | open street | 19 | shared street | 15 | 5.67 | 9.47 |
| park              | 74       | 45         | walking cycling | 17 | new bicycle | 13 | 3.63 | 10.83 |
| new               | 54       | 45         | social distancing | 17 | public transport | 10 | 5.36 | 12.13 |
| use               | 61       | 42         | city street | 17 | walking cycling | 9 | 6.67 | 11.72 |
| lane              | 76       | 41         | new bicycle | 17 | motor vehicle | 9 | 6.76 | 9.27 |
| service           | 62       | 40         | pedestrian space | 15 | more space | 8 | 3.98 | 9.54 |
| space             | 53       | 40         | new lane | 14 | open street | 8 | 3.59 | 8.15 |

Key: Docfreq means Document frequency.
The keyword *street* appears 145 times in 66 reports/observations among reported responses. Further, the keyword *bicycle* appears more frequently in one observation but in fewer reports overall compared to *streets*. Other keywords in the top ten list include *park, new, lane, service,* and *space*. The observations imply that bicycle lanes were significantly affected, whereby new bike lanes were constructed, and others were closed to provide more space for *physical, social distancing*. For instance, a description of the vehicle lane that was converted to bike lane in Ciudad Pal, Spain states that “*vehicle lane converted to bicycle lane on Paseo Maritimo to offset expected increases in vehicle traffic from shut-down relaxation*”. Moreover, the co-occurrence between *street, social, distancing* implies that the streets were modified to increase more space for social distancing.

![Text network for Temporary/Short-term Responses.](image-url)

According to the results in Table 4, the odds of the COVID-19 response causing a permanent change of the transportation facilities varies significantly per space, purpose, function, category, and time that the response covers. Furthermore, the logistic regression results provide the association between various responses and the likelihood of being long-term or short-term. However, the analysis could not portray the exact content of such responses. Therefore, the text mining of selected responses of interest was performed to understand the content of various responses. The section also presents the text mining results for the following types of responses: responses taking place in travel lanes, responses with function “other bike/ped,” and responses whose implementation approach was categorized as “regulatory.” The selection was based on the fact that these values were the only ones that were statistically significant at a 90% confidence level. The text mining results provide more information on the content of the variables of interest than the traditional logistic regression model results.

The logistic regression results show a few dissimilarities when the indefinite observations are considered as long-term compared to short-term. Such dissimilarities involve the changes in the magnitudes and directions of the estimates as well as changes in the statistical significance level. The next section presents the discussion of the results focusing on the five variables of interest.
3.3.1. Purpose of the response

According to the results in Table 4, the responses for economic recovery and public health are less likely to result in permanent changes in the transportation infrastructures. On the other hand, safety-related responses are more likely to result in permanent changes. All three categories are statistically significant at a 95% confidence level when the indefinite observations are considered as long-term. On the other hand, only public health is statistically significant at the same level when the indefinite observations are considered as short-term. Study results show that the economic recovery responses’ odds of permanent changes in transportation infrastructure are 98% lower than that of moving people. Further, the odds of the responses for public health are about 50% to 86% lower than that of moving people. Lastly, the safety-related responses’ odds are between 2.3 and 3.3 times more likely to result in permanent changes of transportation infrastructures.

3.3.2. Space coverage

Results in Table 4 shows that compared to the responses that covered an entire roadway, all other responses are not statistically significant at a 90% confidence level if the indefinite observations are considered as long-term. On the other hand, responses that

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Table 3
Text Network Performance Metrics for Short-term Responses.

| Keyword Frequency | Co-occurrence Frequency | Collocation Association |
|------------------|------------------------|-------------------------|
| Keywords | Count | Keywords | Count | Keywords | Count | Lambda | Z-value |
| street | 540 | bicycle lane | 136 | bicycle lane | 96 | 4.73 | 30.03 |
| city | 360 | traffic street | 108 | physical distancing | 86 | 7.73 | 26.47 |
| bicycle | 299 | physical distancing | 87 | outdoor dining | 63 | 7.31 | 25.45 |
| space | 223 | outdoor dining | 66 | public transport | 48 | 6.05 | 22.28 |
| park | 354 | shared street | 65 | shared street | 36 | 4.59 | 15.60 |
| temporary | 196 | city street | 64 | slow street | 34 | 5.89 | 11.71 |
| lane | 233 | temporary street | 61 | healthcare workers | 32 | 6.60 | 19.54 |
| close | 176 | public transport | 55 | motor vehicle | 32 | 8.11 | 12.20 |
| traffic | 186 | space street | 53 | more space | 31 | 4.08 | 17.86 |
| distancing | 156 | parking space | 51 | social distancing | 31 | 7.02 | 15.86 |

Key: Docfreq means Document frequency.

For instance, whether the response is short or long-term is expected to affect the streets where the responses are applied. However, several keywords that emerged in the short-term responses were not in the long-term responses network. For instance, the keyword temporary signifies that the response was for temporary purposes. For instance, one observation indicated that a temporary bike lane was installed in Austin, Texas, stating: “Temporary bike lanes installed on Congress Ave.”. Furthermore, collocated and co-occurred keywords outdoor dining, slow street, healthcare workers clearly show the responses were temporary. For instance, the outdoor dining involved the removal/closure of the roadway. Such a response cannot be permanent/long-term. Also, responses for healthcare workers, such as reduced/free passes for public transport or bike share, are implemented temporarily.
affected curb and travel lanes are statistically significant at a 95% confidence level. The responses that affected travel lanes and intersections showed the changes in the direction of the estimate. The odds ratios for responses that affected travel lanes suggest that responses that such responses are 43% less likely to be permanent but also about four times more likely to be permanent, depending on how the infinite observations are considered. The less likelihood of being long-term responses can be explained by the importance and functionality of travel lanes for moving people. Thus, any modifications/changes of use of travel lanes are likely to be temporary. In fact, Fig. 5 shows that responses applied on the travel lanes mainly focused on the bicycle lanes as were temporary, as indicated by a large node of the keywords lane, bicycle, and temporary.

Furthermore, the intersection-related responses are about 57% more likely and 51% less likely to be long-term, depending on the consideration of the indefinite observations. The responses that affected parking lanes are 69% – 87% more likely to be permanent. Likewise, curb and park/plaza responses are 46% and 67%, respectively, more permanent. This observation can be attributed to the type of responses adopted in the locations. For instance, at the intersections/curbs, the responses that involved modifying curbs or automating walk signals are likely to be permanent.

The OR of the operational and regulatory are less than one, implying that these responses are less likely to be permanent when compared to physical responses. However, only regulatory responses are statistically significant at a 95% confidence level. The responses for “other bike/ped” are statistically significant at a 90% confidence level. Further, according to the text mining results in Fig. 6, the responses for other bike/pedestrian supports involve changes at the intersections, which may include the signals, walk signal automation, and reductions in speed limit, which are likely to be permanent. On the other hand, space for commerce tended to involve blocking entire sections of roads, which is less likely to be a permanent option.

3.3.3. Function

Responses that created space for commerce, provided other bicycle or pedestrian supports, or had other or miscellaneous functions are likely to be permanent as compared to responses to create space for walking and cycling. Spaces created for commerce are between 9 and 11 times more likely to be permanent compared to space for walking and cycling. Similarly, responses for other bike/ped supports are between 4 and 33 times more likely to be permanent compared to space for bike/ped, while responses for others are about 1.7–2.9 times likely to be permanent. However, only responses for “other bike/ped” are statistically significant at a 90% confidence level. Further, according to the text mining results in Fig. 6, the responses for other bike/pedestrian supports involve changes at the intersections, which may include the signals, walk signal automation, and reductions in speed limit, which are likely to be permanent. On the other hand, space for commerce tended to involve blocking entire sections of roads, which is less likely to be a permanent option.

3.3.4. Category

As shown in Table 4, there are three main implementation approaches (category variable): physical, operational, and regulatory. The OR of the operational and regulatory are less than one, implying that these responses are less likely to be permanent when compared to physical. In fact, regulatory responses are 92%-95% less likely to be permanent when to compared to physical responses. Similarly, operational responses are 13%-15% less likely to be permanent. However, only regulatory responses are statically

| Table 4 | Logistic Regression Results.               |
|---------|------------------------------------------|
|         | Indefinite as long-term                  |
|         | Estimate | OR  | P-value |
|         | Indefinite as short-term                 |
|         | Estimate | OR  | P-value |
| Time (all day every day) | Base |     | |
| No      | 1.382    | 3.98 | 0.007 |
| Yes     | 0.485    | 1.62 | 0.545 |
| Space coverage | Base |     | |
| Entire roadway |     |     | |
| Intersection | 0.454 | 1.57 | 0.642 |
| Curb    | 0.358    | 1.43 | 0.391 |
| Travel lanes | –0.131 | 0.88 | 0.677 |
| Parking lane | 0.518 | 1.68 | 0.282 |
| Parks/plazas/sidewalk | 0.627 | 1.87 | 0.455 |
| Purpose           |     |     | |
| Moving people | Base |     | |
| Economic recovery | –3.975 | 0.02 | 0.004 |
| Public health  | –0.702 | 0.50 | 0.031 |
| Safety       | 1.176    | 3.24 | 0.047 |
| Function      |     |     | |
| Space for bike/ped | Base |     | |
| Space for commerce | 2.208 | 9.10 | 0.110 |
| Other bike/ped | 1.563 | 4.77 | 0.073 |
| Others       | 0.550    | 1.73 | 0.418 |
| Category |     |     | |
| Physical    | Base |     | |
| Operational | –0.166 | 0.85 | 0.653 |
| Regulatory  | –2.553 | 0.08 | 0.004 |
| Intercept   | –1.957 | 0.14 | 0.000 |
| Model Summary |     |     | |
| Number of observations | 487 |     | |
| AIC        | 501.4 | 303.7 |
| BIC        | 564.2 | 366.5 |
significant at a 95% confidence level. This observation reflects that the regulatory responses were more likely to be simplified than others and thus are likely to be permanent. Conversely, operational responses involve substantial infrastructures changes that are less likely to be permanent. Fig. 7 shows key patterns for regulatory responses. It can be observed that most of these responses involved parking. This observation is based on the size of the node for the keyword parking. The co-occurrence of the keywords in Fig. 7 suggests that regulatory responses affected parking meter, parking permit, parking suspended, on-street parking, free parking, among others. It is clear that the parking-related responses, whose summary is presented in Fig. 6, are likely to be on a short-term basis.

4. Conclusions and future studies

This study seeks to explore the long-term impact of COVID-19 on transportation facilities. It uses data from the Shifting Streets COVID-19 Mobility Dataset, which documents ways in which cities around the world modified streets to provide more spacing for social distancing while performing walking, biking or other business. Two analysis methods—text mining and logistic regression—are applied to explore the long-term outcomes of street-level responses to COVID-19.

This study found that responses occurring in travel lanes, the creation of space for outdoor dining, measures to improve access to
work for healthcare workers were intended for the short term. On the other hand, new bicycle lanes and full street closures (a.k.a. ‘open streets’) were more commonly intended to outlast the pandemic. Partial street closures (a.k.a. ‘shared streets’), improvements to public transport, responses meant to curtail disease transmission, and responses taking place inside parks were intended as both short-term and long-term interventions. The text network provided the low-level details of the responses.

The logistic regression results intended to explore the likelihood of the response being long-term (i.e., outlasting the pandemic). In this analysis, five variables were of interest: the temporal coverage of the response (time), the street space affected (space), the purpose and function of the response, and the implementation approach (category). The study found that responses that were applied all day, every day were more likely to be long-term. Further, responses that covered some, but not all travel lanes only were less likely to be long-term than responses that covered the entire roadway. However, the findings for this kind of response do change depending on the consideration of the indefinite observations. Regarding the purpose, compared to responses for moving people, responses for economic recovery and public health were less likely to be long-term while those implemented primarily to improve safety were more likely to be long-term. Furthermore, responses that focused on other (i.e., non-street space) supports for walking and cycling were more likely to be long term compared to those that created street space for walking and cycling. Lastly, regulatory responses were less likely to be long-term than to physical responses.

The study findings have several implications in the post-COVID-19 era. Transportation researchers, practitioners, and the public are looking forward to a “new normal.” Our analyses suggest that new normal will include several modifications to the use and function of public roadways. Responses that require limited resources and/or involve limited changes to traffic patterns, such as automation of walk signal automation and speed limit reductions, are expected to remain beyond the pandemic. More substantial changes, such as reallocations of travel lanes to new uses and new intersection configurations, may also be continued in a post-COVID-19 era. Use of on-street parking spaces for other uses may also be a common post-pandemic feature. More data is needed to support analysis into the role of other factors, such as the planning processes underlying cities’ responses and the distribution of costs and benefits of those responses, to further improve our understanding of the long-term impacts of COVID-19 on the transportation sector. Furthermore, future studies may focus on the heterogenous results across regions, continents, and high vs. low-income settings.

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CRedit authorship contribution statement

Boniphace Kutela: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. Tabitha Combs: Data curation, Writing – review & editing. Rafael John Mwek’iga: Formal analysis, Methodology. Neema Langa: Conceptualization, Writing – original draft.
Declarations 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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References

Abu-Rayash, A., Dincer, I., 2020. Analysis of mobility trends during the COVID-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities. Energy Res. Soc. Sci. 68, 101693 https://doi.org/10.1016/j.erss.2020.101693.

Advani, Sharma, N., Dhyani, R., 2021. Mobility change in Delhi due to COVID and its’ immediate and long-term impact on demand with intervened non motorized transport friendly infrastructural policies. Transp. Policy 111, 28–37. https://doi.org/10.1016/J.TRANPOL.2021.07.008.

Bbc, 2022. Coronavirus pandemic: Tracking the global outbreak - BBC News. Retrieved September 5, 2020, from https://www.bbc.com/news/world/51235105.

Benoit, K., Warabi, K., H., H., Nulty, P., Obeng, A., Müller, S., Matsuoka, A., 2018. quantita: An R package for the quantitative analysis of textual data. J. Open Source Software 3 (30). https://doi.org/10.21105/joss.00977.

Blaheta, D., Johnson, M., 2011. Unsupervised learning of multi-word verbs *. In: Proceedings of the ACL Workshop on Collocations, pp. 54–60.

Combs, T.S., Pardo, C.F., 2021. Shifting streets COVID-19 mobility data: Findings from a global dataset and a research agenda for transport planning and policy. Transport. Res. Interdiscip. Perspect. 9, 100322 https://doi.org/10.1016/J.TRIP.2021.100322.

Csardi, G., 2020. ”igraph” Network Analysis and Visualization. Retrieved from https://igraph.org/r/.

Firth, C.I., Baquero, B., Berney, R., Hoerster, K.D., Mooney, S.J., Winters, M., 2021. Not quite a block party: COVID-19 street reallocation programs in Seattle, WA and Vancouver, BC. SSM - Population Health 14, 100769. https://doi.org/10.1016/j.ssmph.2021.100769.

Fischer, J., Winters, M., 2021. COVID-19 street reallocation in mid-sized Canadian cities: socio-spatial equity patterns. Can. J. Public Health 112 (3), 376–390. https://doi.org/10.17269/s41997-020-00467-3/FIGURES/6.

Habib, M.A., Anik, M.A.H, 2021. Examining the long-term impacts of COVID-19 using an integrated transport and land-use modelling system, 25 (3), 323–346. https://doi.org/10.12265934.2021.1951821.

Hunter, R.F., Garcia, L., de Sa, T.H., Zapata-Diomedi, B., Millett, C., Woodcock, J., Moro, E., 2021. Effect of COVID-19 response policies on walking behavior in US cities. Nat. Commun. 12 (1), 1–9. https://doi.org/10.1038/s41467-021-23937-9.

Kim, Y., Jang, S.-N. (2018). Mapping the knowledge structure of frailty in journal articles by text network analysis. https://doi.org/10.1371/journal.pone.0196104.

Kutela, B., Novat, N., Langa, N., 2021a. Exploring geographical distribution of transportation research topics related to COVID-19 using text network approach. Sustain. Cities Soc. 67, 102729.

Kutela, B., Das, S., Dadashova, B., 2022. Mining patterns of autonomous vehicle crashes involving vulnerable road users to understand the associated factors. Accid. Anal. Prev. 165, 106473.

Kutela, B., Langa, N., Mwende, S., Kidando, E., Kitali, A.E., Bansal, P., 2021b. A text mining approach to elicit public perception of bike-sharing systems. Travel Behaviour and Society 24, 113–123. https://doi.org/10.1016/j.tbs.2021.03.002.

Kutela, B., Teng, H.(., 2021a. Exploring the associated factors for multiple-threats and near-miss incidents at signalized midblock crosswalks. J. Transport. Safety Securty 13 (4), 414–435.

Kutela, B., Teng, H., 2020. Evaluating the influential factors for pushbutton utilization at signalized midblock crosswalks. Saf. Sci. 122, 104533 https://doi.org/10.1016/j.ssci.2019.104533.

Kutela, B., Teng, H., 2021b. The Use of Dynamic Message Signs (DMSs) on the Freeways: An Empirical Analysis of DMSs Logs and Survey Data. J. Transport. Technol. 11 (01), 90–107. https://doi.org/10.4236/jtts.2021.111006.

Marra, A.D., Sun, L., Corman, F., 2022. The impact of COVID-19 pandemic on public transport usage and route choice: Evidences from a long-term tracking study in urban area. Transp. Policy 116, 258–268. https://doi.org/10.1016/J.TRANPOL.2021.12.009.

Mayo, J. (2021). Lane Reallocations During COVID: A Comparison of Interventions and Decision Making Process. https://doi.org/10.17269/S41997-020-00467-3/FIGURES/8.

Paranyushkin, D., 2011. Identifying the Pathways for Meaning Circulation using Text Network Analysis. Venture Fiction Practices 2 (4). Retrieved from www.r-project.org/.

Pardo, C.F., 2021. Unsupervised learning of multi-word verbs *. In: Proceedings of the ACL Workshop on Collocations, pp. 54–60.

Rose, M. (2022). Coronavirus (COVID-19) Cases - Statistics and Research - Our immediate and long-term impact on demand with intervened non motorized transport friendly infrastructural policies. Transp. Policy 111, 28–37. https://doi.org/10.1016/J.TRANPOL.2021.07.008.

Wright, H., Beardon, M. (2021). COVID-19: a chance to reallocate street space to the benefit of children’s health? https://doi.org/10.1080/23748834.2021.1912571.

Yoon, B., Park, Y., 2004. A text-mining-based patent network: Analytical tool for high-technology trend. J. High Technol. Manage. Res. 15 (1), 37–50. https://doi.org/10.1016/j.jhitech.2003.09.003.

Zhang, R., Zhang, J., 2021. Long-term pathways to deep decarbonization of the transport sector in the post-COVID world. Transp. Policy 110, 28–36. https://doi.org/10.1016/J.TRIP.2021.05.018.