

One Year of Social Distancing Behavior on the Streets of Amsterdam (pre-print, version 1)



Summary

To mitigate the spread of the COVID-19 virus, the Dutch government enforced that citizens should keep 1.5-meter distance from strangers in public. We evaluate compliance with this directive by drawing on more than 40.895 hours of video recordings of public space captured by 57 municipal public surveillance cameras in Amsterdam through the first year of the pandemic—from March 2020 to January 2021. This large-scale dataset was analyzed with a computer vision tool to automatically detect people crowding and 1.5-meter contact moments on the video recordings. Our analysis includes observations derived from snapshots every Thursday and Saturday at each full hour between 9 am and 8 pm. The study has two main findings. First, we found a direct relationship between the number of people observed on the street and 1.5-meter contact moments. This finding highlights the importance of crowd management of public spaces for facilitating social distancing compliance. Second, relatively many people were observed between spring and late fall 2020, while the two lockdowns that preceded and succeeded this period coincided with lower numbers, indicating compliance with stay-athome measures. It should be stressed that the current results are preliminary and that the study is limited by the lack of information of who were members of the same household and thus exempt from the 1.5-meter distance rule.



Note that these are preliminary results from a not yet peer-reviewed study in progress. The final results will be available at osf.io/7ek9d. The study was partly financed by ZonMw (project number: 10430022010017) and the Municipality of Amsterdam and was conducted independently by the authors. We would like to thank the police unit Public Order and Safety Amsterdam, in particular Maikel van Scheppingen, Makki el Jouhri, Fehri Gara-Ali, and Ronny van Axel Dongen for their support, interest, and investment in supporting us in the data collection.

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Introduction

Compliance with non-pharmaceutical interventions is critical for mitigating the spread of the COVID-19 virus. The World Health Organization (WHO) recommends eight interventions to slow down transmissions, including maintaining "at least 1 m distance with others" and avoiding "crowded places because there, it is difficult to maintain at least 1 m distance" (WHO, 2020). The effect of interventions on transmission trends is difficult to establish (Flaxman et al., 2020; Lai et al., 2020), not least because of a lack of information on behavioral compliance with intervention measures. Knowledge about compliance with non-pharmaceutical interventions is often anecdotal or based on self-reports, which are notorious for being unreliable due to desirability biases and memory failure (Clifford and Bull, 1978). This is also the case in the Netherlands, where, for example, the Dutch public health institute (RIVM) monitored social distancing compliance with a survey tool. They found a fairly stable trend of compliance over the last year, with only a slight drop in the summer period of 2020 (RIVM, 2021).

The question we address is whether the same picture emerges from direct observation of people's actual behaviors rather than their intentions or their retrospective accounts. In addressing this question, we draw on video footage from public surveillance cameras—a data source that is increasingly recognized as the gold standard for obtaining micro-detailed and ecologically valid information about how people actually behave in social situations (Gilmore, 2017).

Methods

The data comprised video footage of 57 municipal surveillance cameras in Amsterdam, Netherlands (see Figure 1). With the permission of the Dutch Public Prosecutor, we obtained data from the Amsterdam police, and the research was approved by the Ethics Committee for Legal and Criminological Research (CERCO) at Vrije Universiteit Amsterdam. The footage was collected at locations that were expected to be relatively busy in the period of a lockdown (e.g., around grocery stores and public transport points). Video footage of all cameras was recorded on all Saturdays and Thursdays between 5 March 2020 and 30 January 2021 from 9 am to 8 pm—a period that faced dramatic changes in the installment and retraction of various types of interventions, including school closings, a curfew, and bans on large gatherings.

At each full hour, a still frame was sampled, resulting in a total sample of 40895 still frames. To automatically detect people visible in a still frame, we used the algorithm by Hasan and colleagues (2020) as a basis, and on top of that we developed an own algorithm to get a more reliable estimate of the number of people

present and to determine whether they kept a 1.5-meter distance. The algorithm successfully passed performance tests, also on videos recorded during darkness, against a subsample of still frames observed and coded by human coders that was used as the benchmark. For technical and organizational reasons, some intended observation points are missing from the data. The technical reasons include occa-sional camera failures and video conversion failures. Due to organizational issues, there are some weeks completely without footage in our data: two weeks in March 2020 and a 5-week gap from July 23 and August 29. To optimize the available information, reduce bias, and increase precision, we used a statistical approach known as multiple imputation (Rubin, 1987) to compute outcome measures. In this approach, multiple versions of an imputed dataset are generated, the analysis is performed on each of them separately, and the results are then pooled. This method assures that uncertainty about the missing observations is retained in the outcomes while allowing all available data to be used. We applied the method of multiple imputation by chained equations (MICE) as implemented in the R package MICE (van Buuren, 2018) using 20 imputed data instances. The missing weeks in March and August were not imputed because too much data—all data—were missing.

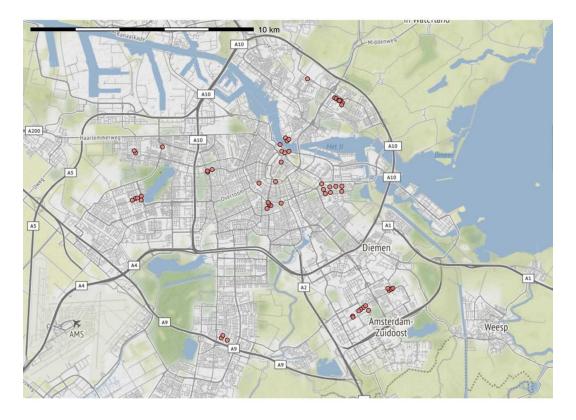
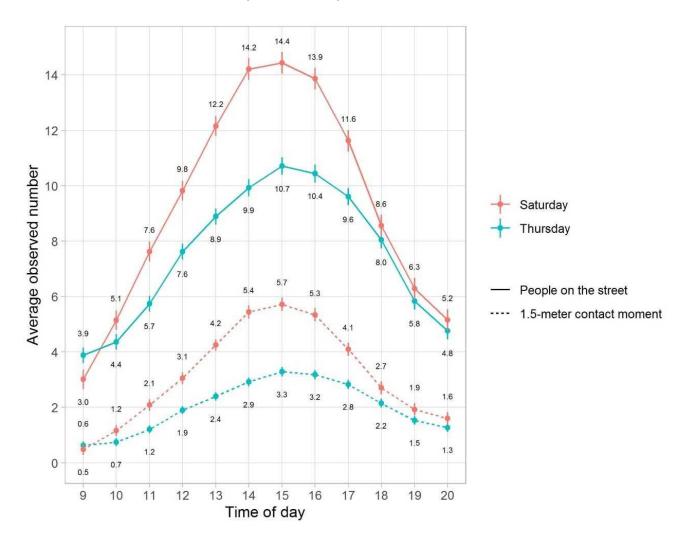


Figure 1. Placement of the municipal cameras used for the study

Results

Figure 2 shows the observed number of people on the street (solid line) and the observed number of 1.5-meter contact moments (dashed line) over the course of the day on Saturdays and Thursdays. The number of people on the street, as well as the number of 1.5-meter contact moments, were higher on Saturdays (in red) compared to Thursdays (in blue). On both days, it appeared to be relatively busy between noon and 6 pm, although on Thursdays, the peak was considerably lower. The number of 1.5- meter contact moments correlates strongly with the number of people on the street (r = 0.81 throughout the study period), which is visualized in the parallel development of these measures over time in Figures 2 and 3. This strong correlation could signal a causal relationship: it might be more difficult for people to keep their distance in relatively crowded settings. In that case, it supports crowd-control policies, which will help to reduce activity peaks and, thereby, help to attenuate the number of 1.5-meter contact moments.

Figure 2: Number of people on the street and 1.5-meter contact moments on Thursdays and Saturdays



In Figure 3, the number of people on the street (red line) and the number of 1.5-meter contact moments (blue line) are presented for the period between March 2020 and January 2021, with the vertical dashed lines representing the averages across the whole measurement period. There are notable fluctuations throughout the year, both with respect to the number of people on the street and the number of 1.5-meter contact moments. From the second half of April until December, the number of people on the streets was above average, except for a decline at the beginning of October. Further, we see that the number of 1.5-meter contact moments closely followed this trend—again stressing that the two phenomena are closely linked.

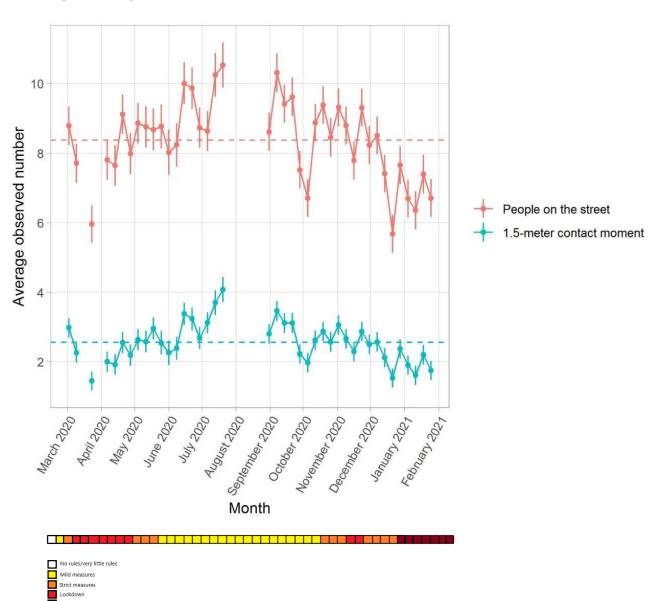


Figure 3: People on the street and 1.5-meter contact moments

To contextualize the temporal fluctuations in the number of people and 1.5-contact moments, we constructed a timeline indicating the strictness of the implemented COVID-19 measures in different periods. We distinguish between five levels: 'no measures/very little measures' (e.g., the Prime-Minister asking us to not shake hands anymore), 'mild measures' (mandatory closing times for bars, limitations to the allowed number of visitors indoors), 'strict measures' (certain sectors closed down, limitations to sport events), 'lockdown' (schools closed, so-called flow locations closed), and 'hard lockdown' (all non-essential shops closed).

The drop in the number of people and the number of 1.5-meter contact moments in the periods March-April and December-February coincided with the introduction of lockdown measures. Note, however, that these observations are not necessarily indicative of causal effects of the lockdowns. Alternative explanations for these findings include the changing weather conditions and the relatively low transmission rates during those months.

Discussion

When it is crowded on the street, people are more likely to engage in contacts within 1.5-meter distance. This finding indicates the importance of crowd management for the mitigation of potential transmissions in outdoor public spaces. We also find that—during the lockdown periods as announced by the government—fewer people are on the street, and less 1.5-meter contact moments are visible. We cannot say, however, whether the observed behavioral changes are caused by the lockdowns as other factors might play a role for behavior in public space. For example, we find that crowding and social distancing behavior in public follow seasonal trends, in which there are more people on the streets and more 1.5-meter contact moments when the weather is pleasant.

The current results are preliminary. Further analysis of the relationship between the implemented non-pharmaceutical interventions and social distancing behaviors is needed. While our study has high ecological validity and reliability, it is limited by the nature of the information that can be derived from the videos. For example, the videos do not contain information about people's personal characteristics (e.g., age, history of illness) or their relationship with others. Future work should address the variations in the behavior of different groups and across different contexts (e.g., public vs. semipublic, indoor vs. outdoor).

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