Avoiding crowded places during COVID-19: Simple Choice or Complex Strategic Decision?

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Abstract

Aim: Policies focused on avoiding crowded places are considered essential in combating the swift diffusion of COVID-19 infections. Adhering to these policies, however, has proven to be more challenging for the population than initially expected. We argue that ambiguity in the recommendation to "avoid crowded places" implicitly forces individuals to make a complex strategic decision.

Subject and Methods: Using a large, representative survey, we examine the effect of key factors, such as context and personal characteristics, on the decision to visit a crowded place amongst 1,048 Dutch citizens.

Results: We find that people use information about the crowdedness on the streets to (inaccurately) predict the behavior of others, in order to either optimize their own decision or violate the recommendation. Moreover, we show that education, age, health risk attitude, and COVID-19 exposure all influence the likelihood of going out.

Conclusion: Although our results show that a majority of the population intends to abide to policy recommendations, the lack of up-to-date, location-specific information often leads to unintentional violation of the recommendations, ultimately leading to crowded areas.

Keywords: Behavioral and social aspects of health, public health communication, collective human behavior, human decision science, cognitive psychology, COVID-19

1. Introduction

Since the outbreak of COVID-19, countries across the globe have attempted to find ways to contain the rapid spread of the virus. Following a period of strict lockdowns, most countries proceeded towards a policy in which citizens were expected to avoid crowded places, as advised by the WHO (World Health Organization, 2020). Limiting movement to local recreational hotspots as well as (inter)national holiday destinations is considered essential in combating the swift diffusion of COVID-19 infections. Even during the "second wave," avoiding crowded places remains the cornerstone of worldwide policies (National Center for Immunization and Respiratory Diseases (NCIRD), 2020). Following policy advice, however, has proven to be more challenging for the population than initially expected. Popular recreation spots often remain well-visited and shopping centers are almost as crowded as they were a year ago, especially in large cities (BBC News, 2020). Over the Summer of 2020, news and social media showed crowded beaches and partying adolescents almost on a daily basis.

The increase in people visiting crowded places appears irrational from a health perspective, but might be less surprising than expected. Accurately assessing the risk of self- behavior proves to be hard, the urge to recreate seems to grow over time, and the duration of the current situation is testing the limits of human patience and self-control (Huremović, 2019). Moreover, what is considered "crowded?" This uncertainty increases the number of factors and potential outcomes individuals consider (Martínez-Marquina, Niederle, & Vespa, 2019). Until today, little to no attention has been provided to the thought process that underlies the decision to leave the home, against most policy recommendations, and visit popular recreation areas or crowded shopping streets. Understanding the human thought process from a behavioral perspective will help governments to be more effective in implementing COVID-19-related policies.

This paper investigates the decision of individuals whether or not to avoid crowded places, in a representative sample of the Dutch population, aiming to identify decisive factors underlying this choice. We expect the dependency of the outcome of one's own action on the (unobservable) actions of others to dominate the decision-making process. Therefore, we specifically examine the effect of social context on the decision to visit a crowded place. Moreover, we examine the effect of predications of other people's behavior on the decision to go. The aim of this paper is threefold: First, we discuss which decisional processes and conflicts arise due to the ambiguity in the current policy, through the lens of a theoretical framework. Here we provide an overview of why people would consider to go outside, which thought processes they may undertake, and how multiple lines of individual reasoning might materialize on the community level.[1] Second, using experimental data we demonstrate that (social) information provision influences the decision-making process of individuals when policy is ambiguous. Finally, we show which personal characteristics have a significant effect on the decision not to go and how this differs per context. The latter also allows us to draw conclusions on which decisional processes drive the behavior of individuals.

[1] Note that our paper focuses on practical generalizability. We strive to identify to what behavior the current policy recommendations, combined with the limited information availability for the decisionmaker, leads. By doing so, we make a trade-off between a rigid, experimentally controlled theoretical framework and real-life ambiguity, by observing the behavioral response instead of focusing on one specific behavioral predictive model. We discuss further this trade-off in the limitations section.

2. Literature Background

2.1 The Need to Leave

Psychology is unanimous about the inherent human need for social interaction. Baumeister and Leary claim that the need for frequent interactions with others is a necessity for emotional stability (Baumeister & Leary, 1995). We desire both close individual contact, as well as the ability to function in social groups (Bugental, 2000). Not meeting these requirements leads to invasive negative effects, including, but not limited to physical health and mental well-being (Baumeister & Leary, 1995). Poor social relationships are estimated to have an effect on mortality similar to smoking 15 cigarettes daily (Holt-Lunstad & Smith, 2012).

The COVID-19 pandemic threatens the ability to meet these basic social needs. This leads to a clear cognitive conflict: people are craving for social contacts, regardless of rapidly rising contaminations with the virus. Such a cognitive conflict, better known as cognitive dissonance, can be dealt with in two ways: changing the behavior or changing the reasoning (Festinger, 1957). From a societal perspective, reasoning in favor of keeping distance at all cost, taking no risk, would be preferred. However, the need to socially interact is growing: we observe society-wide violations of the universal policy discouraging social interactions (BBC News, 2020). Going out and being amongst people (albeit within the set regulations) is gaining traction over the safer, more certain option to stay at home to avoid health risks.

2.2 Strategic Decision-Making

Acknowledging that the motivation to recreate is strong, the actual decision to "go" or "not to go" to a crowded location depends on the information that is available to the individual at the moment of making the decision. The recommendation to avoid crowded areas is not black or white, and it requires each individual to estimate which spots are considered popular at a given point in time. Although we can assume that every community has a relatively objective view of what is considered a crowded area, the recommendation to avoid these areas implicitly requires an individual to correct for the current situation: how busy will a potentially crowded area be at the moment that I intend to visit it? The degree of crowdedness is determined by the number of people considering to go, their thought processes, and their final decision.

We argue that the seemingly simple choice to visit or avoid a crowded place implicitly involves at least three complex strategic decision-making aspects. First, the choice generally draws parallels with the tragedy of the commons. Hardin describes the tragedy in which a shared yet unregulated common good (in this case, the location for recreation), is spoiled by society because each individual acts according to his or her self-interest, so "depleting" the common good (Hardin, 1968). The similarity lies especially in the fact that collective cooperation would retain the common good, but the individual interest conflicts with the collective maintenance of the good. In this situation, each individual selfishly wants to be in the minority group that visits the recreation area. When too many people act selfishly, the area becomes too crowded and the location no longer meets the "avoid crowded areas" requirements to minimize the spread of COVID-19 infections. In a worst-case scenario, "depletion of the good" could be the closure of the area for recreation, or even reimplementation of a full lockdown.

Second, and more formally, the dependency of each individual's outcome on the choice of the remainder of the population closely resembles the classic game theoretical prisoner's dilemma: going out will lead to a positive outcome if the majority of the population stays away, and only leads to a negative outcome if the majority of the population goes. This dilemma shows us that staying home is not a Nash equilibrium (e.g. an outcome of a decision in which no player has an incentive to deviate from his strategy; Nash, 1950). If everybody stays at home, each individual can improve his or her personal situation by going out. Going out, however, could be considered Nash equilibrium: when everybody is going out, staying at home would not improve somebody's personal situation, when they would be the only person at home. Note that we assume that staying at home while everybody else is recreating comes at a (small) disutility, based on the fear of missing out (Przybylski, Murayama, Dehaan, & Gladwell, 2013) and not being able to meet the social craving. This makes the decision process oddly circular, and the outcome of the process depends heavily on the moment each individual breaches this circle.

Therefore, third, the decision process to optimize the outcome of the decision concerns *k*-level thinking and cognitive hierarchy theory (Camerer, Ho, & Chong, 2004; Stahl, 1993). The core of this theory is that a person will determine strategy depending on the likely actions of others. The levels refer to the reasoning level someone expects the others to have, or "depth". For instance, level 0 thinkers are considered non-strategic, choosing at random. Level 1 thinkers assume a majority of level 0 thinkers, and will strategically choose considering a random distribution of level 0 thinkers' decision. Level 2 thinkers will, at their turn, assume a majority of level 1 thinkers, and so forth. In our example, we could hypothetically assume that level 0 thinkers "naively" stay away from a recreation area. As such, level 1 thinkers would come to the conclusion to go as the area will not be crowded. Consequently, level 2 thinkers stay away again, and so forth. The *k*-level framework states that each person believes to be at the highest level of thinking, with everyone else below that level, giving this person the unique advantage to best adopt a strategy. In reality however, the average population hardly seems to reach level 2 (Camerer et al., 2004; Ho & Su, 2013). The implications of the decision to leave home and visit a crowded location during the pandemic are crucial, since citizens likely aim to anticipate the behavior of the majority. When most people are at the same (fairly) low reasoning level, but believe they are "outsmarting" their fellow citizens, the chances of an unexpectedly crowded recreation area become very high. Ironically, even when effort is exerted to outsmart the majority and recreate when the majority stays home (thus intending to meet the policy requirements), the implications of cognitive hierarchy theory suggest an "accidental" or implicit escalation of crowdedness.

2.3 Explicit Escalation

In addition to accidental escalation due to the application of wrong strategies by individual citizens, we must also consider explicit escalation, including conscious violation of policy recommendations. In this context, we consider the possibility of the proverbial sheep leaping the ditch: once a large enough group will ignore the policy recommendation, more will automatically follow. These people are, in contrary to the strategic thinkers, no longer intending to *avoid* crowded places. In pandemics this situation is called behavior contamination (Huremović, 2019). We discuss two cognitive processes that potentially influence the decision to ignore policy recommendations once violations by others are observed.

A prevalent view in behavioral science is that these kinds of "deliberate" violations are the result of a loss of self-control or a dominating need to recreate (Huremović, 2019). Boredom and frustration resulting from the ongoing pandemic increases the vulnerability to violate the recommendations (Brooks et al., 2020; Huremović, 2019). Observing others ignoring the recommendations functions as a "broken window": a small violation validates further violations, causing a spread through society (Keizer, Lindenberg, & Steg, 2008). This broken window effect, or bad apple effect, is strong even when just a small group of violators is observed (Kerr et al., 2009; Rutte & Wilke, 1992). In this context, seeing others doing something you would also like to do could provide enough of an incentive for citizens to join: why would you stay away if others don't?

An alternative view explaining why individuals would follow others to crowded places, despite regulations not to do so, involves how people deal with ambiguity. Besides uncertainty about other people's decisions, we also need to consider that people are unsure about the definition of crowded places, or ambiguous regarding the interpretation of the recommendation. Should one take the recommendation as a strict rule, or interpret it more loosely? When ambiguity rises, we tend to use informational social influence to guide our decision (Deutsch & Gerard, 1955). This could lead to contradictions. For example, during the initial loose recommendation to wear face masks in public in the Netherlands, compared to the predominately mandatory use in the rest of Europe, 64% of Dutch citizens were in favor of making face masks mandatory. However, only 17% already wore them at that time (De Hond, 2020). Even when our personal opinion or preference might deviate, in practice we conform to (what we think is) the majority opinion in ambiguous situations (Allen, 1965). It is crucial to observe from this example that even in a contagious disease pandemic, in which rationally safety is absolutely not in numbers, other people's behavior is still valued in situations of ambiguity. Observing others violating the recommendation to avoid crowded places could therefore be interpreted as the opinion of the majority, and act as information for one's own judgement.

The distinction between the two views lies predominately in the underlying intention of the conscious violation. Under the former, the intention can be categorized as ill-intentioned, to the extent that there is no attempt to validate the violation of the recommendation at the start. This does not exclude the possibility that individuals will exhibit post-hoc justification, fabricating reasons why the violation was acceptable or ethical, potentially in response to social disapproval (for instance, after not getting infected with the COVID-19 virus, people could argue that they were correctly assessing the risk ex-ante) (Curley, Yates, & Abrams, 1986; Haidt, 2001). Under the latter, the intention to deviate from the recommendation originates from confusion. We argue that this behavior reflects the inability to self-assess the ambiguity or uncertainty, leading to herd behavior (Muchnik, Aral, & Taylor, 2013). Distinguishing between these motivations might be possible by looking at the behavioral response to increasing social violations: for people motivated by ill-intention, going to a crowded place is linearly related to others going; for uncertainty-motivated people, this relationship might only be detrimental when a large enough group signals the "okay" to go. Regardless, however, both motives will inevitably lead to escalation.

3. Materials and Methods

3.1 Participants

We surveyed a panel of 1,048 individuals via Flycatcher, a well-regarded Dutch research organization with access to a high-quality panel used for top research (Bults et al., 2011; Peperkoorn et al., 2020), about their choice whether to go or not to go to a hypothetical recreational hotspot. Our randomly drawn sample from this panel was reimbursed for participation. This sample is heterogeneous in relevant personal characteristics, such as age (M=43.70, SD=12.52), education, and gender (42% male). For an extended overview, see appendix table S1. This research was reviewed and approved by Maastricht University's Ethical Review Committee Inner City Faculties (ERCIC_195_09_06_2020).

3.2 Methods

Each respondent is asked to envision the following situation: *You live within 20 kilometers of a beach, river, forest, or lake. Under normal circumstances, you (and your household) will seek recreation, cooling and refreshing at this area when temperatures exceed 25 degrees Celsius. You do not have a comparable alternative at home.* We ask each participant to decide whether they will visit this area tomorrow, given that it will be 30 degrees Celsius, in five different situations. For the first two situations, the government's recommendation differs: 1) "Stay home", and 2) "Avoid crowded places". For the remaining three conditions, we keep the government's recommendation constant ("Avoid crowded places"), but we provide additional information about the situation on the streets: 3) "You see that it is still very quiet on the streets", 4) "You see that the streets are slowly getting busier", and 5) "You do not notice any difference in the degree of crowdedness as compared to last year". We respectively label these levels of context as "Low", "Medium", and "High". All scenarios are presented to the respondents in a randomized order.

We ask each respondent to state whether they will visit the recreation location in each of the scenarios. Next, for each randomly presented scenario, we ask participants what percentage of all other respondents they think will answer the previous question with "yes". This percentage provides us with an indication of the expectation that participants have about the behavior of others.

Furthermore, we collect data via the Dutch Bureau of Statistics (CBS) on the local intensity of COVID-19 infections, hospitalizations, and COVID-19 related deaths. These statistics are matched to each individual in the sample at the four-digit postal code level. Additionally, we ask the respondents to state their general, social, and health-related risk attitudes on a scale from 0 to 10 (Falk, Dohmen, & Huffman, 2016).

Although the same recommendation of avoiding crowded places is a COVID-19 policy cornerstone throughout Europe (World Health Organization, 2020), the experienced situational context and timing of our survey is important to ensure external validity. The Dutch government issued an "intelligent lockdown" from March 15th until May 11th 2020. Until June 1st 2020, Dutch citizens were asked to stay home as much as possible. From June onwards, the recommendation to avoid crowded places became the main policy recommendation. Our respondents completed the survey during the first half of July 2020, five to six weeks after the introduction of this recommendation. The timing of our data collection ensures that respondents had ample experience in dealing with the key policy recommendation and that the responses accurately reflected their current behavior. We furthermore consider it important that no new changes in the recommendations were announced at the time, such that the anticipation of new rules, or the signaling of a more liberal approach interfered with the validity of the response.

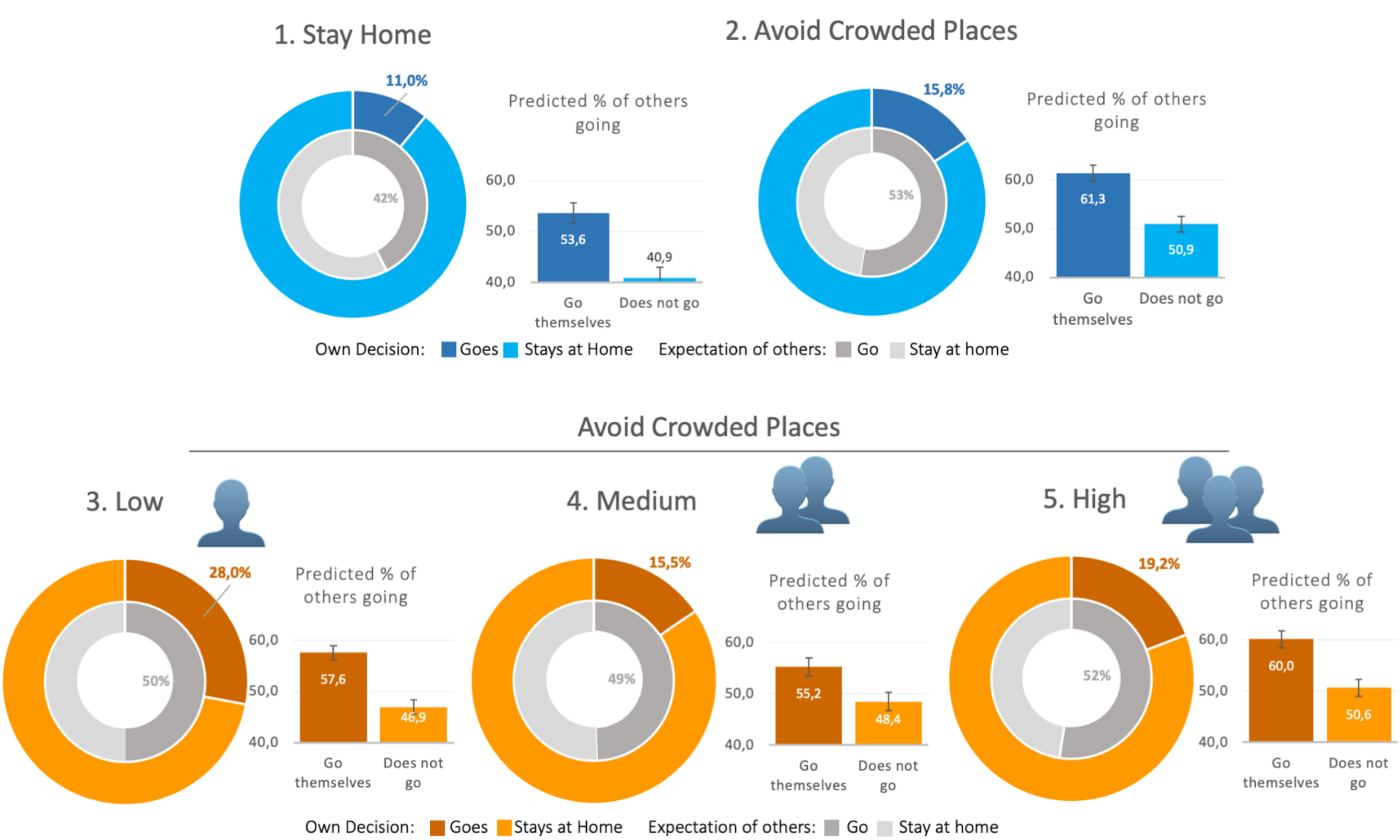
4. Statistical analyses and results

4.1 The effect of context on decision making

Figure 1 presents whether or not respondents will visit a crowded area. In all scenarios, the vast majority of the respondents is not planning to go the recreation area. Although this appears encouraging for the policy objective to avoid crowded places, an average of 19% of all respondents across all five scenarios still decide to go.

Figure 1.1 shows the percentage of respondents indicating to go to the recreational area when the advice is to "stay home" (10.97%). The inner ring shows the average expected percentage of others to visit the crowded place (42%). Looking at the difference between the recommendation conditions "Stay home" (1.1) and "Avoid crowded places" (1.2), we observe a difference of just 5%. Finally, the bar graph shows the same expected percentage of others to visit a crowded place, but split by group of respondents that indicate to go themselves (M = 53.61, SD = 20.21) versus people that indicate to stay at home (M=40.92, SD = 20.51). The difference between these two groups is statistically significant (z= -6.07, $p < .001$).

Figure 1 – Descriptive Statistics



Note: The graph shows the percentage of respondents indicating to visit the crowded place in the outer ring, for each context. The inner ring shows the average expected percentage of others to visit the crowded place. The bar graph shows the same expected percentage of others to visit a crowded place, but split by respondents that indicate to go themselves versus respondents that indicate to stay at home. Figure 1.1 shows the metrics under the policy "stay home" without any further context. Figure 1.2 shows the same metrics but in the condition of "avoid crowded places". Figure 1.3, 1.4, and 1.5 show the graphics in this same condition, but each for a different level of crowdedness on the stress (low, medium, and high crowdedness, respectively). For an overview of these statistics, see Appendix Table S2.

When we add context about the level of crowdedness on the streets, we observe an additional increase in the number of respondents intending to leave the home. It is noticeable that providing a *clear* context about the crowdedness on the streets, regardless whether this is low (1.3) or high (1.5), causes a steep increase compared to the middle condition (1.4) and even no context (1.2). Respondents are more likely to go to the area of recreation when they expect it to be quiet. This is in line with both the official policy recommendation as well as strategic thinking. More surprising is that respondents are also more inclined to visit a popular area when they have reason to believe that it will be crowded at this location. This is directly opposite to the official policy recommendation, and not in line with game-theoretical predictions. This preliminary result suggests that respondents' strategic thinking (in the low context) as well as social norms (in the high context) play a role in their decision whether to go, or not.

We then investigate the estimation that respondents make about other's behavior. We observe that respondents substantially and consistently overestimate the number of other people intending to go. Respondents expect, on average across all scenarios, that roughly 50% will decide to leave the home and recreate. Furthermore, the predicted percentages do not significantly change between scenarios. More specifically, however, this shows that the changes in one's individual decision to go are not reflected in the prediction of other citizens' behavior. For instance, introducing the "low crowdedness" context (1.3) compared to no context (1.2) almost doubles the number of respondents planning to go to the area of recreation, but the change in the predicted number of others going decreases by just 2.5%. In sum, the expectations about others' behavior is a lot more negative than one's own behavior, and more negative than the behavior of the collective.

There is also a relationship between going out and the expectations about others. Non-parametric rank sum tests show consistently that, regardless of the scenario, respondents indicating a willingness to recreate themselves also predict a significantly higher number of people to make the same decision, compared to respondents indicating to stay home (all are significant for p <.001; for an overview of these statistics, see Table S2). The prediction is significantly correlated with citizens' own decision to go: for each percentage point increase in the prediction that others will go, the marginal effect of going themselves increases with an average of 0.3% (results are not presented in the table: ranging from 0.2% to 0.4%, $p<.001$ throughout all contexts).

4.2 Predictors

A key question is which factors are decisive for choosing to leave the home for recreation in each of these conditions. Table 1 investigates the role of personal characteristics in the choice for recreation per condition using a logit regression. The results show that education plays a key role in the decision to go, despite the regulation. The low education group turns out to be most likely to abide by the rules. The middle-educated category (post-secondary vocational degree, undergraduate education, or higher level of high school) are generally more inclined to go, compared to the low education group (post-secondary vocational education or lower-level high school). The most highly educated respondents (undergraduate degree or higher) indicate an even higher willingness to go. The effect of education is most profound in the low (for middle education the marginal effect is 12.9%, z=2.43, p=.015; for high education the marginal effect is 17.9%, z=3.29, p=.001) and high context conditions (middle: 10.6%, z=2.41, p=.016 and high: 11.0%, z=2.51, p=.012, respectively). In the "medium" condition, we find no effect of education.

We also observe an effect for age, but not for gender. The effect for age is negative across all contexts. In the low crowdedness context, both age brackets have a significantly negative marginal effect (-9.7%, z=-2.27, p=.023, and -20.9%, z=-5.12, p<.001, respectively), whereas for all other contexts we observe older respondents (50+) to be less likely to visit the recreation location, compared to the 30 year and younger category. Interestingly, the impact of personal characteristics seems to diminish when the streets are getting busier: in the highly crowded context, both the significance as well as the strength of the effects of education and age decrease as compared to the "low" context.

Table 1 – Logit Regressions: Respondent Characteristics and Decision to Go

Marginal effects resulting from logit regressions

		No context	Low	Medium	High
Education	Middle	1.073	1.129*	1.060	1.106*
		(1.85)	(2.43)	(1.43)	(2.41)
	High	1.095*	1.179**	1.069	1.110*
		(2.27)	(3.29)	(1.61)	(2.51)
	Female	0.984	1.006	0.963	0.995
		(-0.65)	(0.20)	(-1.57)	(-0.20)
Age	31 - 50	0.967	0.903*	0.990	0.991
		(-0.92)	(-2.27)	(-0.29)	(-0.25)
	Above 50	0.907*	0.791***	0.926*	0.919*
		(-2.57)	(-5.12)	(-2.12)	(-2.16)

Risk attitude	General	1.008	0.983	1.004	1.002
		(1.01)	(-1.76)	(0.55)	(0.21)
	Social	0.995	0.997	0.989	0.991
		(-0.70)	(-0.29)	(-1.61)	(-1.22)
	Health	1.016*	1.048***	1.020**	1.023**
		(2.57)	(5.54)	(2.96)	(3.16)
	Chi^2	33.63	70.12	29.26	26.36
	N	964	964	964	964

Note: Education is relative to the baseline category "Lower education" and age is relative to the baseline category "30 years or younger." *z*-statistics in parentheses. Standard errors are clustered at the individual respondent level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The general and social risk attitudes do not have a significant influence on the decision of respondents. The degree to which respondents are willing to take risk with their own health, however, is important throughout all contexts. For each incremental increase of willingness to take risk on this domain, the probability that a respondent will go increases with 1.6% (z=2.57, p=.01) to 4.8% (z=5.54, p<.001) per context. This result implies that the decision to go depends more on respondent's own health considerations than on the fear to contaminate others.

4.3 Additional Explanatory Variables

4.3.1 Similarity and Imaginability

The hypothetical nature of self-reported vignette studies negatively affects their validity compared to actual behavioral measures (this is also referred to as the intention-behavior gap; Sheeran & Webb, 2016). The decision to go and visit a crowded place on a hot summer day will be influenced by the degree to which each respondent in our sample can relate to this specific scenario. For instance, a person living in a city center without a garden will likely better understand the motivation to go out of the house as compared to a person living in a rural area with big garden. To test whether these location-dependent characteristics influence the decision to go, we measure two additional indicators: level of similarity (e.g., to what extent the situation mimics their own situation) and the level of imaginability (e.g., to what extent are respondents able to imagine being in such a situation). For a summary of these metrics in our sample, see appendix Table S1.

We find that similarity increases the likelihood of visiting a crowded place. Panel A of Table 2 shows that for each increase on a similarity scale from 1 to 10, the marginal increase of going out ranges between 2.3% and 1.5% depending on the context (no context: z=4.90, p<.001 and high context: z=-3.07, p<.01, respectively). Beyond similarity, imaginability increases the probability of going out in the low context (1.8%, z=2.49, p<.05) and high context (1.2%, z=2.03, p<.05). In sum, both the similarity and imaginability of the situation increases the probability of visiting the recreation area, in most contexts.

Table 2 – Logit Regressions: Location Dependent Characteristics and Decision to Go

		No context	Low	Medium	High
Panel A					
Relatability	Similar	1.024***	1.019**	1.023***	1.015**
		(5.25)	(3.22)	(4.90)	(3.07)
	Imaginable	1.004	1.018*	0.999	1.012*
		(0.80)	(2.49)	(-0.19)	(2.03)
	Chi^2	33.63	70.12	29.26	26.36
	Controls	Yes	Yes	Yes	Yes
	N	964	964	964	964
Panel B					
COVID-19 exposure	Reported Cases	1.023	1.076	1.072	1.035
		(0.61)	(1.51)	(1.80)	(0.80)
	Hospital admissions	0.973	0.972	0.948	0.963
		(-0.79)	(-0.63)	(-1.51)	(-0.96)
	Deceased	1.010	0.968	0.997	1.012
		(0.43)	(-1.10)	(-0.13)	(0.46)
	Chi^2	32.26	62.90	29.09	28.19
	Controls	Yes	Yes	Yes	Yes
	N	840	840	840	840

Note: Panel A shows the marginal effect of the reliability measures on the decision to go. Panel B shows the marginal effect of COVID-19 different exposure indicators, using postal codes, on the decision to go. The measures are per 100 inhabitants, and transformed to natural logarithm due to a highly skewed distribution. Note that sample B consist of a smaller sample due to missing values in the COVID-19 database. Both panels are controlling for all personal characteristics presented in Table 1: education, gender, age, and risk attitude. z-statistics in parentheses. Standard errors are clustered at the individual respondent level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3.2 COVID-19 exposure

To generalize our results to other situations, and to show that policy and context drive the behavioral intensions that we observe, we assess the impact of COVID-19 exposure on the decision of our respondents to go. It is plausible that the survey participants experience the context we present to them in the light of their own experience of the COVID-19 threat. In order to investigate the influence of other variables on our findings, we match all individual respondents to COVID-19 metrics that are publicly available through the Dutch Ministry of Public Health, using respondent postal codes (RIVM, 2020). Specifically, we standardize reported COVID-19 cases, hospital admissions, and COVID-19-related deaths such that for each postal code the value shows the ratio per 100 inhabitants. After transformation to natural logarithm, Panel B of Table 2 shows no effects of local COVID-19 metrics on the decision to go, for any context.

Taken together, we added both COVID-19 measures as well as the similarity and imaginability measures as controls in the main regression in Table 1 (see S2 Table). We observe only minor significance changes and no noteworthy changes in interpretation or direction of our previously discussed main results.

5. Conclusion

Public health policies to contain COVID-19 infections are under heavy scrutiny. An important pillar of public policies in almost any country is the recommendation to “avoid crowded places.” This appears to be a straightforward message, but in reality, it is not, since it inevitably introduces considerations of other people’s expected actions in citizens’ own decision-making process. Although the results in this paper suggest that the majority of citizens adhere to the policy recommendation, the results also suggest that people are implicitly forced to make a correct estimation of the situation outside. This is not trivial to each individual. The results not only show that a vast majority of respondents is unable to make an accurate estimation about others’ behavior, but also that a wrong estimation could lead to a worsened outcome.

Providing information regarding the situation outside initially leads to a rational choice (e.g., when it is calm, the majority intends to go, and when it is reportedly getting crowded, more respondents intend to stay home). However, once people know that it gets even more crowded outside, respondents indicate a greater willingness to go out again, possibly leading to an escalation in crowdedness. These observations seem to indicate behavior contamination (Huremović, 2019): the stronger the expectation that others will go, the more likely it is that people will go themselves (Keizer et al., 2008). Our results suggest this explicit violation of the public health regulation is more likely a result of using social cues for ambiguity management than a bad-apple effect. Comparing the behavioral trend from the “low” to the “high” context, we see that moving to more ambiguity (medium crowdedness context) leads to fewer people going (e.g., providing no context is almost identical to the medium context, strengthening the ambiguous interpretation of the medium context). Since we do not observe a linear increase in violation over intensifying crowdedness contexts, but a parabolic relation, we believe it is likely that we witness the social context as informative to behavior, instead of provoking “violating” behavior.

The heterogeneous effects of education on the low and high context suggests that educational background is more important in the rational or strategic (low context) decision, than in the escalation (high context). Thus, we conclude that in the low context situation, highly educated people act strategically and in the medium context the social norm is leading in coping with the ambiguity. In the high context, social norms lead to escalation. The context that is given to people in their decision-making process is thus detrimental, but does not have a uniformly positive effect. Additional relevant factors such as willingness to take risk with one's own health and the similarity to one's own situation all increase the likelihood to visit crowded places.

It is also evident that people underreact to the behavior of others. In general, we observe incorrect pessimism about other people's behavior: across all conditions, people expect far more people to go than the collective intention to do so. However, individuals also underestimate the effect context has on others, even when it has a profound effect on our own behavior. In other words: when the context influences people to go, people underestimate the increase in crowdedness as a result of other people making the same judgement due to the same change in context. This causes an escalation in the "low" context: Although the crowdedness context signals a quiet situation at the location of recreation, people do not take into consideration that the majority will come to the same conclusion. As such, our findings result in the somewhat paradoxical prediction that it will be busiest in the low crowdedness context.

6. Limitations

We strive to identify how the current (Dutch) COVID-19 policy recommendations, combined with limited information availability, influences behavior of individuals. In doing so, we intentionally strike a balance between a rigid experimentally controlled design, and elicitation of real-life ambiguity that closely reflects the current situation that individuals find themselves in. Loosening the experimental controls often comes at the cost of increasing the likelihood of omitted variables. Below, we discuss three main limitations of this study.

First, to achieve real-life ambiguity, our experiment is intentionally ambiguous in two dimensions: the location of recreation and the level of crowdedness. The first ambiguity increases the probability that the participant empathizes with the hypothetical situation. Specifying the location would surely have increased uniformity in believes about the expectations of crowdedness, travelling factors, or density of the location (e.g., how crowed is a beach compared to a forest or city center?). We acknowledge that omitted variables directly related to the preferred location might influencing the decision. However, keeping the location as a general category increases the likelihood that participants are able to envision themselves in this hypothetical location, regardless of their personal preference. This means our results can be generalized. Indeed, respondents in the sample their ability to envision themselves in this situation (average imaginability score of more than 6 out of 10), even though respondents might not necessarily be in this situation (average similarity score is only 4 out of 10). The second ambiguity is on the degree of "crowdedness." This is not stated as an objective measure, but as a subjective experience that depends on the interpretation of the participant. For example, "the streets are slowly getting busier" aims to elicit a general tendency of increasing crowdedness in the community, but could be influenced by the literal interpretation of what the individual considers "the streets" as well as "getting busier." Moreover, we consider these conditions to be at least ordinal in our interpretation, but the proportional distance between these levels can only be assumed. We are therefore unable to exclude that, in both dimensions, the interpretation of the ambiguity may lead to other reasoning and thus other behavior than we anticipate. However, note that these ambiguities are present in real-life decisions as well. We argue that the value of generalizability (at least partially) compensates for these potential omitted influences.

Second, we take a wide variety of individual factors and traits into consideration, but must acknowledge that additional personal traits might matter as well. Although we include risk aversion (in multiple relevant domains), demographic differences, and personal exposure to COVID-19 in our analysis, we do not include personality traits. Moreover, we expect that people with a garden (or perhaps even a balcony) might find the need to recreate outdoors significantly less acute as compared to (large) families in apartments without such amenities. We specifically ask the respondents to consider a situation in which the area of recreation is the only available means of recreation, but we cannot exclude the possibility that other individual differences influence our results.

Finally, we frame our experiment as a one-shot game even though in real-life, people are able to update their information. Information about traffic jams, live news coverage of popular spots, and even witnessing crowdedness themselves once they are on the road will potentially change behavior. For some people, this information will influence their decision on the day itself, for others their commitment to their initial decision will be less easily swayed. However, we note that we do not argue that our key take-away is that all popular locations will inevitably end up crowded due to the ambiguous policy. The main result of our paper is that this policy combined with no clear and updated information of the behavior of other participants (e.g., state of the recreation spot) leads to an unintended suboptimal group decision following an (seemingly) optimal individual decision. Without correct information or information updating, this could lead to an escalation of crowdedness.

7. Implications

The COVID-19 pandemic demands significant self-control from society to stay home. The recommendation to avoid crowded places creates a sense of freedom and offers the possibility to act dynamically given the circumstances. The definition of this policy advice, however, also offers freedom in interpretation. Consequently, the freedom is implicitly asking more from the population than it initially seems. “Use your common sense” is often the accompanied advice, but our results show that more and better information concerning the context is essential to make an optimal decision.

The results of this research are not predominately pessimistic. Besides the fact that the majority of respondents indicates to stay home, we also identify a strong inclination to avoid crowded places. Only after feeling that nobody stays home any longer are people legitimizing their own violation of the recommendation. Furthermore, the existing pessimism that society has regarding the behavior of others could lead to an escalation of the situation. Providing up-to-date information could be detrimental for an accurate estimation of the situation. This information could reinforce and stimulate positive behavior. Both going out as well as staying at home are rational and ethical choices.

It is, however, the relevant context that determines whether going or staying leads to a rational decision, or escalation. Without this information, the outcome of a decision will remain uncertain.

Additionally, discouraging unwanted behavior should be tailored to the individuals that are more inclined to ignore the policy recommendation. Young as well as highly educated people are less sensitive to policy recommendations in the calmer contexts, and should thus be discouraged accordingly. They draw valid conclusions, but do not seem to be aware of the potential harmful consequence when a large part of society independently reasons in the same way. Here too, facilitating relevant information could offer a solution, and avoid escalation.

Finally, the risk profile of each individual could offer a potential policy approach. Finding that the risk attitude regarding citizens' own health plays a key role in their decision to go or stay home, suggests that campaigns emphasizing and educating people about their own health risk could improve the collective behavior of society.

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1. Supporting Information

S1 Table – Summary Statistics

Summary Statistics

		Mean	SD	Minimum	Maximum
Personal Characteristics	Education Category	2.46	.63	1	3
	Male	42%			
	Age Category	2.18	.74	1	3
	Age	43.78	12.53	18	67
Risk Attitude	General	5.09	1.92	1	10
	Social	5.23	1.95	1	10
	Health	3.87	2.02	1	9
Relatability	Similar	4.06	2.64	1	10
	Imaginable	6.28	2.55	1	10
COVID-19 exposure	Reported Cases	.0004188	.0005787	0	.0041598
	Hospital admissions	.000108	.0001425	0	.001125
	Deceased	.0000516	.0000736	0	.0005043
	N	927			

Note: Age categories are coded as 1 (18-30), 2 (31-50), and 3 (50+). Risk attitude is measure on a 11-point scale. For Health, a maximum risk score of 10 is never given. Relatability is measured on a 10-point scale. COVID-19 exposure measures are absolute values per 100 inhabitants. In our statistical analysis, these metrics are transformed logarithmically.

S2 Table – Statistics on the expectations of others' going

Predicted Ratios of others' going

		Total	I will go	I will not go	*p*-value
Stay at Home	No context	42.31	40.92	53.61	.00***
		(20.85)	(20.51)	(20.21)	
Avoid crowded Places	No context	52.54	50.89	61.32	.00***
		(19.93)	(19.78)	(18.41)	
	Low	49.90	46.93	57.58	.00***
		(22.25)	(21.08)	(23.34)	
	Medium	49.44	48.40	55.19	.00***
		(20.55)	(20.05)	(22.29)	
	High	52.38	50.57	60.03	.00***
		(21.79)	(21.26)	(22.38)	
	N	1048			

Note: First column shows the overall average predicted percentage of other's going. The latter columns show the same statistic, split depending on the participants going themselves ("I will go") versus staying home ("I will not go"). The size of these subgroups fluctuates per condition and context. Standard deviation in brackets. P-value based on non-parametric ranksum test. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

S2 Table – Fully Integrated logit regression: Personal and Location Dependent Characteristics and Decision to Go

Integrated Model: Marginal effects resulting from logit regressions

		No context	Low	Medium	High
Education	Middle	1.072*	1.126*	1.063	1.105*
		(1.88)	(2.23)	(1.47)	(2.30)
	High	1.084*	1.160**	1.056	1.096*
		(2.13)	(2.85)	(1.32)	(2.19)
	Female	1.002	1.024	0.975	1.013
		(0.09)	(0.70)	(-1.03)	(0.46)
Age	31 - 50	0.983	0.926	1.006	1.020
		(-0.44)	(-1.58)	(0.17)	(0.53)
	Above 50	0.922*	0.812***	0.938	0.945
		(-2.06)	(-4.23)	(-1.73)	(-1.47)
Risk Attitude	General	1.004	0.981	1.003	0.999
		(0.45)	(-1.81)	(0.35)	(-0.10)
	Social	0.996	0.996	0.989	0.988
		(-0.62)	(-0.49)	(-1.51)	(-1.58)
	Health	1.015*	1.044***	1.015*	1.023**
		(2.33)	(4.85)	(2.37)	(3.14)
Relatability	Similar	1.024***	1.017**	1.023***	1.016**
		(4.90)	(2.63)	(4.70)	(3.00)
	Imaginable	1.002	1.014	0.998	1.010
		(0.39)	(1.84)	(-0.35)	(1.56)

COVID-19 exposure	Reported Cases	1.023	1.074	1.072	1.032
		(0.64)	(1.47)	(1.85)	(0.75)
	Hospital admissions	0.984	0.977	0.957	0.970
		(-0.51)	(-0.52)	(-1.28)	(-0.79)
	Deceased	1.005	0.968	0.992	1.010
		(0.24)	(-1.10)	(-0.33)	(0.40)
	Chi^2	62.22	69.83	50.10	41.58
	N	840	840	840	840

Note: Education is relative to the baseline category 'Lower education' and age is relative to the baseline category '30 years or younger'. All COVID-19 exposure measures are stated per 100 inhabitants, and transformed to natural logarithm due to the skewed nature of the distributions. The sample is smaller compared to table 2 due to missing values in the COVID-19 exposure data. *z*-statistics in parentheses. Standard errors are clustered at the individual respondent level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$