Managing the meaning of data in public health: from maths to cues to action.

Cristina Oliva

KINGSTON BUSINESS SCHOOL
Kingston University
Kingston Hill, Kingston upon Thames KT2 7LB

Cristina Oliva
c.oliva@kingston.ac.uk

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"Data
are just summaries
of thousands of stories.
Tell a few of those stories
to help make the data meaningful."

Dan Heath
"Made to stick"

Acknowledgements.

I would like to take this opportunity to heartily thank my supervisors. Dr Emmanouil Noikokyris and Prof Giampiero Favato, for their continuous encouragement over the years. They unreservedly supported my desire to make sense of scientific data to change people's behaviours during unprecedented times of public health crisis.

I am also grateful to my loving family: my doctoral journey was longer than anticipated, taking away from them time and attention.

I promise I will make up for it.

Reading, Berkshire.
July 22nd, 2024.

Cristina Oliva

Table of contents

Introduction to my doctoral research journey.

My doctoral research journey has not been linear, but I am unsurprised.

I am a trained medical oncologist who has been passionately dedicated to clinical research throughout my life. I have contributed to developing several innovative medicines for various conditions, each with distinct mechanisms of action.

After all these years, I firmly believe that drug development is a blend of resilience and science. It demands intricate attention to detail, creativity, and the courage to change direction when the "right" information becomes available.

My doctoral journey was not different.

My initial research idea was to model the uncertainty correlated to the clinical development of innovative treatments using a possibilistic rather than probabilistic algorithm. The model used fuzzy math, a generalisation of real numbers. The fascinating side of this research was the possibility of communicating challenging maths by way of an intuitive visualisation: a simple triangle.

The emergency of the global COVID-19 pandemic prompted a necessary redirection of my research activities. Maintaining the primary focus on the value of innovation in life science, I turned my attention to the impact of COVID-19 changes in society and behaviours on the established paradigm of developing new and innovative medicines.

I contributed to a collaborative consensus paper on the impact of COVID-19 on clinical trials, the primary source of accepted evidence to grant regulatory approval to new medicines. The research discussed how the crisis affected the management of ongoing oncology clinical trials and the planning of future trials. [1]

The inexorable progression of the pandemic brought me back to my medical roots, motivating me to contribute to the identification of the main determinants of COVID-19 mortality in Italy, my country of birth and one of the most severely affected by the pandemic.

We published the first model to identify the elderly living in nursing homes as a primary target for COVID-19 mortality. The study findings indicated that when the force of the infection increases, the timely isolation of elderly and diabetic residents could significantly reduce the death toll in subsequent COVID-19 waves.

We essentially 'drew a face' on the maths. Using the Health Belief Model, we suggested that the 'flatten the curve' narrative does not convey perceived susceptibility and severity adequately because of the identifiable victim effect cognitive bias. Knowing the cumulative number of infections and deaths may fail to encourage people to change their behaviours – but knowing that an elderly relative is at high risk could help individuals make better choices. [2] Reflecting on the controversial impact of policies and news on people's behaviours, I intuitively "saw" a gap in the communication of epidemiological data: from "flatten the curve" to "manage the meaning" of COVID-19 data.

This became the "big idea" which ultimately inspired my research.

NARRATIVE ABSTRACT.

Mathematics took centre stage during the COVID-19 pandemic that decimated jobs, placed millions of vulnerable lives at risk, and posed an existential threat to younger generations.

Social and traditional media platforms reported daily updates about the number of expected pandemic victims. R, the metric used to measure the transmissibility of viruses, became a household term as case numbers doubled rapidly. The government, public, and mass media focused on this number to communicate the pandemic risk.

Never before had mathematics been so intrinsically linked to policymaking.

When governments decided to implement drastic isolation measures, they responded to mathematical models warning of the risk of millions of potential deaths. On the basis of maths, countries endured months-long lockdowns, forcing schools, restaurants, cafés, and non-essential businesses to close their doors.

Public health policies aimed to mitigate the risk of infection from close contact by wearing masks, maintaining social distancing, and staying at least two meters away from others. Both responses required individual action and a change in usual behaviour. However, media reports indicated that many people were not following the recommended guidelines. This prompted governments to introduce stricter measures to enforce compliance and encourage behavioural change.

Simple data visualisation became the primary means of communicating the pandemic's spread to the public. The "flatten the curve" line chart became an instantly recognisable symbol, entering the everyday vocabulary of the pandemic. "Flatten the curve" became the dominant way of communicating that physical distancing, mask-wearing, and other public

health measures would decrease the peak number of cases and prevent the healthcare system from becoming overwhelmed. However, the curve did not effectively communicate the risk of infection to individuals. As a result, it failed to instil a personal sense of urgency to change their behaviours and avoid close contact in response to the viral threat.

Most of us needed a narrative to make sense of our actions.

Maths alone is not compelling enough to expect people to change their behaviour and maintain the desired change in the long term. The framing of risk messages would significantly impact the formation of people's beliefs and subsequent actions.

Our project aimed to "manage the meaning" of public health data so that individuals would choose socially responsible behaviours rather than reluctantly adhering to a set of rules imposed by public authorities.

Translating mathematical variables into cues for action would enhance the impact of public health policies in response to future public health crises.

Keywords*: protective behaviours; COVID-19; median visit time; close contact; exposure risk.*

Key notions.

Close contact:	Being close to someone with COVID-19 for at least 15 minutes within 24 hours.
Risk of exposure:	Degree of crowding x duration of the visit.
Social distancing:	To limit physical closeness and contact with others, especially to avoid catching or transmitting an infectious disease.
Positivism:	A research philosophy recognising only that which can be scientifically verified or capable of logical or mathematical proof.
Constructivism:	Philosophy, which implies that reality is constructed through human interactions.
Utilitarianism:	The doctrine that actions are right if they are useful or for the benefit of a majority.
Health Belief Model:	Cognitive theory asserts that behavioural change interventions are more effective when addressing an individual's perceptions.
Protection Motivation Theory:	This theory explains how persuasive communication influences behaviour.
Cognitive biases:	Errors in judgement that influence human cognition under uncertainty.

"Flattening the curve": A concise way of communicating a significant public health message that physical distancing and other public health measures will reduce the peak number of cases.

Median visit duration time: A new feature of Google Maps reports the median visit duration time for retail premises, such as restaurants, pubs, coffee shops, supermarkets, banks, pharmacies, gas stations and public offices.

SYNTHESIS: TRANSLATING MATHS INTO CUES FOR ACTION.

The context: social distancing to reduce close contact risk of exposure to COVID-19.

COVID-19 primarily spreads through close contact among individuals. When defining what constitutes close contact, two key factors to consider are proximity (being closer to an infected person increases the risk of exposure) and the duration of exposure (spending more time near an infected person increases exposure risk).

According to a generally accepted definition, there is a risk of exposure if someone is less than 6 feet away (equivalent to approximately 1.8 meters) from an infected person (laboratory-confirmed or a clinical diagnosis) for a total of 15 minutes or more over 24 hours. [3] The determination of close contact should generally apply regardless of whether the individuals involved were wearing respiratory personal protective equipment (PPE).

From the definition of close contact, we can determine that an individual's risk of exposure to COVID-19 is calculated by multiplying the level of crowding (the number of people within a 1.8-meter radius, which covers an area of 10.4 square meters) by the duration of the visit (the time spent within that imaginary "circle," expressed as a fraction of 15 minutes):

$$Risk\ of\ Exposure = Crowding\ \left(\frac{people}{10.4\ m^2}\right)\ x\ Visit\ Duration\ \left(\frac{minutes}{15}\right) \qquad [1]$$

Visit duration is positively correlated to the risk of COVID-19 transmission since longer exposure time increases the risk of transmission (for example, time spent in a premise longer than 15 minutes is more likely to result in transmission than two minutes of contact).

Consequently, the close contact risk of COVID-19 transmission is higher on crowded premises where people usually spend over 15 minutes.

Evidence suggests that social distancing, alongside other health measures, significantly reduced disease transmission. [4-6]

Social distancing effectively contains the pandemic spread of an infection, but only if most people adhere to the rules.

In Great Britain, early mobility data showed a drastic drop in transport use since January 2020, suggesting a sense of people's adherence to social distancing rules. However, later data from May 2020 indicated a progressive relaxation of public adherence to social distancing well before the official easing of the measures in summer 2021. [7]

A similar phenomenon was observed on the opposite side of the Atlantic. While many Americans were initially practising social distancing, variations in adherence became evident over time. A study conducted by Stanford University revealed that around 40% of Americans had not followed social distancing guidelines since mid-March 2020. [8]

The emphasis on social distancing incorporates understanding which social interactions are critical, the significance of physical space in these interactions, and the inherent value of distancing itself. Change requires a shared belief that compliance is necessary and that the new behaviour will produce the expected outcome. [9]

Based on evidence of past pandemics, diverse factors influence public compliance during such times. The next chapter will summarise the key themes emerging from an essential review of the literature on individual motivation to adhere to protective behaviours.

LITERATURE REVIEW.

During the COVID-19 pandemic, Public Health authorities have reported a general lack of motivation to follow the recommended social distancing behaviours to protect themselves and others from the virus. [10] Demographic, psychological, and social factors may have played a significant role in influencing the adoption of social distancing behaviours during the pandemic, although it is essential to approach generalisations about these findings with caution.

Age may play a role in adherence, with older individuals more likely to practice social distancing [11], although this is not always a consistent finding. [12] Individuals with higher socio-economic status and educational levels are typically more engaged in social distancing practices. [13]

Psychological aspects, like perceived vulnerability to infection, generally promote compliance with social distancing [14] Increased perception of severity—believing in the severe health risks if infected—also correlates with greater adherence to preventive measures. [15-16] Low-risk perception can lead to the view that stay-at-home directives are extreme or unnecessary. The likelihood of engaging in preventative behaviours also rises if individuals believe in their efficacy, face no barriers to participation, and feel capable of performing them successfully. [17]

In-depth knowledge about the disease, particularly regarding symptoms and social distancing practices, is positively linked to adherence. [18] Lower levels of social responsibility and a focus on self-interest, such as prioritising personal risk over the risk posed to others, have been associated with non-compliance with social distancing measures. [19]

Political beliefs also emerged during the COVID-19 pandemic, as seen in the United States, where political affiliation influenced social distancing behaviours. Supporters of the Republican Government were less likely to adhere to social distancing practices than Democrats, attributed to differing perceptions of virus-associated risk. [20]

Policy analysis of COVID-19 mitigation strategies identifies a complex interplay of variables influencing adherence to social distancing measures.

Public health messaging plays a critical role in promoting and maintaining behaviour changes at the population level. However, there is limited understanding of what makes public health messages effective in communicating health risks and what factors shape the public's reaction to these messages. [21]

The imperative to deliver a more meaningful crisis communication by engaging the public in risk-related decision-making has been one of the key findings of a highly controversial review of the policy responses to COVID-19. [22]

This research seeks to fill this gap: how to translate scientific maths into meaningful cues for action.

At the heart of the problem lie dissonant research paradigms.

A research paradigm can be defined as a "collection of logically held together assumptions, concepts, and propositions that orientates thinking and research." [23] Understanding paradigms as collective beliefs within a specific area of expertise emphasises the core principles that those in a particular research field consider relevant. Furthermore, viewing a paradigm as a representative example of research is based on the idea that paradigms serve as templates for conducting research in a specific domain.

The imminent threat of the COVID-19 pandemic challenged the existing research philosophy paradigm. Biomedical and Social Sciences have faced significant challenges in responding to the COVID-19 Public Health crisis. [24] Dissonant research paradigms contributed knowledge that did not inherently lead to societal impact. [25] Normative interventions aimed to limit the pandemic's spread and consequences presented unique hurdles for health systems, revealing a notable paradox. While an unprecedented amount of scientific data became rapidly available, the efficient translation of this knowledge into public health messaging has proven challenging. Addressing the broader need to carefully explain the meaning and relevance of this scientific data in a way that effectively informs and influences individual behaviours remains compelling. [26]

The advent of the COVID-19 pandemic provided a unique opportunity to operationalise this principle, given the extreme uncertainty evident in both media channels and national community dialogues. [27] The clear communication of the "meaning of data" can proactively counteract the issues of denialism, digital misinformation (fake news), and other manifestations of politically and socially induced ignorance. [28]

Translating divergent research paradigms into effective public health messaging involves bridging gaps between different perspectives, methodologies, and terminologies used in various research fields. The meaning of data, however, is crucial to communicate scientific findings effectively to the general public to promote better understanding and, ultimately, the necessary behavioural changes.

The Positivism Paradigm of Life Sciences.

The main objective of positivist research is to establish causal links or cause-and-effect relationships that eventually predict and manage the phenomena being studied. [29]

Positivism employs the hypothetico-deductive approach to confirm pre-established hypotheses. In life sciences, hypothetico-deductive reasoning involves information from the patient that is gathered and used to construct a hypothesis, which is then tested or a further hypothesis is constructed. The hypotheses should be confirmed by responses to treatment; thus, the process involves repeated reassessment. [30]

Studies grounded in positivist epistemology offered insights into the medical causes of the COVID-19 virus's spread. For example, early research suggested that control measures were needed to block over 60% of transmissions to control the virus's transmission effectively. Additionally, in the absence of specific antiviral treatments or vaccines, controlling the outbreak primarily depends on the timely identification and isolation of symptomatic individuals. [31] On the other hand, when medical findings are not presented in clear and straightforward language, it leaves a portion of the population feeling indifferent or disengaged from these results. The complexity and limitations of case data can be confounding factors in the communication of close contact risk of infection to the general population. [32]

Constructivism of Social Sciences.

Social constructivism implies that knowledge is constructed through human activity, and reality is invented jointly by the members of that society. Individuals create meaning through their interactions with each other and the environment in which they live. [33] Positivism is a philosophical stance that emphasises that knowledge should be gained through observable and measurable facts, whereas constructivism states that reality is a social construct. [34] Unlike positivist approaches, which often rely on quantitative data, constructivism prioritises qualitative insights and the surrounding context. This approach delves into individuals' beliefs, motivations, and behaviours rather than just numbers, aiming for a deeper comprehension of social interactions.[35] Constructivists believe that social constructs such as language, awareness, shared interpretations, and tools shape our understanding of reality. This paradigm emerged in response to the limitations of positivism in the field of social sciences. [36] There can be causal explanations in sociology, but there is no need for a hypothesis before starting research. By stating a hypothesis at the start of the study, researchers risk imposing their views on the data rather than those of the actors being researched. Instead, a grounded theory should allow ideas to emerge as the data is collected, which can later be used to produce a testable hypothesis. [37]

During the COVID-19 pandemic, researchers explored the spread of the COVID-19 virus from a sociological perspective, determining the relationship with religious beliefs, family, parental education [38], social insurance, mental health, life satisfaction, personality traits, and behavioural responses. [39] Studies also highlighted ignored psychological factors during the implementation of COVID-19 control measures, such as the negative impact on relationships among people due to moral distress and their perception of empathy towards others. [40] This showed that even though the control measures led to health advantages, the actions had some unintended consequences from a social perspective. Sequential studies on in-depth analysis tested the impact of fear, denial, and stigma on behaviours and choices. [41-42]

The COVID-19 pandemic highlighted the vital importance of comprehending people's beliefs, social and environmental contexts, and psychological well-being when implementing appropriate and effective public health measures. [43]

Utilitarianism of Public Health interventions.

Public health aims to protect and improve the health of entire populations. Its core purpose is to promote the well-being of as many people as possible by implementing measures and policies that target the broadest groups. Public health takes a utilitarian approach, seeking to maximize benefits and minimize harms for the greatest number of individuals. [44]

From a normative perspective, utilitarianism seems a coherent choice to guide decisions about the appropriate courses of action in Public Health. [45]

Utilitarian approaches are inherently consequentialist, meaning they measure the ethical worth of actions, strategies, or systemic frameworks based solely on their outcomes. Consequentialism does not assess actions based on their inherent attributes or the motives of the individuals performing them. For consequentialists, and by extension, utilitarians, no action is innately right or wrong. Instead, actions are viewed as tools that can vary in effectiveness in promoting positive outcomes. Utilitarianism assesses the ethical significance of actions, policies, procedures, or guidelines based solely on their impact on society's overall utility or well-being. The utilitarian objective of public health policies is to amplify a beneficial outcome, specifically the population's well-being. Thus, public health measures are assessed, at least to some extent, based on their positive and negative impacts on population health. [46]

One of the notable advantages of utilitarianism is its potential to challenge the disproportionate allocation of resources to a select few. [47] However, the reverse side of this merit is that utilitarianism might endorse the marginalisation of minority groups if it augments the utility for the majority. This brings up the apprehension that utilitarian values might inadvertently promote dominance by the majority. This concern has been often referred as “the tyranny of the majority” [48] This argument became particularly evident during nationwide lockdowns when the benefits of isolation for the majority outweighed the difficulties experienced by a minority in seeking care due to the non-availability of public means of transportation and limited healthcare facilities. [49] The challenges of utilitarianism can be mitigated by principlism (also called utilitarianism principlism), a normative ethical framework originally developed to aid practical decision-making in healthcare. This approach strives to circumvent deep-seated disputes within normative ethical theories, which often stall consensus on actions. However, during crises when resources are limited, public health priorities become more prominent. This leads to a noticeable shift towards the utilitarian aspects of principlism, emphasizing outcomes and the greater good. [50]

Bridging the gap: a novel paradigm to turn data into cues for action.

The outbreak of the COVID-19 pandemic has significantly impacted healthcare systems, presenting unforeseen challenges that necessitated the implementation of change management strategies to adapt to the new contextual conditions. During the COVID-19 pandemic, public health practitioners were constantly faced with having to make programmatic decisions with less-than-perfect data. Research methods in Public Health should not be seen in isolation from each other, but include review, synthesis and interpretation of secondary data from multiple sources that bear on the same question to make public health decisions. [51] A combined methodological approach to addressing different facets of a research issue, using different methods which complement each other, is increasingly recommended as a means of establishing the external validity of the research. [52]

Public health research needs to transition from a model grounded in a biomedical model of disease-specific interventions to emphasise changes in the most significant determinants of health: our beliefs and social values. [53]

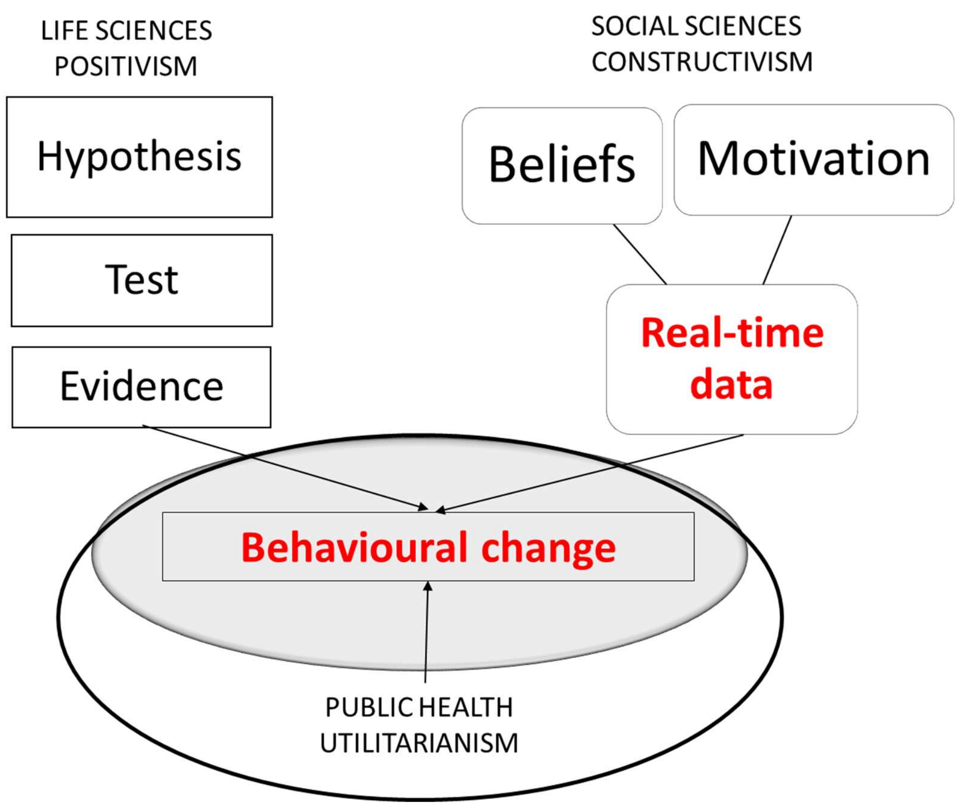
This research identified two main gaps hindering a transformative change in the Public Health research paradigm.

Firstly, there is a pressing need to assimilate a diverse range of existing or emerging data from various sources to offer a more comprehensive policy analysis. This includes data from big datasets collected outside the traditional research paradigm and insights from technological devices and social media channels. Using mobile data would allow flexible navigation through research, journeying in real-time alongside study subjects and accumulating or leveraging data from as many sources as needed. This approach ensures that relevant behavioural shifts are observed and continuously monitored. [54]

Secondly, the gaps in communication and lack of shared understanding became evident during the COVID-19 pandemic. [55] In an era saturated with information, the simplicity of data visualisation became the cornerstone of public communication. The now iconic "flatten the curve" graphical representation underscored the efficacy of preventive measures in curtailing the infection spike. However, this illustration inadequately conveyed the individual-level close contact risk of infection, failing to evoke a responsible behavioural response to maintain personal safety boundaries. [56]

Most of us need a narrative to make sense of our actions. When trying to get people to change and commit to new behaviours, how we present risks matters. It shapes how they think and how they act. New data on the risk of exposure could have been presented to encourage people to act responsibly instead of just following rules they might disagree with. "Managing the meaning of data" translates mathematical projections into clues for action, a new way for Public Health policies "to make sense" for most individuals, improving their adherence to utilitarian behaviours.

FIGURE 1: Gaps in research paradigms: turning real-time data into cues for action.
While Public Health decisions will continue to be grounded in the validity of medical data, this research identified two main gaps hindering a transformative change in its research paradigm: the use of real-time data from mobile and social media sources and the translation of numerical outcomes into cues for action. "Managing the meaning of data" is essential to encourage responsible behaviours and improve adherence to Public Health interventions.



POSITIONING: RESEARCH THEORY AND CONCEPTUAL FRAMEWORK.

Research theory.

Translating scientific data into cues for action and prompting behavioural change is a challenge in public health communication. Several theories help bridge the gap between data and action by offering frameworks to shape message design, delivery, and reception. Presently, over thirty behavioural change psychological theories exist, clustered into five main theoretical perspectives: 1) biomedical, 2) behavioural, 3) communication, 4) cognitive, and 5) self-regulatory. [57] Each perspective encompasses several theories. They complicate the choice of the most suitable theory to underpin a research design. The most commonly used theories are those from the cognitive perspective. [58]

Cognitive perspective.

The cognitive perspective includes theories like the health belief model (HBM), social-cognitive theory (SCT), the theories of reasoned action (TRA), planned behaviour (TPB), and the protection motivation theory (PMT). The core discourse central to these theories is the emphasis on cognitive factors in driving behaviour change. They commonly believe that attitudes, beliefs, and anticipations of future scenarios and results primarily shape health-related behaviours. [59] When presented with multiple choices, these theories suggest that individuals will opt for the behaviour they believe has the highest probability of yielding positive outcomes. The main applications of the Social Perspective Theories are summarised in Table 1 below.

Table 1: Applications of Social Perspective Theories to the COVID-19 pandemic.

Social Perspective Theories	***Application***	***Example***
Health Belief Model (HBM)	Convert scientific data into clear messages about an individual's susceptibility to a disease, its severity, the benefits of preventive action, and the barriers to such action.	If data shows a high risk of close contact risk of COVID-19 in a particular location, messages could emphasise the severity, personal risk, and benefits of social distancing.
Theory of Planned Behaviour (TPB) and Theory of Reasoned Action (TRA)	Data shapes attitudes toward behaviours, clarifies subjective norms, and enhances perceived behavioural control.	For promoting hand hygiene, emphasise the positive attitudes of peers, influence perceptions about the social norm, and provide information about easy access to sanitisers.
Social Cognitive Theory (SCT)	Utilise observational learning. Share data through stories or testimonials from relatable figures or peers.	Use influencers or community leaders to demonstrate a desired behaviour, like mask-wearing, and share stories of positive outcomes.
Protection Motivation Theory (PMT)	Use data to motivate protective health behaviours by emphasising both the severity of and personal vulnerability to a health threat and the effectiveness of the recommended protective behaviour.	Translate data on close contact risk of COVID-19 infection into meaningful information about an individual's vulnerability to this risk and the effectiveness of protective behaviours.

Choice of research theory: individual beliefs.

The choice of the primary theory underpinning my research design was mainly motivated by the predictive ability of the models in COVID-19-related behaviours.

A 2022 systematic review of the literature, including 32 studies, provided conclusive evidence of the Health Belief Model predictive ability ($R^2 > 25\%$) in most of the studies included (87.5%). From this, nearly half (43.7%) of the studies, HBM had explained 50% and above variance of

COVID-19-related behaviour and intention. [60] Earlier studies had already provided evidence of the predictive ability of the HBM of COVID-19 protective behaviours. [61-70]

Based on the evidence from the literature related explicitly to the ability to predict COVID-19 protective behaviours, the Health Belief Model was chosen as the primary theory underpinning my research design.

The leading theory: the Health Belief Model.

Drawing extensively from behavioural and psychological theories, a central aspect of the Health Belief Model is that behaviour change interventions are more effective if they address an individual's specific perceptions. The Health Belief Model (HBM) assumes that an individual's behaviour can be predicted through their perceptions across six key variables. [71] Firstly, it suggests that a person is more inclined to engage in healthy behaviours if they perceive themselves as susceptible to an adverse health outcome. Secondly, the model indicates that the greater the perceived severity of this health outcome, the more motivated the person will be to take preventative action. These first two factors deal with the individual's perception of the threat posed by a health issue. Thirdly, the individual must believe that the behaviour will yield significant positive benefits. Fourthly, the model asserts that perceived barriers to adopting preventative behaviour can deter action. Fifthly, it incorporates believing in one's confidence in performing the behaviour effectively. Lastly, the HBM includes a 'cue to action', a factor that triggers the adoption of preventative behaviour, which could stem from various external or internal stimuli.

The HBM has been widely employed to explain the determinants of health-related behaviours, ranging from adherence to preventive measures to acceptance of complex lifestyle changes in the context of chronic illnesses. Several studies have demonstrated its efficacy in predicting behaviours that lead to adherence to positive health changes. [72]

While the Health Belief Model offers a promising framework for research in public health communication, its adoption has been hindered by various theoretical shortcomings. Firstly, each HBM construct's predictive power varies when applied to different health behaviours, raising the issue of the hierarchy of perceptions in explaining the variance of observed behaviours in a specific health context. [73] Concerning the main constructs, perceived benefits and severity were significantly associated with COVID-19-related behaviours (96.7% of the studies), while perceived barriers significantly predicted COVID-19-related behaviours in 64% of the studies included in a systematic review. Perceived susceptibility was the third most frequently significant predictor of COVID-19-related behaviours in 59.4% of the studies. [60]

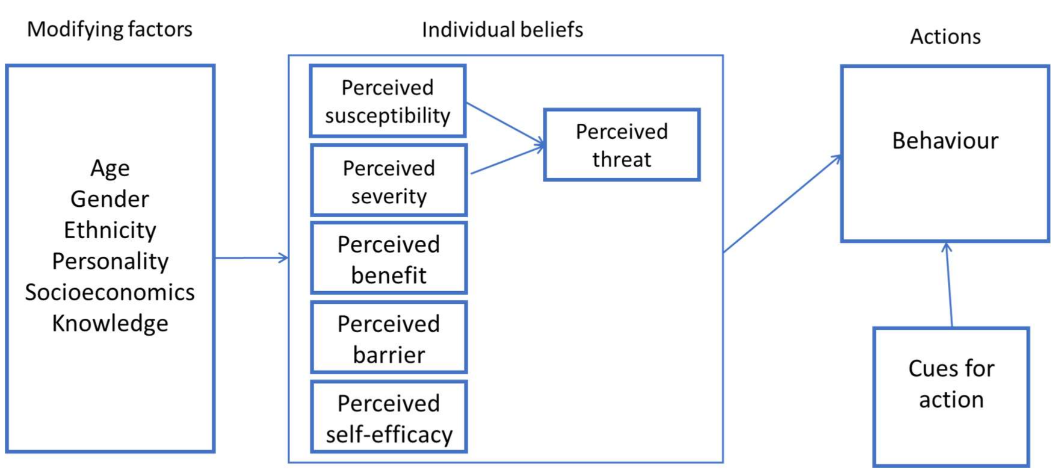
Secondly, the Health Belief Model is based on the value-expectancy theory [73], which draws on rational choice assumptions. A fundamental assumption of the health belief model is that people have choices and are capable of making good health decisions when presented with information. During the pandemic, limited knowledge about COVID-19 has led to heightened anxiety and fears, primarily due to the unfamiliarity and unpredictability of this new health threat. [74] The COVID-19 pandemic has been implicated in several psychological challenges faced by many people. These challenges can arise due to the fear of being infected with COVID-19 and engaging in preventative behaviour. The fear of COVID-19 can impair the individual's ability to make rational choices. [75]

Thirdly, an implicit assumption embedded in the HBM is that individuals universally access identical information about health conditions and process the information in the same way.

[73] Cognitive approaches highlight how limited processing capacity and reliance on mental shortcuts, heuristics, can lead to systematic errors in judgement and decision making. [76] Cognitive biases can shape our understanding, often at an unconscious level, of events such as the COVID-19 pandemic, affecting our response to mitigate the effects of the pandemic. These biases are systematic and predictable errors of judgment affecting human thoughts in situations of uncertainty, such as the COVID-19 pandemic. Facing a crisis, our brain references situations we have already experienced, leading to a belief bias. [77]

The individual HBM constructs are helpful, depending on the health outcome of interest, but for the most effective use of the model, it should be integrated with other models that account for the environmental context of the COVID-19 pandemic.

Figure 2: Conceptual framework of the health belief model (modified from Glanz K, Rimer BK, Viswanath K. Health behaviour, and health education: theory, research, and practice. Hoboken, NJ: John Wiley & Sons, 2008.)



Addressing fear: the Protection Motivation Theory.

The Protection Motivation Theory (PMT) was developed to explain how persuasive communication influences behaviour, focusing specifically on the cognitive processes determining whether individuals will adopt a recommended behaviour.

While many core constructs between the Health Belief Model and PMT are similar, the introduction of PMT aimed to address a main gap in understanding the psychological and cognitive driver of protective behaviour: fear. [78]

PMT examines how fear can motivate people to adopt protective behaviours. It analyses the cognitive processes involved in evaluating threats and coping strategies. According to the theory, people make two key appraisals:

- Threat appraisal: This involves assessing the perceived severity of the threat and one's vulnerability to it. A high-threat appraisal can induce fear.
- Coping appraisal: This involves evaluating the effectiveness of potential coping responses and one's ability to carry them out.

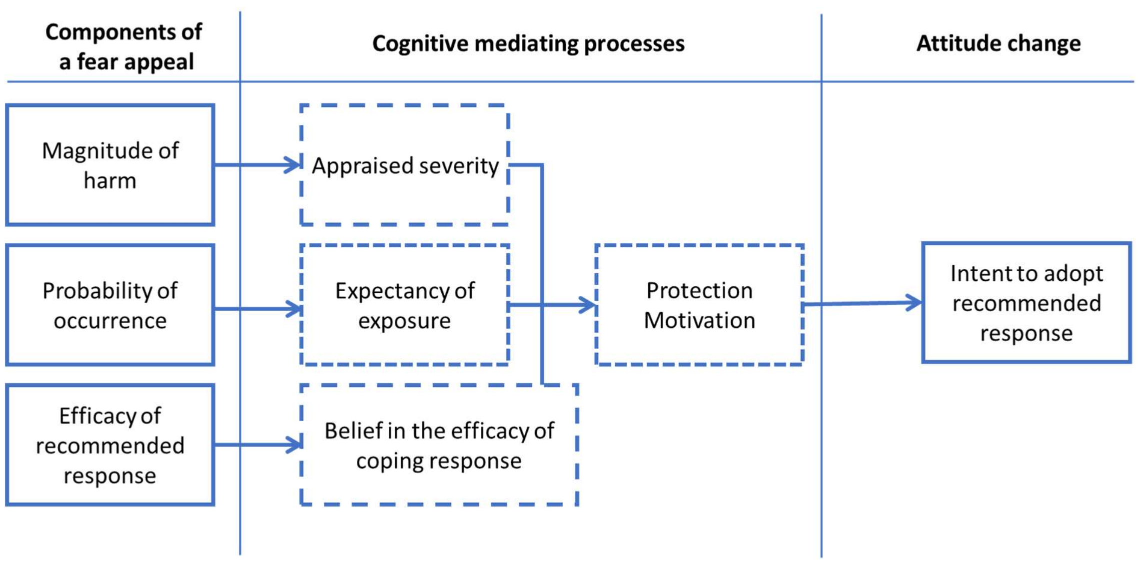
Based on these appraisals, people may exhibit adaptive responses (taking protective actions) or maladaptive responses (ignoring or minimizing the threat). PMT suggests that fear can prompt protective behaviours, especially when the threat is perceived as severe, the person feels vulnerable, and the coping strategies are seen as effective and doable.

Within PMT, the assessment of a threat is based on (1) an individual's perception of the problem's severity (perceived severity), (2) their assessment of the likelihood of being impacted by the condition (perceived vulnerability), and (3) their belief in the benefits of unhealthy behaviours (perceived rewards). Consequently, when perceived severity and vulnerability are elevated, and perceived rewards are minimal, there is a heightened inclination towards adopting health-protective behaviours. [79]

In the PMT model, fear acts as a mediator connecting perceived vulnerability and severity with the appraisal of a threat. Thus, when an individual feels susceptible to a significant health risk, their fear intensifies, enhancing their motivation to engage in preventive or protective actions. In the context of global pandemics like COVID-19, widespread fear and anxiety emerge as people grapple with the absence of definitive treatments. Additionally, the fear stemming from the potential increase in patient morbidity and mortality escalates public concern, often leading to widespread panic, stress, and mental health issues. [80]

Figure 3: Conceptual framework of the Protection Motivation Theory.

Adapted from: Rogers R. W. (1975). A Protection Motivation Theory of Fear Appeals and Attitude Change1. The Journal of psychology, 91(1), 93–114. https://doi.org/10.1080/00223980.1975.9915803



The meaning of data: Cognitive Biases.

When confronted with a crisis, such as the COVID-19 pandemic, our brain recalls previous experiences, resulting in an individual and collective belief bias. This is partly because cognitive biases challenge our logical reasoning [81] and can misguide our choices. These biases represent consistent and foreseeable mistakes in judgment that influence human cognition, especially in uncertain situations like the COVID-19 pandemic.

A viewpoint published in 2020 by the Journal of American Medical Association (JAMA) 2020 acknowledged four primary cognitive mistakes observed during the COVID-19 pandemic. These biases caused a preference for the immediately perceivable rather than the statistical, the current over the forthcoming, and the direct instead of the indirect. [82]

The identifiable victim effect.

Individuals react more intensely to threats to tangible lives, such as those they can easily visualise as their own or those of loved ones, compared to the less immediate "statistical" data presented in reports about the broader impacts of a crisis.

Optimism bias.

Individuals possess a deep-seated, neurally-mediated tendency to anticipate outcomes that are often more favourable than reality. [83] During the early stages of the pandemic, models presented best-case, worst-case, and most likely outcomes, underscoring the inherent risks. [84] A prudent strategy would have focused on minimising fatalities by steering clear of the worst-case scenario. However, due to optimism bias, many acted under the presumption that the best-case scenario was the most probable.

Present bias.

A third factor leading to misdirected policy responses is the presence of human bias toward the immediate, meaning people often favour immediate rewards over greater benefits in the future. [85] This inclination to value the immediate can overshadow the importance of helping those visibly in need today.

Omission bias.

The fourth contributing factor is the widespread prevalence of omission bias. This is the tendency to favour harm occurring due to inaction rather than as a direct result of one's actions. [86] This bias sheds light on why some parents choose not to vaccinate their children, even when they are aware that the risks of harm are higher without vaccination.

Research framework: a conceptual synthesis of relevant theories.

Both HBM and PMT have been successful in predicting protective behaviour. They both have similarities and differences, and they have the potential to complement each other.

Both models are very similar in their main constructs/variables. They both consider the vulnerability of the individual, the severity of possible illness, barriers, and benefits.

The main advantage of HBM is that it explicitly recognises the importance of meaningful communication as a "cue for action", the stimulus needed to trigger the decision-making process to accept a recommended health action or to change a protective behaviour. [87]

PMT deals with fear and irrationality. The important advantage is that PMT specifies clearly what the information needs to contain (threat and advice on how to avoid this danger) to be effective.

Both theories put meaningful communication of data at the core of their constructs. This demonstrates how both theories could complement each other. The flexibility of HBM in having more neutral cues to action, relatively independent health motivation and clear recognition of psychological and demographic variables combined with PMT's acknowledgement of dysfunctional response induced by fear and clear advice on how to frame information could help to overcome some of the disadvantages of individual models. [73]

Cognitive bias bridges the gap between meaningful data communication and cues for action by defining the most likely predictable errors of judgment affecting human thought in situations of uncertainty.

By aligning the key concepts from the three most relevant theories to the COVID-19 pandemic, we can develop a novel conceptual framework robust enough to clearly define the research questions and find appropriate, meaningful answers.

Table 2. Research conceptual framework.

	Theories		
	Health Belief(s)	**Protection Motivation Theory**	**Cognitive Bias**
Beliefs / Constructs / Bias	Perceived severity Perceived benefits	Appraised severity	Present bias
	Perceived barriers	Belief in efficacy of coping response	Omission bias
	Perceived susceptibility	Expectancy of exposure	Optimism bias

RESEARCH QUESTIONS AND DESIGN.

Research questions.

The most prevalent method of sharing mathematical insights on COVID-19's spread was through straightforward visual data. The media frequently utilised line charts to emphasise the significance of health guidelines. The idea of "flattening the curve" was introduced to stress the need to decrease COVID-19 cases and prevent overwhelming healthcare systems. However, the researchers contend that these line charts did not adequately convey the severe infection risk. Consequently, the critical message of maintaining distance to prevent transmission was not effectively communicated to many.

The risk of exposure to COVID-19 infection was a pivotal chance to interpret the significance of the COVID-19 data accurately. The conceptual research framework helped define a meaningful research question at three specific times during the containment of the pandemic when adherence to social distancing was controversial.

The first research question, at the beginning of the pandemic (December 2020).

During the pandemic, the Italian Government introduced 73 legislative acts to curb the spread of the pandemic. [88] These regulations gave individuals a balance between reducing exposure risk and maintaining personal freedoms. Mandates such as maintaining a two-meter distance and avoiding large gatherings became new legal stipulations in daily routines.

Since no current information was available to help people make informed decisions about their activities, this study aimed to make the risk versus benefits' trade-off' more visible by estimating the exposure risk by activity and location in urban areas.

Research questions: *When people are allowed to go out, how can they reduce their close contact risk of exposure to COVID-19? Which activity is riskier? Within the same activity, are there premises where the risk of exposure is lower than others?*

The second research question, at the emergence of the Delta variant (June 2021).

The ancestral form of severe acute respiratory syndrome COVID-19 (SARS-CoV-2) that emerged from China in April 2020 was mainly replaced by the B.1.617.2 mutation or DELTA variant. As of June 2021, it had spread to 74 countries worldwide. [89] The Delta variant became dominant during the second wave of the COVID-19 pandemic due to its competitive advantage, the ability to reduce the close contact risk of infection from minutes to seconds. By reducing the close contact risk from 15 min to 15 seconds, the Delta variant would significantly increase the risk of exposure to COVID-19.

Research question: *Should public health decision-makers change their response to the Delta variant? Should individuals commit to their protective behaviours?*

The third research question: the Green Pass (August 2021).

Under intense epidemiological, economic, and social pressures, Italian policymakers began to consider implementing a domestic COVID-19 pass policy. This policy, known as the "Green Pass," aimed to increase the number of venues accessible to individuals with proof of vaccination or immunity. Therefore, since August 6, 2021, individuals showing their Green Pass would have complete freedom of access to indoor leisure activities such as restaurants, cafeterias, coffee shops, sports events, shows, museums, cultural exhibitions, swimming pools, gyms, and recreational facilities.

The Green Pass domestic policy rests on a single epidemiological premise: individuals vaccinated or previously infected with COVID-19 who produce antibodies to the virus will then be immune to re-infection (at least for some nontrivial time). Under this epidemiological condition, limiting access to public premises for Green Pass holders would create a sort of safe "immunity bubble" where the close contact risk of getting infected by COVID-19 would be virtually equal to zero. The Green Pass would implicitly signal the community that the certificate holders and others would be safe around them.

Third research question: *Did the perceived "immunity" against COVID-19 risk of exposure reduce risk-mitigating behaviours (ex-ante moral hazard)?*

The following Table illustrates the link between theoretical constructs and research questions.

Table 3: Link between beliefs, relevant theories and research questions.

	Theories			Research questions
	Health Belief(s)	**Protection Motivation Theory**	**Cognitive Bias**	
Beliefs / Constructs / Bias	Perceived severity Perceived benefits	Appraised severity	Present bias	When people are allowed to go out, how can they reduce their close contact risk of exposure to COVID-19?
	Perceived barriers	Belief in the efficacy of coping response	Omission bias	Should public health decision-makers change their response to the Delta variant? Should individuals commit to their protective behaviours?
	Perceived susceptibility	Expectancy of exposure	Optimism bias	Does a perceived "immunity" against COVID-19 risk of exposure reduce risk-mitigating behaviours (ex-ante moral hazard)?

Research design

New real-time data to inform the research.

Mobility data: a source of real-time information.

The widespread adoption of mobile phones has generated substantial volumes of human behavioural data, now acknowledged as a valuable resource for understanding population movements. This data holds significant potential to create an important social innovation. Technology is no longer viewed as just a functional tool but a powerful force for social and cultural change in public health. Mobile devices and broadband access enable faster, more personalised access to information, and help shift the focus from traditional, provider/led models toward patient empowerment and preventative care. [90]

Two common forms of mobility data derived from mobile devices are operator and crowdsourced data. Cellular service providers collect operator data through regular device connections to nearby cell towers or when calls, messages, or emails are transmitted. In contrast, crowdsourced data is obtained from the geographic information of mobile devices receiving GPS signals and is collected through participating applications when users activate location services. Crowdsourced data collection is a participatory method of building a dataset with the help of a large group of people.

Both types support similar population-level analyses, including the examination of general movement trends, connectivity analysis quantifying inter-community mobility, and points of interest analysis highlighting activity patterns related to specific locations, such as visits to grocery stores or hospitals.

Despite their analytical similarities, the geospatial precision of location information provided by crowdsourced and operator data differs, imposing certain limitations on analysis. Crowdsourced data employs geographic coordinates to pinpoint device locations within a sample. Complex aggregation techniques allow de-identified but specific location data points in crowdsourced data to reveal changes in regional movement trends and patterns. Operator data, on the other hand, relies on the density of cell towers, which varies by geographic location (urban centres typically have more densely distributed towers compared to rural and remote areas).

Data from mobile devices offer nearly real-time information, a valuable resource for decision-making purposes amid public health crises. Crowdsourced data typically exhibits a delay of approximately one week to allow for processing, whereas operator data becomes accessible the following day. The ability to obtain a nearly real-time depiction of the present situation enables public health authorities to proactively prepare and respond promptly to an infectious disease outbreak.

Crowdsourced and operator data have their advantages in the realm of mobile data, and the choice between them often depends on specific use cases and objectives.

The collection of crowdsourced data relies on GPS signals and latitude-longitude coordinates, which can pinpoint a device's location more accurately than operator data, which relies on cell tower density.

Crowdsourced data can often be accessed in real-time or with minimal delay, making it valuable for applications that require up-to-the-minute information. This is particularly important in situations like tracking the spread of infectious diseases or monitoring live events.

Data collected from crowd sources can provide fine-grained insights into user behaviour and preferences, allowing for a more comprehensive understanding of user behaviour and movement patterns.

Collected crowd data undergoes de-identification and aggregation processes to protect user privacy. This can make it more appealing from a data privacy perspective, as it minimises the risk of exposing individuals' sensitive information. Aggregate and anonymised data at source are publicly available via apps, simplifying data collection and allowing the option to share the dataset of mobility data.

Data collection can be easily scaled up to cover large geographic areas or accommodate a higher volume of data, making it suitable for studies that require extensive coverage.

Examining these benefits within the context of Public Health ultimately influenced the decision to utilise crowdsourced mobility data to inform the research. Public availability in real-time and de-identification at source played a significant role in the choice of source of primary data.

Data of interest: visit duration data.

Google introduced a new feature in October 2020 on Google Maps that enables the collection of visit duration data for individual retail establishments. However, this data is made available only for stores that meet specific criteria related to their daily customer traffic.

This feature essentially reveals how long customers typically spend in a particular store. It calculates visit duration based on customer visit patterns observed over the preceding weeks, and it is presented in units of time, specifically in minutes.

Obtaining Google Maps visit duration data involves a blend of various sources and methodologies, incorporating location-based services, mobile applications, and GPS technology.

With the user's consent, Google Maps uses location-tracking technology on mobile devices. When users enable location services on their devices and use Google Maps or other apps with location-based features, the app collects information about the device's geographic coordinates over time.

GPS signals from satellites to pinpoint a device's location with high accuracy. Additionally, it can use nearby Wi-Fi networks and cell towers to enhance location accuracy, especially in urban areas where GPS signals may be less reliable.

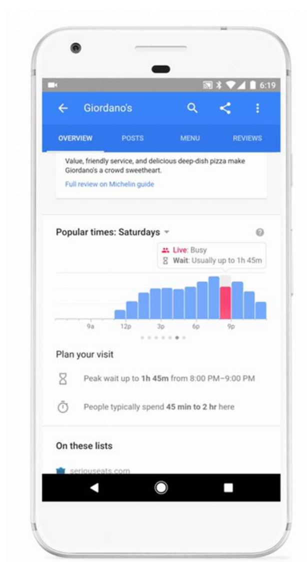
When users navigate to a destination, the app records the start and end points and the trip's estimated duration.

Google aggregates and anonymises location data to protect user privacy. Personal identifiers are removed from the data and grouped or summarised to provide insights without revealing individual users' identities.

Machine learning algorithms are employed to analyse the collected data. These algorithms can identify patterns, traffic conditions, and average visit durations at specific locations.

Google can collect data from users who opt-in to contribute location information. This data may include information about visit durations at specific points of interest, restaurants, stores, and more. Users can voluntarily rate and review locations, adding information about their experiences, including visit duration. Users can control their location settings and choose to turn off location services or customise app permissions to limit data collection.

Figure 4: Screenshot of Google Maps' visit duration time by premise.



Internal and external validity of visit duration time data.

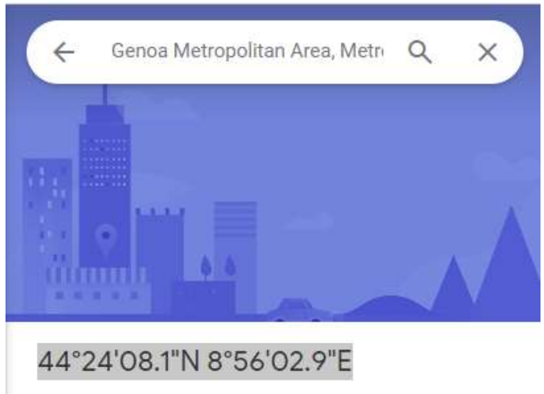
Introducing new primary data sources, such as Google Maps' visit duration, raises two substantial inquiries regarding the validity of the research design. Firstly, regarding internal validity, the question arises about how accurately the observed outcomes reflect the reality within the population under study. Once the study's internal validity is established, the focus shifts to external validity, prompting us to inquire whether the findings apply to comparable individuals in a different context or setting.

The selection of the metropolitan area of Genoa as the geospatial location for this research contributed to minimising the risk of potential bias.

Concerning internal validity, the first issue is the geospatial comparability of visit duration data. Google recommends the use of "geospatial anchors" to position real-world data. A "geospatial anchor" enables to integrate data precisely by latitude, longitude and altitude. Consequently, visit duration data should be collected from a precisely defined location.

In the research design of the studies included in the submission, data were manually collected from all the retail activities resident in the Genoa metropolitan area, which were visible on Google Maps and reported visit duration time. Google identifies the metropolitan area of Genoa with the anchor: 44°24'08.1 "N 8°56'02.9 "E.

Figure 5: Screenshot of the Google Maps' geolocation anchor coordinates for the Genoa Metropolitan Area.



This methodological decision aligned with Google's advice to refrain from cross-regional comparisons due to potential discrepancies in the data, which could lead to misleading conclusions.

Analysing mobility data in urban areas necessitates a comprehensive grasp of the urban layout and road infrastructure specific to the chosen location. My background drove the selection of this specific location, as I was born and raised in the metropolitan area of Genoa.

Secondly, the research design must grapple with the challenge of crowding, one of the two primary factors influencing the risk of close contact, alongside visit duration time. Attempting to precisely count the number of individuals within a 10.4 square meter area (roughly equivalent to the area of a circle with a 6-foot radius) around you at any given moment is a near-impossible task. However, estimating the maximum number of people, one should anticipate being in proximity to any public office or retail establishment is feasible.

In Italy, maximum crowding standards are governed by regulations outlined in the UNI10339 norm. This norm establishes the maximum permissible number of individuals for design considerations, specifying limits for each square meter of floor area across various categories of public offices and retail establishments. A maximum crowding standard was established for commercial establishments to ensure the resumption of activities following the initial lockdown phase, allowing for 13.3 square meters per person (for instance, a 40 square meter room can accommodate up to three individuals). In May 2020, the National Institute for Occupational Accident Insurance (INAIL) issued a technical document about coffee shops and restaurants, establishing a maximum crowding standard of 4 square meters per person. There have been no alterations to the crowding standards since the issuance of the Prime Ministerial Decree addressing COVID-19 risk mitigation in April 2020. Consequently, equation [1] can be rewritten as [2], the product of a constant (Kc) and a single variable (visit duration):

$$Risk\ of\ Exposure = Kc\ x\ Visit\ Duration \qquad [2]$$

Lastly, the decision regarding visit duration as the primary data source or geospatial location did not significantly impact the external validity of the research design. The research's primary objective was not to generalise visit duration within the metropolitan area of Genoa to the broader population.

Instead, the research aimed to discover an intuitive, numerical method to effectively convey the risk of exposure when going out, thus aiding policymakers in communicating the importance of implementing stringent containment measures to curb the spread of COVID-19. These measures were imposed as mandatory regulations for the general populace, often without a transparent explanation of why these restrictions were necessary preventive actions rather than arbitrary infringements on personal freedoms. The ultimate goal was to translate mathematical data into actionable insights, allowing everyone to comprehend the potential risks associated with leaving their homes and to make informed decisions regarding daily activities within their community. In this context, replicating the local observations would enhance the meaningfulness of communicating the risk of close contact, ultimately influencing individual behaviours.

Materials and Method.

Primary data: visit duration data.

Visit duration data were collected from all the retail activities located in the Genoa metropolitan area, which were visible in Google Maps and reported visit duration time. Google does not report visit duration for those activities which do not generate a reliable number of daily mobility data. The sample was then aggregated into defined premises, including:

- Pubs
- Pizza restaurants
- Fine-dining restaurants
- Gyms
- Hair salons
- Fast-food restaurants
- Food supermarkets
- Shopping centres
- Retail shops (non-food)
- Coffee shops
- Banks
- Pharmacies
- Post offices
- Gas stations

Data on visit duration by store were non-random since we did not use a sample and were non-normally distributed. Consequently, the median visit duration by activity was calculated. The choice of median values is consistent with Google's method to calculate mobility data changes across different categories of places. [91]

Research method.

The three studies estimated the risk of exposure to COVID-19 by location and activity in crowded metropolitan areas. The risk of exposure to COVID-19 was defined as the product of crowding (people within a six-foot distance) and exposure duration (fraction of 15 min).

The three studies followed the **epidemiological investigation method**, collecting and analysing data of interest (visit duration time) to determine whether a significant difference may exist between exposures in different premises. [92] The manuscripts were prepared in adherence to the STROBE (STrengthening the Reporting of OBservational studies in Epidemiology) reporting guidelines.[93]

Data availability and originality.

All data supporting the findings of the publications included in this thesis are available within the published articles and/or their supplementary materials online.

All articles were published under a Creative Commons Attribution (CC BY) license and the entire database was made freely available online immediately upon publication as Open Access.

No financial support was received for the research, authorship, and/or publication of the articles.

No part of the articles or the thesis has been generated by an AI model: all ideas and contents are original and generated by a human author.

AI-powered assistants, such as Grammarly® or Microsoft Copilot®, were used to correct spelling and grammar errors and to improve the clarity, conciseness, and overall readability of the submitted thesis.

HIGHLIGHTS OF THE ESSAYS.

Summary.

Study one.

Title:

Risk of exposure to COVID-19: visit duration data can inform our daily activities choices.

An epidemiological investigation using community mobility data from the metropolitan area of Genoa, Italy.

Authors:

Cristina Oliva and Giampiero Favato

Citation:

Oliva, C., & Favato, G. (2021). Risk of Exposure to COVID-19: Visit Duration Data Can Inform Our Daily Activities Choices: An Epidemiological Investigation Using Community Mobility Data from the Metropolitan Area of Genoa, Italy. International journal of environmental research and public health, 18(9), 4632. https://doi.org/10.3390/ijerph18094632

Research questions:

- When people are allowed to go out, how can they reduce their risk of exposure to COVID-19?
- Which activity is riskier?
- Within the same activity, are there premises where the risk of exposure is lower than others?

Methodology and data:

An epidemiological investigation used the newly available mobility data to estimate the risk of exposure to COVID-19 in crowded retail premises of Genoa's metropolitan area (Italy).

Aggregated and anonymised visit duration data (n=561) were manually collected from Google Maps and then categorised into 14 everyday activities, from grocery shopping to post office visits. The entire study sample can be found in the online Supplementary Material at: https://www.mdpi.com/article/10.3390/ijerph18094632/s1.

Median visit duration informed the estimation of the close contact risk of exposure to COVID-19 by type of activity.

Synthesis of the results:

The relative risk of exposure (lowest absolute risk = 1) revealed a significant variation in the risk of COVID-19 exposure based on the chosen activity and the duration spent at a retail location:

1. HIGH RISK (minimum relative risk > 10): fine-dining restaurants, pizza places, pubs and gyms.

2. MEDIUM RISK (minimum relative risk >5, but likely to exceed the threshold of HIGH RISK based on the duration of the visit): fast-food restaurants, coffee shops, hair salons, and shopping centres.

3. LOW RISK (relative risk always <5): retail shops (non-food), grocery supermarkets, pharmacies, banks, post offices and gas stations (lowest risk observed = 1).

Main contributions of the study:

The primary methodological challenge was measuring the time component of close contact risk of exposure: how long do individuals spend in a particular store or location within a specific community? For the first time, the study used primary data, the median visit duration, a novel feature of Google Maps, to assess the risk of COVID-19 exposure during various daily activities in a specific location: the metropolitan area of Genoa, Italy.

By making the full dataset available, other researchers could verify the results and replicate the analysis, strengthening the validity of the conclusions.

This study's main contribution is defining a single number to indicate the relative risk of exposure to COVID-19 for most of the activities we need to perform daily. Additionally, for a given activity, it enables us to select locations within our community that present a reduced exposure risk. For instance, if you plan to visit the post office, Google Maps can assist in picking a location with the briefest average visit duration. Using publicly accessible visit duration data, the study offers a straightforward method to guide personal decisions about going out. By simply steering clear of or limiting time in crowded premises, the close contact risk of COVID-19 infection can be mitigated.

Google's visit duration data is accessible for locations near anyone, regardless of the observer's geolocation. This characteristic enhances the data's relevancy and trustworthiness, potentially improving individual adherence to protective behaviours. Risk data by location can help us rethink our daily routine and make informed, responsible choices when we decide to go out.

The intuitive numerical format adopted to express exposure risk can aid policymakers in communicating the critical need for behavioural changes needed to curb the spread of COVID-19. These measures were mandated to the public without a clear rationale, making them seem less like essential preventative actions and more like arbitrary restrictions on personal freedom. Individuals might respond differently if informed that dining out presents the most significant absolute risk of COVID-19 exposure (ranging from 10 to 26), which is fifty times greater than filling up at a gas station or 20 times more than grocery shopping.

The empirical determination of risk defined in the study can inform national and local public health policies to contain the pandemic's diffusion.

Limitations:

The study may exhibit selection bias due to its reliance on data from only those smartphone users who have activated the Location History setting, which is not the default setting. This inherent limitation stems from the utilisation of GPS mobility data. Moreover, the aggregated mobility data, both spatially and temporally, does not account for variations in individual phone usage, which precludes in-depth cohort analyses based on attributes like age, gender, or income.

Authors' contributions to research:

Conceptualisation, C.O. and G.F.; methodology, C.O. and G.F.; data collection, C.O.; data analysis, C.O.; writing—original draft preparation, C.O.; writing—review and editing, G.F.; project administration, C.O.

Study two

Title:

From 15 Minutes to 15 Seconds: How the Delta Variant Changed the Risk of Exposure to COVID-19.

A Comparative Epidemiological Investigation Using Community Mobility Data From the Metropolitan Area of Genoa, Italy

Authors:

Cristina Oliva and Giampiero Favato

Citation:

Oliva, C., & Favato, G. (2022). From 15 Minutes to 15 Seconds: How the Delta Variant Changed the Risk of Exposure to COVID-19. A Comparative Epidemiological Investigation Using Community Mobility Data From the Metropolitan Area of Genoa, Italy. *Frontiers in public health*, *10*, 872698. https://doi.org/10.3389/fpubh.2022.872698

Research questions:

- Should public health decision-makers change their response to the Delta variant?
- Should individuals commit to their protective behaviours?

Methodology and data:

The primary objective of the observational investigation was to verify the initial competitive advantage of the Delta variant: reducing the close contact risk from 15 min to 15 seconds, the Delta variant would significantly increase the risk of exposure to COVID-19.

We compared the absolute risk of viral exposure from retail locations, as estimated in June 2021, with similar figures from December 2020, predominantly linked to the original strain of COVID-19. Both data batches were collected and evaluated using the same approach, which utilised Google's median visit duration time from a sample of retail locations (n=808) in the metropolitan area of Genoa, Italy. The entire study sample can be found in the online Supplementary Material at: [https://www.frontiersin.org/articles/10.3389/fpubh.2022.872698/full#supplementary-material.](https://www.frontiersin.org/articles/10.3389/fpubh.2022.872698/full#supplementary-material)

The secondary objective was to compare the population's relative risk of exposure, obtained by setting the lowest risk by premise = 1, before and after the Delta variant. The dominance of the new variant should not increase the population's relative risk attributable to COVID-19, assuming that the current mitigation strategies are maintained.

The study used game theory to test the hypothesis that the Delta variant was a new round of the COVID-19 evolutionary game, a stable form of the "prisoner's dilemma".

Synthesis of the results:

Non-parametric statistical methods refused the null hypothesis that the median visit durations for retail activities observed in our two data sets were identical. The Kruskal-Wallis two-tailed and Mood tests highlighted the statistical significance of the differences in medians between the two observations.

The absolute risk of exposure by retail activity displayed a notable (p-value < 0.0001) difference in risk exposure to the Delta variant versus the original COVID-19 strain, contingent upon the activity selected and the time spent at a premise.

By setting the minimal absolute risk of exposure (gas stations) to 1, the relative exposure risk for retail activities was derived in both datasets. For many activities, the relative risk remained unchanged, resulting in a smaller difference in relative risk compared to the absolute risk between the Delta variant and the ancestral strain. Contrasting with the absolute risk, the

Kruskal-Wallis two-tailed test and the Mood test concurred that the null hypothesis (that the two medians were identical and originated from the same group) could not be rejected.

The Delta variant's absolute exposure risk grew noticeably compared to the ancestral strain, attributed to its faster diffusion time (competitive advantage). However, the median relative exposure risk remained largely unaltered. The two pieces of evidence satisfy the conditions of our working hypothesis: the Delta variant was not a "game changer" in the COVID-19 pandemic but rather a new round of the viral evolutionary game, a stable form of the "prisoner's dilemma".

The optimal individual response remains to adhere to protective behaviours and recognise the exposure risks of social activities. Activities demanding prolonged interaction, such as sipping drinks at pubs or, notably, dining at any restaurant (including fast food), might pose greater exposure risks than anticipated.

Consequently, public health decision-makers should not deviate from the chosen strategies to control the pandemic based on universal vaccination and social distancing.

The best response strategy for individuals is to commit to protective behaviours already in place, understating social activities' risk of exposure. The risk of exposure to COVID-19 for social activities which invite a longer duration of time, such as enjoying a drink in a pub or a wine bar, or, most risky, consuming a meal in restaurants of any kind (including fast food), can be higher than expected.

Main contributions of the study:

The study's primary contribution was the choice of the theory of games to explain how viruses evolve (Delta variant) when they compete against one another (ancestral strain) in a test of evolutionary fitness and predict which strategy will dominate this contest.

The game design was directly correlated to the variable of interest, the risk of exposure: a defined population (the residents of the metropolitan area of Genoa, Italy) and the COVID-19 virus always play the same Tit-for-Tat strategy. The success of the population strategy is measured according to the population's absolute and relative risk of exposure to the viral infection.

Publicly available data informed the game, Google's mobility data on the average time customers spend in each location from a sample of retail premises in Genoa's metropolitan area (Italy).

By making the full dataset available, other researchers could verify the results and replicate the analysis, strengthening the validity of the conclusions.

The comparative analysis between the risk of exposure to the ancestral form of COVID-19 and the one attributed to the Delta variant provided relevant insights relevant to public health policy.

Since the best response strategy in an evolutionary stable game is to commit to the current containment strategies, public health decision-makers should not deviate from the chosen strategies to control the pandemic based on universal vaccination and social distancing.

The study addresses a popular question: since the Delta variant spreads so fast, what is the point of maintaining protective behaviours when we go out? The empirical determination of the risk of exposure showed that the Delta variant does not seem to change the relative risk of exposure. Responsibly limiting activities which require longer duration time, such as dining at a restaurant, continues to be the best response to COVID-19 and its variants. Individual deviations from the dominant strategy could offer COVID-19 a fighting chance against humanity.

The analysis comparing exposure risks from the original COVID-19 strain to those of the Delta variant yielded insights relevant to public health direction.

Given that the most effective strategy in a stable evolutionary game is to adhere to existing containment methods, public health authorities should remain steadfast in emphasising universal vaccination and social distancing as primary pandemic control measures.

A common query addressed in this study is: with the rapid spread of the Delta variant, do protective behaviours still matter when venturing out?

The empirical risk assessment indicates that the Delta variant has not notably shifted the relative exposure risk. Thus, conscientiously minimising prolonged activities, like eating out at a restaurant, remains the best response to COVID-19 and its variants. Any significant deviation from this dominant strategy might increase the risk of close contact exposure to the virus.

Limitations:

Firstly, this study might face selection bias since it depends on data from smartphone users who have activated the Location History setting, which is not turned on by default. Secondly, the study's use of aggregated mobility data, both in time and space, does not reflect the varied ways individuals utilise their phones, which rules out detailed cohort studies based on criteria like age, gender, or income. Lastly, exposure risk to COVID-19 and its variants can be affected by numerous local factors such as pollution, climate, and seasonal variations. To mitigate the influence of these diverse confounders, the study was confined to residents of a single metropolitan region, Genoa, Italy, and data collection was restricted to one week from 28/06/2021 to 02/07/2021.

Authors' contributions to research:

C.O. contributed to the conception and design of the study, organised the database, performed the statistical analysis, and wrote the first draft of the manuscript. G.F. reviewed the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Study three

Title:

An unintended consequence of COVID-19 immunity passports— quasi-experimental evidence of moral hazard observed after implementing the domestic Green Pass policy during the second wave of the COVID-19 pandemic in Italy

Authors:

Cristina Oliva

Citation:

Oliva C. (2024). An unintended consequence of COVID-19 immunity passports-quasi-experimental evidence of moral hazard observed after implementing the domestic Green Pass policy during the second wave of the COVID-19 pandemic in Italy. Frontiers in public health, 12, 1345119. https://doi.org/10.3389/fpubh.2024.1345119

Research question:

- Does a perceived "immunity" against COVID-19 risk of exposure reduce risk-mitigating behaviours (ex-ante moral hazard)?

Methodology and data:

The research aimed to present quasi-experimental observational evidence concerning the moral hazard brought about by the immunity certification (Green Pass). This was achieved by measuring differences in the median duration of visits to public venues consequent to relaxing protective behaviours of the passport holders before and after its implementation.

Primary data regarding visit duration at retail locations (n=506), including retail stores, banks, and public offices sourced from Google Maps in the Genoa metropolitan area in Italy, was utilised. Two primary factors influenced the time frame selection for the two observations.

First was the unanticipated introduction date of the domestic Green Pass policy on August 6, 2021. The second factor was the availability of a convenience sample of visit duration data observed six weeks before the Green Pass policy's introduction, specifically from June 28, 2021 (as referenced in Study 2).

The entire study sample can be found in the online Supplementary Material at: https://www.frontiersin.org/articles/10.3389/fpubh.2024.1345119/full#supplementary-material

Synthesis of the results:

For the four venues where the Green Pass was a prerequisite for entry (specifically, coffee shops, fast foods, pizzerias, and fine-dining restaurants), there was a significant increase in the duration of visits compared to data from before its rollout (June 28, 2021). Conversely, other stores or offices that did not mandate the Green Pass saw no significant extension in the median visit duration. Implementing the domestic Green Pass policy increased the median time spent at locations where it was obligatory.

Main contributions of the study:

This study aimed to test the moral hazard hypothesis in a quasi-experimental setting by comparing changes in Google's visit duration data to measure the time customers typically spend on retail premises or public offices. The research made several contributions.

Firstly, the study used innovative data primary data to inform the analysis. To determine visit duration, Google publicly available data by premise were collected. A pairwise comparison of median visit time per premise was performed at a six-week interval before and after the introduction of the Green Pass in the defined metropolitan area of Genoa, Italy. By making the full dataset available, other researchers could verify the results and replicate the analysis, strengthening the validity of the conclusions.

Secondly, this study provided the first evidence of moral hazard observed after introducing a domestic Green Pass policy, which occurs when individuals are incentivised to increase their exposure to risk because they do not bear the full or any consequences of that risk. Based on this premise, the moral hazard is a "rational" behavioural choice that can and should be predicted ex-ante.

Thirdly, the unintended consequences of the Green Pass policy indicated that reducing visit duration time for social activities should remain a key priority to contain the spread of COVID-19.

Lastly, using publicly available Google visit duration could mitigate the unintended consequences of utilitarianism by democratising public health decisions during a crisis. The public dissemination of Google visit duration data can potentially empower individuals to make informed decisions about social distancing and the risk of exposure.

Limitations:

The research employs Google data to measure visit lengths, contingent upon users enabling Google Location History. This sample might not fully represent the broader population.

The data collection is confined to the metropolitan region of Genoa, Italy. Hence, the findings may not be extrapolated to other Italian cities, regions or nations with differing sociocultural or economic backgrounds.

The research was conducted over 12 weeks in the summer. While aimed at minimising seasonal biases, this duration may not comprehensively reflect the long-term impacts of the Green Pass policy or shifts in behaviours during alternate seasons.

Lastly, the study posits that the length of a visit directly impacts exposure risk. Nonetheless, other elements like ventilation, sanitising measures, and individual actions during the visits might also play a pivotal role in determining risk.

Author's contributions to research:

CO is the sole author of the published paper.

CO: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing.

RESEARCH FINDINGS IN THE CONTEXT OF THE CONCEPTUAL FRAMEWORK.

The initial study investigated the close-contact risk of exposure to determine which activities were riskier regarding COVID-19 exposure and how these risks could be mitigated.

Drawing from the Health Belief Model and the Protection Motivation theory, the research examined the perception of exposure severity and weighed it against perceived benefits. Through the perspective of 'present bias', findings indicated that individuals often favour immediate gratification, such as dining out, over more significant future gains, like lowering their exposure risk to COVID-19.

This research's main contribution was enlightening individuals about the absolute and relative risks of COVID-19 exposure. The notion of the risk associated with visit duration could help individuals make more informed decisions about their daily activities.

The second study delved into the implications of the emerging Delta variant's fear. The rapid increase in close-contact risk challenged the perceived efficacy against infection, creating a potential barrier to maintaining protective behaviours. A prevalent omission bias might lead individuals to adopt a 'why bother?' mindset, questioning the utility of measures like mask-wearing and maintaining distance. This aligns with the notion that people often favour potential harm resulting from inaction rather than adopting preventive steps that may prove futile.

This innovative research uniquely employed game theory – a mathematical representation of strategic interactions – to determine the optimal response against COVID-19 variants. Once again, leveraging Google Maps data, akin to the prior study, to monitor the duration of visits in various settings, it was discerned that the absolute exposure risk with the Delta variant amplified six times when compared with the original COVID-19 strain. However, in relative terms, the exposure risk variances for diverse activities remained somewhat consistent with that associated with the original virus.

The research's results emphasised that the most prudent strategy was adhering to the basic guidelines and persisting with protective behaviours, potentially curtailing time spent in high-risk environments.

The third study observed the potential unintended consequences of introducing COVID-19 immunity certificates, referred to as the Green Pass in Italy. The Green Pass validated one's immunity from the COVID-19 infection, granted to those who could provide evidence of their vaccination or immunity status. Drawing from the Health Belief Model and the Protection Motivation Theory, individuals choose (trade-off) between the marginal disutility of risk-mitigating behaviour and the marginal benefit of self-protection. The marginal benefit of self-protection is simply the marginal change in the perceived probability of infection.

Holding such an immunity "certificate" might induce an "optimism bias", where one feels their risk is comparatively small. This skewed perception could inadvertently lessen the motivation to practice protective measures, leading to a "moral hazard".

This study is the first to provide evidence of "ex-post" moral hazard associated with introducing a domestic Green Pass policy, and the median visiting time on premises that required digital immunity control significantly increased after introducing the domestic Green Pass policy, contrary to other public premises where access remained free of limitations. Democratising access to visit duration data can empower individuals to make informed decisions about social distancing and the risk of exposure.

In Table 4 below, the main study results are mapped in the context of the conceptual framework underpinning the research.

Table 4. Main results in the context of the conceptual research framework.

	Theories			**Research questions**	**Main result**
	Health Belief(s)	**Protection Motivation Theory**	**Cognitive Bias**		
Beliefs / Constructs / Bias	Perceived severity Perceived benefits	Appraised severity	Present bias	When people are allowed to go out, how can they reduce their close contact risk of exposure to COVID-19?	Visit duration time significantly increases close contact risk of exposure to COVID-19.
	Perceived barriers	Belief in the efficacy of coping response	Omission bias	Should public health decision-makers change their response to the Delta variant? Should individuals commit to their protective behaviours?	The Delta variant is an evolution of the game against COVID-19, not a game changer. The best response is to commit to the original protective behaviours.
	Perceived susceptibility	Expectancy of exposure	Optimism bias	Does a perceived "immunity" against COVID-19 risk of exposure reduce risk-mitigating behaviours (ex-ante moral hazard)?	Perceived immunity creates moral hazard and increases close contact risk of exposure to COVID-19.

RESEARCH CONTRIBUTIONS, LIMITATIONS AND FUTURE RESEARCH.

Contributions.

The previous chapter highlighted the results and contributions of the three studies submitted for examination. Here, this section provides an overarching review of the significance and contributions of the research.

Public health is about translating data into cues for action.

Public Health is fundamentally about transforming data into actionable insights. At its core, the field involves collecting, analysing, and interpreting scientific data about the health of populations. However, that is only part of the process. Public health's essence is translating that data into meaningful information to guide interventions, policies, and public behaviour.

The research offers significant theoretical and empirical contributions that advance understanding of the meaningful communication principle.

Identification of the heart of the problem: dissonant research paradigms.

The review of relevant theories revealed two critical gaps hindering the translation of data into change in individual behaviour:

- The lack of integration of a wide variety of current and emerging data from multiple sources to provide a comprehensive view of the determinants of threats to public health.
- The need for "managing the meaning of data" by transforming meaningful information into narratives to "make sense" of the recommended utilitarian behaviours.

A novel conceptual research framework.

Cognitive theories, mainly the Health Belief Model and the Protection Motivation Theory, put meaningful data communication at the core of their constructs. Cognitive bias bridges the gap between data communication and cues for action by defining common errors in judgment under uncertainty. Aligning the constructs of the three theories, a conceptual framework takes shape, providing a novel roadmap for the research.

New real-time data to inform the research.

Newly available primary data on the length of visit duration were manually collected from Google Maps. The three studies included are the first and only in the literature to use median visit duration as primary data to inform the research. A systematic literature review was conducted in June 2023 to monitor the adoption of the newly available Google visit duration data for monitoring close contact risk of COVID-19 infection. Details concerning the review method have been published in the PROSPERO database. [94] The review identified n=475 studies, and n=22 of them were included for full-text analysis. The only two papers using median duration time by premise were the published studies 1 and 2 included for examination.

Open research.

All three studies included in this thesis adhere to the main principles of Open Research as outlined by UK Research and Innovation (UKRI). [95] This includes accessibility through Open Access publication and transparency by making datasets publicly available. These practices enable other researchers to verify the results and replicate the analysis.

Democratising research data.

The empirical determination of risk as a function of visit duration could help individuals make better decisions about their daily activities. The public dissemination of visit duration data empowers individuals to make informed decisions about social distancing and the risk of exposure.

The intuitive, easily accessible proxy for the risk of exposure offers a straightforward method to "tell a story" with data and to guide personal decisions about going out.

The geospatial anchoring of Google Maps' visit duration makes data accessible for premises near anyone, enhancing data relevance and trustworthiness.

Relevance of research to Public Health.

The empirical determination of close contact risk of exposure defined in the research can inform future Public Health policies to contain pandemic infections.

The possibility to compare the risk of exposure at different points in time provides relevant insights to inform the response to future health crises.

Using publicly available visit duration data could allow an early policy analysis and mitigate the unintended consequences of a utilitarian approach during a crisis.

Impact.

Studies 1 and 2 were included in the WHO COVID-19 Research Database. The objectives of the WHO database are inclusivity, research quality and relevance, as demonstrated by the choice of a very restricted number of reputable bibliographic sources (Medline, ProQuest Central, Web of Science, and Europe PMC).

The Italian government showed interest in the research. In May 2021, Prof. Favato (co-author) was invited to present the results of Study 1 to Prof. Gianni Rezza, an epidemiologist, currently Director of Prevention Programmes at the Italian Ministry of Health, the equivalent of the British JCVI (Joint Committee on Vaccination and Immunisation). Predicting the risk of exposure to COVID-19 by activity based on visit duration confirmed the containment priorities and emergency measures in place at the time by the Italian Government. Despite popular and economic pressures, the Italian government never lifted the restrictions on dining out.

Over two years later, in December 2023, the story was made public in a letter to the Guardian contributing to the controversial review of the British policy ‘Eat out to help out’. The Guardian spontaneously added a link to the Study 1 open-access web page with the intent to give public evidence of the negligence underlying this policy decision. [96]

Limitations.

Drawing from the discussion of the limitations of the individual studies, two general risks of bias are relevant to the methodological choice to use real-time, crowdsourced data to inform the research.

The first is the risk of selection bias since data collection depended solely on data from smartphone users who have enabled the Location History feature, which is not activated by default. This constraint is a direct result of using GPS mobility data. Furthermore, when examining mobility data aggregated over space and time, individual differences in phone usage are not considered, making it challenging to conduct detailed cohort studies using factors such as age, gender, or income.

The second is the risk of generalisability of the results since the data collection was confined to the metropolitan region of Genoa, Italy. Hence, the findings may not be extrapolated to other Italian cities, regions or nations with differing sociocultural or economic backgrounds.

Paradoxically, the last limitation could lead to a promising stream of future research.

Future research.

The global prevalence of mobile phones generates extensive data on human behaviour at the individual and collective levels. This data began to be recognised as a vital tool for understanding human behaviour around ten years ago. This recognition marked the birth of computational social sciences, a dynamic research area with applications ranging from social networking and urban transport planning to economic development, emergency management, and, more recently, public health.

Models of human mobility derived from mobile network data present a solution to overcome the drawbacks of traditional public health methodologies. Using the geographical coordinates (longitude and latitude) of mobile phones within the network makes it possible to estimate the location of these devices. This capability lays the groundwork for creating relevant human mobility models at individual and population scales.

Additionally, future research will integrate mobility with social data, critically important for public health, especially in managing infectious diseases that spread through human contact.

Mobile phone location data can be both highly revealing and surprisingly easy to re-identify, posing a significant threat to individual privacy even when technical safeguards are in place. Additionally, the value and risk of such data change with the social and political context: mappings that once seemed innocuous can suddenly become sensitive when circumstances shift (for example, during conflicts or public health crises). Researchers also face a tension between harnessing the benefits of real-time mobility data for social good (like pandemic response) and ensuring that ethical obligations – particularly around privacy, data minimization, and equitable representation – are respected. These complexities underscore the need to go beyond legal compliance and consider broader societal implications, power imbalances, and the potential for unintended harm. [97] Private companies are key drivers of innovation in mobile location data because they invest heavily in developing new technologies and services that rely on real-time geospatial information (for example, ride-hailing apps or smartphone navigation tools). At the same time, public trust hinges on these private-sector actors demonstrating accountability, considering bias, and providing clear information about how data is collected and shared, especially since much of the data they collect can be linked to individuals' everyday movements. [98].

Within the boundaries of data privacy, the ubiquity of mobile devices is a unique opportunity for future research, which will enable researchers to study human behaviour outside traditional clinical settings, moving away from dependence on self-reported data. This ability to passively collect comprehensive behavioural data paves the way for advancements in early diagnosis and prevention of a variety of health issues, from obesity to mental health crises. Such developments promise to ease the burden on healthcare systems and bring significant advances to the field of public health.

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FULL TEXT OF THE PUBLISHED STUDIES INCLUDED IN THE THESIS.

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Article

Risk of Exposure to COVID-19: Visit Duration Data Can Inform Our Daily Activities Choices: An Epidemiological Investigation Using Community Mobility Data from the Metropolitan Area of Genoa, Italy

Cristina Oliva and Giampiero Favato *

Institute of Leadership and Management in Health, Kingston Business School, Kingston University, Kingston-upon-Thames KT2 7LB, UK; c.oliva@kingston.ac.uk

* Correspondence: g.favato@kingston.ac.uk

Abstract: COVID-19 spreads mainly among people who are in close contact. Policymakers mostly resorted to normative measures to limit close contacts and impose social distancing. Our study aimed to estimate the risk of exposure to COVID-19 by location and activity in crowded metropolitan areas. The risk of exposure to COVID-19 was defined as the product of crowding (people within a six feet distance) and exposure duration (fraction of 15 min). Our epidemiological investigation used aggregated and anonymized mobility data from Google Maps to estimate the visit duration. We collected visit duration data for 561 premises in the metropolitan area of Genoa, Italy from October 2020 to January 2021. The sample was then clustered into 14 everyday activities, from grocery shopping to the post office. Crowding data by activity were obtained from pre-existing building norms and new government measures to contain the pandemic. The study found significant variance in the risk of exposure to COVID-19 among activities and, for the same activity, among locations. The empirical determination of the risk of exposure to COVID-19 can inform national and local public health policies to contain the pandemic's diffusion. Its simple numerical form can help policymakers effectively communicate difficult decisions affecting our daily lives. Most importantly, risk data by location can help us rethink our daily routine and make informed, responsible choices when we decide to go out.

Keywords: COVID-19; risk; exposure; visit; duration

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1. Introduction

Policymakers mainly resorted to normative measures to mitigate the individual risk of exposure to COVID-19. Over the last 12 months, the Italian Government promulgated 73 Acts containing urgent measures to contain the pandemic [1]. These norms imposed on individuals the trade-off between mitigation of the risk of exposure and personal freedom. Stay home (lockdown), avoid crowds (limited opening hours and restricted access to stores), and wear a mask became new legally binding constraints to our everyday life. A constant, systematic media campaign made everyone aware of what not to do, and the consequences of breaking the law. For the first time, the Prime Minister asked social media influencers to promote the adherence to public health policies, leveraging the connection to the civic sense of younger users [2].

When people are allowed to go out, what can they do to reduce their risk of exposure to COVID-19? Which activity is riskier? Within the same activity, are there premises where the risk of exposure is lower than others?

The aim of our study was to estimate the risk of exposure to COVID-19 by location and activity in crowded metropolitan areas.

Although social and leisure activities have been identified as significant public health hazards related to the diffusion of COVID-19, the Centers for Disease Control (CDC) admittedly "cannot provide the specific risk level for every activity in every community". No method or dataset in the extant literature can help individuals make informed decisions about the risk of exposure to COVID-19 when they decide to go out.

Our epidemiological investigation used for the first time the newly available mobility data to estimate the risk of exposure to COVID-19 in crowded retail premises of Genoa's metropolitan area (Italy). The newly obtained granularity of risk data could inform people's daily choices when deciding to go out, increasing the individual acceptance of containment measures and reducing the exposure to COVID-19 at a personal and community level.

2. Materials and Methods

2.1. Risk of Exposure to COVID-19: A Working Definition

COVID-19 spreads mainly among people who are in close contact [3]. Factors to consider when defining close contact include proximity (closer distance likely increases exposure risk) and exposure duration (longer exposure time likely increases exposure risk). Although data are still limited, 15 cumulative minutes of exposure at a distance of 6 feet or less can be used as an operational definition for close contact [4]. As recommended by CDC, the determination of close contact should generally be made irrespective of whether the contact was wearing respiratory personal protective equipment (PPE). The impact of wearing a mask on reducing the exposure risk for specific daily activities is addressed in the "Discussion" Section 4. From the CDC's definition of closed contact, we derived a working definition of risk of exposure to COVID-19 for daily activities:

$$\text{Risk of exposure} = \text{crowding} \times \text{visit duration} \tag{1}$$

2.2. The Measurement of Crowding

To determine the exact number of people standing in the 10.4 square meters (approx- imately to the area of a circle of 6 feet radius) around you at any given time is virtually impossible. What is possible is to estimate the maximum number of people you should expect around you in any public office or retail premise. In Italy, maximum crowding standards are regulated by the UNI10339 norm, which sets the maximum number of people allowable for design purposes, for each square meter of floor area, concerning various categories of public offices and retail premises [5]. To guarantee the resumption of activities after the first lockdown phase, the maximum crowding standard attributed to commercial establishments was set at 13.3 m^2 per person (example: three people can enter a 40 m^2 room) [6]. In May 2020, the National Institute for Occupational Accident Insurance (INAIL) produced a technical document about coffee shops and restaurants. It set the maximum crowding standard at 4 square meters per person [7]. We used both sets of crowding norms as multiplicands to determine the risk of exposure to COVID-19 before and after the Government's containment measures.

2.3. New Data: The Measure of Visit Duration

The real methodological issue was estimating the time multiplier: how long do people stay in a specific store or premise in a given community? A new feature of Google Maps allowed collecting data on the mean visit duration by individual retail premise. Google made visit duration data available in October 2020, only for store with an acceptable level of customers' daily traffic. Due to the Covid-19 limitations to mobility, we waited approximately three months (30 December 2020) before collecting visit duration data from a significant number of retail stores by type of activity.

This new feature shows how much time customers typically spend in a specific store. Visit duration is based on customer visits patterns over the past several weeks and is expressed in units of time (minutes). Most retail stores show the visit duration as a range (e.g., 90–180 min), while food supermarkets indicate a mean value (e.g., 20 min) [8].

Data were collected from all the retail activities resident in the Genoa metropolitan area which were visible in Google Map and reported visit duration time. Google does not report visit duration for those activities which do not generate a reliable number of daily mobility data. We manually collected visit duration data for 561 retail activities, banks and public offices located by Google Maps in the metropolitan area of Genoa, Italy. The sample was then clustered into 14 everyday activities, from grocery shopping to going to the post office.

Interpreting mobility data in metropolitan areas requires an in-depth understanding of the urbanism and road mapping of the selected area. The choice of the location was determined by the fact that one of the Authors was born and raised in the metropolitan area of Genoa. Data collected for the study, including individual location data and a data dictionary defining each field in the set are available in the online Supplementary Material.

2.4. Statistical Analysis

We calculated the median visit duration by activity for both the upper and the lower limit of the range using the statistical software MedCalc (MedCalc Software Ltd, Ostend, Belgium). We used these values as multipliers to estimate the risk of exposure to COVID-19 by type of activity. The choice of median values is consistent with Google's method to calculate mobility data changes across different categories of places [9]. The descriptive statistics are reported in the online Supplementary Material.

The contact risk of Covid-19 transmission was defined by CDC as a deterministic model, the product of one constant value (crowding) by one variable (duration). To estimate the risk of exposure by activity, we used the median visit duration by location type as reported by Google Map. Data on visit duration by store were non-random, since we did not use a sample, and non-normally distributed. We tested the significance of the estimated parameter (median visit duration by retail activity, φ_i) by testing the hypothesis [10]:

Hypothesis 0 (H0): $\varphi_i = 0$.

Hypothesis 1 (H1): $\varphi_i \neq 0$.

$$(\varphi_i - 0)/(\text{Std.error } \varphi_i) \cong t_{n-m} \quad (2)$$

where m is the number of parameters.
For $\alpha = 0.05$

$$(\varphi_i - 0)/(\text{Std.error } \varphi_i) > 2 \quad (3)$$

To estimate the standard error of the median, visit duration data by retail activity were resampled with replacement 1000 times using the statistical software Resampling Stat in Excel version 2 (Resampling Stats, Inc., Arlington, VA, USA). The significance of the derived parameter, the median value of visit duration, is reported in Table 1: all parameters resulted significantly different from 0 ($\alpha = 0.05$).

We then tested the accuracy of the contact risk model by regressing the median visit duration by store type against the predicted risk values and checking for normality of residuals. The normal plot of residuals for the four scenarios (crowding norm UNI10339 and DPCM 2020, lower and upper median values of visit duration by retail activity) are reported in Figure 1. In all four scenario the hypothesis of normal distribution of residuals could be accepted (Kolmogorov-Smirnov test).

Table 1. Significance of estimated parameter: median visit duration by retail activities.

Retail Activities	Median Visit Duration by Retail Activity in the Metropolitan Area of Genoa (Italy) Source: Google Maps 30 December 2020									
	Lower Limit of the Range					Upper Limit of the Range				
	Sample (n)	Median Visit Duration (Minutes)	Variance	Standard Error of the Median (Resampled)	Significance of Median Values (α = 0.05)	Sample (n)	Median Visit Duration (Minutes)	Variance	Standard Error of the Median (Resampled)	Significance of Median Values (α = 0.05)
Pubs	22	60	3.8	3.8	15.6 **	22	120	167.2	12.9	9.3 **
Pizza restaurants	41	60	0.8	0.8	73.1 **	41	120	154.4	12.4	9.7 **
Fine-dining restaurants	36	60	12.6	12.6	4.8 **	39	150	222.4	14.9	10.1 **
Gyms	10	53	13.9	13.9	3.8 **	10	120	143.7	12.0	10.0 **
Hair salons	14	30	6.2	6.2	4.8 **	14	90	305.3	17.5	5.2 **
Fast-food restaurants	19	25	4.2	4.2	5.9 **	11	45	64.6	8.0	5.6 **
Food supermarkets *	170	20	1.8	1,8	11.1 **	N/A	N/A	N/A	N/A	N/A
Shopping centres	16	20	2.98	1.73	11.6 **	16	60	93.5	9.7	6.2 **
Retail shops (non-food)	13	20	2.4	1.5	13.0 **	86	25	0.4	0.7	38.2 **
Coffee shops	14	18	10.6	3.3	5.4 **	10	60	38.7	6.2	9.6 **
Banks	38	15	0.1	0.4	38.9 **	14	45	0.1	0.3	134.3 **
Pharmacies *	35	15	6.09	2.5	6.1 **	N/A	N/A	N/A	N/A	N/A
Post offices	57	15	6.2	2.49	6.0 **	11	45	0.1	0.2	189.8 **
Gas stations *	20	10	2.4	1.5	13.6 **	N/A	N/A	N/A	N/A	N/A

* Google Maps only reported the average visit duration. ** Significantly different from 0 (values > 2 at α = 0.05).

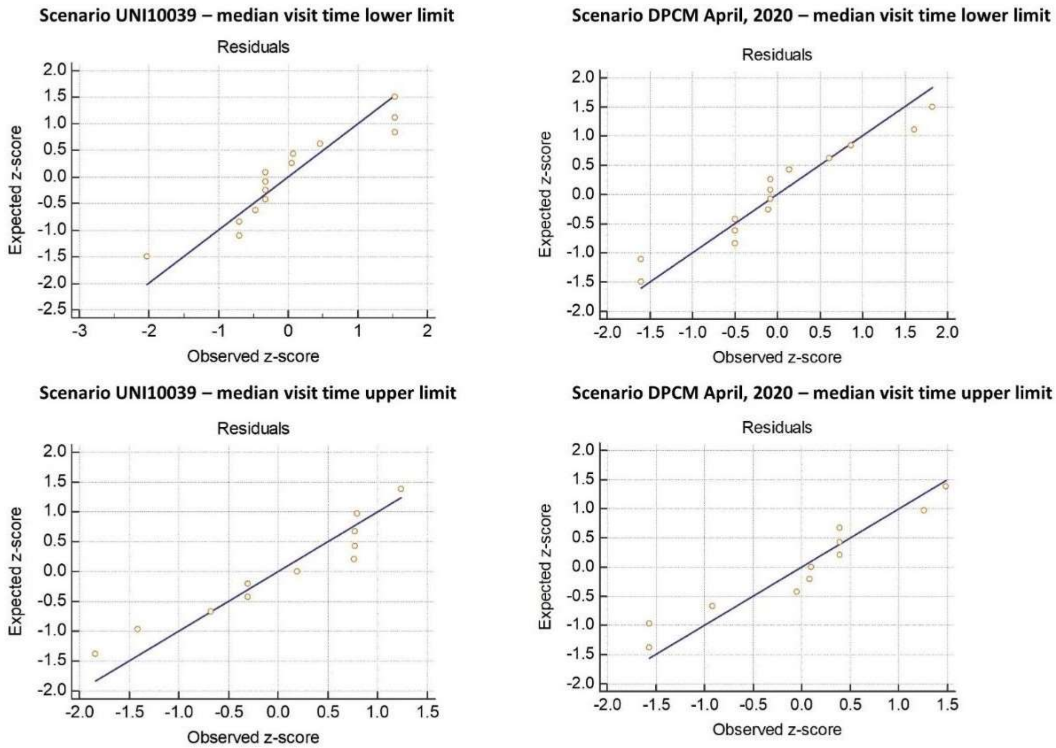

Figure 1. Regression of median visit duration against predicted contact risk for the four scenarios: controlling for normality of residuals.

The estimated predictors (median visit time by retail activity) was regressed against the predicted contact risk for four scenarios: crowding norm UNI10039 and DPCM 2020, lower and upper values of visit duration. The figure shows the Q-Q plot distribution of residuals. For all scenarios the hypothesis of normal distribution of residual could be accepted (Kolmogorov-Smirnov test).

3. Results

3.1. Study Sample and Inputs to the Model

Food supermarkets (n = 170), post offices (n = 57) banks (n = 38), and pharmacies (n = 35) were among the most represented locations in the dataset (53.5% of total). This is not surprising, since they fulfil vital needs of our daily life and they have not been subject to forced closures even during the first and second lockdown (in April and December 2020, respectively). Social activities, such as pizza restaurants (n = 41), fine dining (n = 39), pubs (n = 22), fast-food (n = 19), and coffee shops (n = 14), represented 24% of the total locations included in the sample, a true testament of the importance of personal contact in our culture. More controversial activities, such as hairdressers (n = 14) and gyms (n = 10) were also significantly represented in the sample.

The median visit duration was reported as a range (upper and lower limits) for 11 out of 14 retail activities: for grocery shops, pharmacies and gas stations, Google Map displayed only the median average visit duration. The median visit time's confidence intervals offer a plausible explanation to this reporting difference. While the dispersion is narrow for in-and-out daily activities (such as grocery shopping or filling-up the car at a gas station), the variance of time spent in other activities can be better expressed as a range. For example, a quick lunch in a restaurant takes on average less time than a three-course dinner. Table 2 reports detailed information on the study sample and the inputs used to calculate the risk of exposure to COVID-19 by retail activity.

Table 2. Study sample and inputs to the model.

	Visit Duration by Retail Activity in the Metropolitan Area of Genoa, Italy (Source: Google Maps, 30 December 2020)												Crowding Standard (Maximum Number of People Allowed Per Square Meter)	
	Lower Limit of the Range						Upper Limit of the Range							
Retail Activities	Sample (n)	Median Visit Duration (Minutes)	95% Confidence Interval of the Median		MIN Median Visit Duration (Minutes)	MAX Median Visit Duration (Minutes)	Sample (n)	Median Visit Duration (Minutes)	95% Confidence Interval of the Median		MIN Median Visit Duration (Minutes)	MAX Median Visit Duration (Minutes)	UNI10339 (October 2008)	DPCM Anti Covid-19 (April 2020)
Pubs	22	60	45	60	15	90	22	120	120	150	90	180	0.66	0.250
Pizza restaurants	41	60	60	60	20	120	41	120	120	150	90	180	0.66	0.250
Fine-dining restaurants	36	60	60	90	30	90	39	150	120	150	60	180	0.66	0.250
Gyms	10	53	20	60	5	90	10	120	90	120	45	150	0.66	0.250
Hair salons	14	30	25	45	10	60	14	90	60	123	60	180	0.80	0.250
Fast-food restaurants	19	25	15	30	10	45	11	45	45	65	30	90	0.25	0.250
Food supermarkets *	170	20	20	20	5	45	N/A	N/A	N/A	N/A	N/A	N/A	0.20	0.200
Shopping centres	16	20	20	27	10	30	16	60	60	90	45	90	0.20	0.200
Retail shops (non-food)	13	20	18	25	15	30	86	25	25	25	10	90	0.20	0.075
Coffee shops	14	18	15	25	10	30	10	60	45	60	45	90	0.20	0.075
Banks	38	15	15	15	10	30	14	45	45	45	45	90	0.20	0.075
Pharmacies *	35	15	15	15	10	20	N/A	N/A	N/A	N/A	N/A	N/A	0.20	0.075
Post offices	57	15	15	20	10	25	11	45	45	45	45	60	0.20	0.075
Gas stations *	20	10	10	10	10	15	N/A	N/A	N/A	N/A	N/A	N/A	0.20	0.075

* Google Maps only reported the average visit duration.

A simple vertical and horizontal analysis of visit duration data by activity provides valuable insights on the potential risk of exposure to COVID-19 when we go out.

The vertical analysis shows that we spend at least one hour in restaurants and pubs, a visit duration which is three to six-fold higher than any other activity. Moreover, the median visit duration to restaurants and gyms more than doubles at the upper limit of the range, providing a clear indication that social activities and indoor exercise should be, and are, a key priority for the containment of the diffusion of COVID-19.

The horizontal comparison between lower and upper limits of the median visit time range reflects our collective behavior's typical traits, making the differences more credible. For example, a quick espresso at the bar counter takes about 17 min, while an aperitif followed by an animated discussion about football can go on for an hour. Even fast food can be not so fast in Italy: a hamburger gobbled up between two lectures takes about 25 min, but if we sit down to plan the evening with our friends, then the median duration of the visit can almost double.

We used both publicly available norms (UNI10339 and DPCM, 19 April 2020) to define the maximum crowding standard (number of people per square meter) expected for each activity included in our sample.

3.2. Absolute and Relative Risk of Exposure to COVID-19 by Retail Activity under Crowding Norm UNI10339 (Antecedent the First Lockdown in March 2020)

The absolute values show a quite alarming variance of risk exposure to COVID-19 depending on our choice of activity and time spent on a retail premise. The range of exposure goes from a minimum of 1.39 when we stop at a gas station to a record high of

68.64 if we decide to reward ourselves with a nice dinner out in a fine dining restaurant. Within the same activity, the risk of exposure for a quick work-out in a gym is 9.1, but it can more than double for prolonged fitness training (20.8). It is even worse for coffee shops: an espresso at the counter gives an exposure of 9.7, while our beloved habit of continuing an animated conversation at a table can cost us a risk over three times higher (33.3).

Daily errands such as grocery shopping or going to the bank, pharmacy or post office seem to carry a much lower risk of exposure to COVID-19 (ranging from just above 2 to 4). This is a relief, not only because such activities are indispensable to our daily lives, but also because they are an essential part of older people's daily routine, most vulnerable to COVID-19 infection [11].

Table 3 summarizes the absolute and relative risk of exposure to COVID-19 by retail activity before the first lockdown initiated on 9 March 2020.

Table 3. Absolute and relative risk of exposure to COVID-19 before the first lockdown (crowding norm UNI10339, October 2008).

Retail Activities	Median Visit Duration (Minutes)		Median Visit Duration as a Fraction of 15 min		Crowding (People in the Contact Area)			Absolute Risk of Exposure to COVID-19		Relative Risk of Exposure to COVID-19 (Gas Stations = 1)	
	Lower Limit	Upper Limit	Lower Limit	Upper Limit	UNI10339 Crowding Standard (People Per Square Meter)	Close Contact Area in Square Meters (CDC, Oct 2020)	Max of People in the Contact Area	Lower Limit	Upper Limit	Lower Limit	Upper Limit
	a	b	a/15	b/15	c	d	c × d	(a/15) × c × d	(b/15) × c × d	[(a/15) × c × d]/1.39	[(b/15) × c ×d]/1.39
/Fine-dining restaurants	60	150	4.00	10.00	0.7	10.4	6.86	27.46	68.64	19.8	49.4
Pizza restaurants	60	120	4.00	8.00	0.7	10.4	6.86	27.46	54.91	19.8	39.5
Pubs	60	120	4.00	8.00	0.7	10.4	6.86	27.46	54.91	19.8	39.5
Fast-food restaurants	25	45	1.67	3.00	0.7	10.4	6.86	11.44	20.59	8.2	14.8
Coffee shops	18	60	1.17	4.00	0.8	10.4	8.32	9.71	33.28	7.0	23.9
Gyms	53	120	3.50	8.00	0.3	10.4	2.60	9.10	20.80	6.5	15.0
Hair salons	30	90	2.00	6.00	0.2	10.4	2.08	4.16	12.48	3.0	9.0
Shopping centres	20	60	1.33	4.00	0.2	10.4	2.08	2.77	8.32	2.0	6.0
Retail shops (non-food)	20	25	1.33	1.67	0.2	10.4	2.08	2.77	3.47	2.0	2.5
Food supermarkets *	20		1.33		0.2	10.4	2.08	2.77		2.0	
Pharmacies *	15		1.00		0.2	10.4	2.08	2.08		1.5	
Banks	15	45	1.00	3.00	0.2	10.4	2.08	2.08	6.24	1.5	4.5
Post offices	15	45	1.00	3.00	0.2	10.4	2.08	2.08	6.24	1.5	4.5
Gas stations *	10		0.67		0.2	10.4	2.08	1.39		1.0	

* Google Maps only reported the average visit duration.

3.3. Absolute and Relative Risk of Exposure after the First Lockdown (Crowding Norm DPCM, 19 April 2020)

Following the first lockdown, the Italian Government decided to reduce the crowding standards for all premises open to the public. Figure 2 shows the reduction in the number of close contacts expected in a three-foot radius compared to the previous norm (UNI10339). The drop exceeded 60% for most daily activities, while only gyms, hair salons, and shopping centers were unaffected by the new norm.

Left scale: the grey columns report the maximum number of people allowed by the UNI10339 (October 2008) norm in a six-feet radius space by retail activity. The blue columns report the maximum number of people allowed by the Prime Ministerial Decree (DPCM) anti-COVID (April 2020) by retail activity. Right scale: the red line shows the percent reduction in the number of closed contacts determined by the DPCM by comparison with the UNI10339 norm.

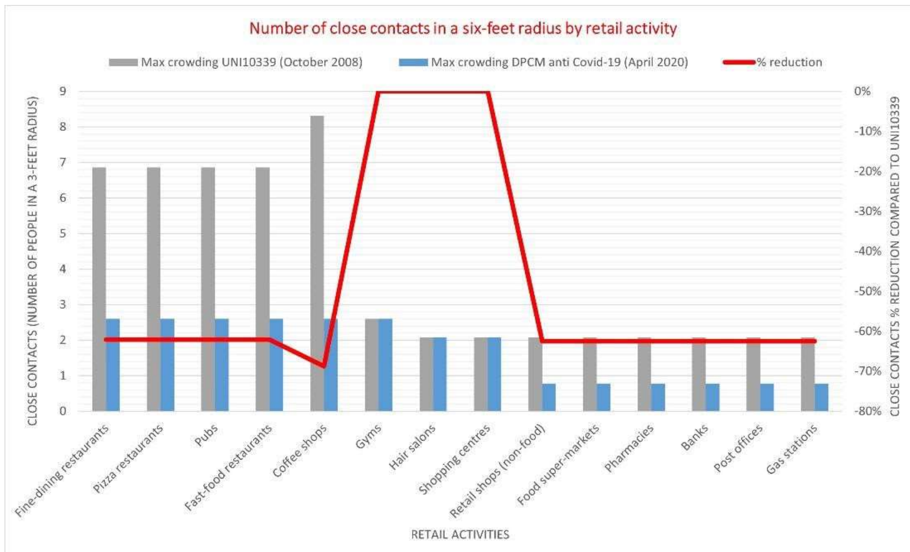

Figure 2. Number of close contacts in a 6-feet radius by retail activity.

Table 4 summarizes the impact of the reduction of crowding standards on the risk of exposure to COVID-19 after the DPCM in April 2020. In summary, the new crowding norm introduced after lockdown substantially confirmed a three-tier risk structure for daily activities:

(1) HIGH RISK (minimum relative risk >10): fine-dining restaurants, pizza restaurants, pubs and gyms;
(2) MEDIUM RISK (minimum relative risk >5, but likely to exceed the threshold of HIGH RISK based on the duration of the visit): fast-food restaurants, coffee shops, hair salons, shopping centers;
(3) LOW RISK (relative risk always <5): retail shops (non-food), grocery supermarkets, pharmacies, banks, post office and gas stations.

Table 4. Absolute and relative risk of exposure after the first lockdown (crowding norm DPCM, April 2020).

	Median Visit Duration (Minutes)		**Median Visit Duration as a Fraction of 15 min**		**Crowding (People in the Contact Area)**			**Absolute Risk of Exposure to COVID-19**		**Relative Risk of Exposure to COVID-19 (Gas Stations = 1)**	
Retail Activities	**Lower Limit**	**Upper Limit**	**Lower Limit**	**Upper Limit**	**DPCM Anti Covid-19, Crowding Standard (People Per Square Meter)**	**Close Contact Area in Square Meters (CDC, October 2020)**	**Max Number of People in the Contact Area**	**Lower Limit**	**Upper Limit**	**Lower Limit**	**Upper Limit**
a		**b**	**a/15**	**b/15**	**c**	**d**	**c × d**	**(a/15) × c × d**	**(b/15) × c × d**	**[(a/15) × c × d]/0.52**	**[(b/15) × c × d]/0.52**
Fine-dining restaurants	60	150	4.00	10.00	0.250	10.40	2.60	10.40	26.00	20.0	50.0
Pizza restaurants	60	120	4.00	8.00	0.250	10.40	2.60	10.40	20.80	20.0	40.0
Pubs	60	120	4.00	8.00	0.250	10.40	2.60	10.40	20.80	20.0	40.0
Fast-food restaurants	25	45	1.67	3.00	0.250	10.40	2.60	4.33	7.80	8.3	15.0
Coffee shops	18	60	1.17	4.00	0.250	10.40	2.60	3.03	10.40	5.8	20.0
Gyms	53	120	3.50	8.00	0.250	10.40	2.60	9.10	20.80	17.5	40.0
Hair salons	30	90	2.00	6.00	0.200	10.40	2.08	4.16	12.48	8.0	24.0
Shopping centres	20	60	1.33	4.00	0.200	10.40	2.08	2.77	8.32	5.3	16.0
Retail shops (non-food)	20	25	1.33	1.67	0.075	10.40	0.78	1.04	1.30	2.0	2.5
Food supermarkets *	20		1.33		0.075	10.40	0.78	1.04		2.0	
Pharmacies *	15		1.00		0.075	10.40	0.78	0.78		1.5	
Banks	15	45	1.00	3.00	0.075	10.40	0.78	0.78	2.34	1.5	4.5
Post offices	15	45	1.00	3.00	0.075	10.40	0.78	0.78	2.34	1.5	4.5
Gas stations *	10		0.67		0.075	10.40	0.78	0.52		1.0	

* Google Maps only reported the average visit duration.

4. Discussion

This study used the mean visit duration for the first time, a new feature of Google Maps to determine the risk of exposure to COVID-19 for many daily activities in a specific community, the metropolitan area of Genoa, Italy. The study found a significant variance in the risk of exposure among different activities and, for the same activity, among different locations. Since the study was informed by publicly available mobility and crowding data, this simple method could inform individual choices when deciding to go out, containing the risk of COVID infection by merely avoiding or reducing exposure to crowded locations. Since this study is the first of a kind, we should answer some fundamental methodological questions before recommending its wider adoption. The first question concerns the appro- priateness of mobility data to inform COVID-19 analysis of risk exposure. Google publicly discloses aggregated, anonymised GPS location data at metropolitan level containing users' density and proximity data. Accepted applications of location data include changes to population-level mobility and clustered behaviours useful to understand the risk of close contact, retrace likely diseases introduction and, most importantly, to inform the projections of risk of disease [12]. The second question is about the use of crowding standards, which measure the maximum number of people allowable in a premise rather than the actual number of individuals in the store at any given time. Actual crowding data can be ob- tained by learning location profiles from heterogeneous mobility datasets based on gravity models [13]. Collecting individual mobility data requires massive computational capacity and a standard for exchanging data between mobile operators and regulators (Mobility Data Specification). The outcomes of gravity models can inform public health policies but are of little help when making individual decisions about going out. Conversely, crowding standards are easier to understand for the general public: based on the DPCM norm, you should expect at least one but no more than three people in your closed contact risk area, a circle of six feet radius. If you can see more than three people around you, you know that the premise is overcrowded. The third question concerns the accuracy of predicting the risk of exposure to COVID-19 by activity based on crowding standards and the visit duration.

Predicting the risk of exposure to COVID-19 by activity based on crowding standards and the visit duration accurately reflects the containment priorities and emergency mea- sures in place so far by the Italian Government. Most of the activities have been affected by a drastic reduction of crowding standards, after the DPCM in April 2020. Restaurants and pubs have been closed down during the lockdown in April and December. Their opening hours have been drastically reduced across the period, with no service in the premises allowed after 6 p.m. Gyms are still closed. Coffee shops, fast-food restaurants, and hair salons have also been closed down during lockdown, and their opening hours reduced as well when re-opening has been allowed. Retail shops (non-food) were closed during the lockdown, but their activity resumed as usual when the lockdown was lifted. Activities showing the lowest risk level, such as grocery supermarkets, pharmacies, banks, post offices and gas stations, have never been closed and their store hours never reduced.

When we include the use of facial masks, the assessment of exposure to COVID-19 based on crowding standards and visit duration may have underestimated the risk for social activities, already ranked at the highest level of concern. When eating a meal or sipping a coffee, you necessarily put your mask down. Considering that face masks may significantly reduce the exposure to the virus [14], the risk of exposure to COVID-19 for restaurants of any kind (including fast food), pubs, and coffee shops can be greater than expected. Also, the notion of crowding standards may have contributed to understate the risk of social activities. Crowding standards account for the maximum allowable people per square meter, but they do not tell us how long the same person stays at least 15 min in a six-foot radius. Social activities, such as dining out, sitting at a coffee shop, or having a burger meal at the table carry a higher likelihood to have the same individuals around for longer than fifteen minutes than moving along the aisle of a supermarket or making an enquiry at the desk of a bank or a post office. Exercising at a gym or having your hair done at the hairdresser are also likely to carry a higher risk than filling a prescription at the pharmacy or refuelling your car. We can conclude that the use of face masks and the likelihood of permanence in a six feet radius does not change the distribution of the risk of exposure to COVID-19 as found by our study.

The risk of exposure to COVID-19, measured as the product of crowding standards times median visit duration, can be useful to inform public health policies and individual decision about going out.

The intuitive, numeric form that we chose to define the risk of exposure can help policymakers effectively communicate the urgency of drastic containment measures to limit the diffusion of COVID-19. These measures are currently imposed on the general population as mandatory norms, without a transparent explanation of why these prohibi- tions are necessary preventive measures and not just arbitrary limitations of individual freedom. Prohibitions are generally poorly tolerated and, in the long run, the adherence to the new norms on daily lifestyle sharply decreases [15]. As an example, eating out is an essential part of the Italian lifestyle. The prolonged closure of restaurants, followed by a severe limitation of their opening hours (take-away and delivery only after 6 p.m.) has generated a vast dissatisfaction in the population, craving for social contact after a full year of distancing. It is conceivable that individuals would react differently if they were told that dining out carries the highest absolute risk of exposure to COVID-19 (from 10 to 26), fifty times higher than refuelling the car at a gas station or 20 times higher than grocery shopping. The use of a numerical indicator would have probably placated sooner the controversy about the re-opening of gyms and hair salons, which may carry a risk of exposure similar to dining out in case of prolonged duration of the visit [16,17].

This study's main contribution is defining a single number to indicate the relative risk of exposure to COVID-19 for most of the activities that we need to perform in our daily lives. Moreover, for the same activity, it allows us to choose between different locations in our community where the absolute risk of exposure is lower. For example, when you decide to go to the post office, Google Maps can help you choose the location with the shortest mean duration of the visit. In Genoa's metropolitan area, the post office in Via Dante shows a mean visit duration of 45 min, while the post office in Via Ilva has a mean visit duration of just 15 min. The two offices are both downtown, only 700 m away from each other: a ten-minute walk can bring the risk of exposure to COVID-19 down to one third [18].

This research presents some limitations. The study is subject to a risk of selection bias in the population for whom data is available, limited to smartphone users who have turned on the Location History setting, which is off by default. This is a general limitation imposed by the use of GPS mobility data [19]. Spatially and temporally aggregated mobility data also do not capture differences in how individuals use their phones, making unfeasible any further cohort analysis (e.g., by users' age, gender or income). No data privacy issue is associated with the mobility data used to inform our risk model. Google Map publicly provides the duration of visit data by premise in a strictly aggregated and anonymised form. No personally identifiable information, such as an individual's location, contacts or movement, was made available at any point.

5. Conclusions

Our study enables everyone to understand the potential risk of going out and to make a responsible choice of daily activities in the community of residence.

Firstly, we used a working definition of risk of exposure leading to a simple, numerical value. Everybody understands the absolute and relative difference between two numbers: as an example, ten is simply five times higher than two.

Secondly, the definition of the two main factors of risk, crowding and visit duration, is intuitive.

Crowding refers to the number of people standing in a circle of three feet radius centred around you. The visit duration simply refers to the number of minutes you spend on average in a store or public office. The new feature of Google Maps allows everyone to

be informed about the mean visit duration for many locations in their community. Since the crowding standards are the same for each type of activity, this simple, easy to get information can guide everyone's daily routine activities.
The possibility to measure the risk of exposure by a single location can inform national and public policies aimed to contain the COVID-19 pandemic. More importantly, using a local, numeric value to define the risk can help policymakers make explicit the rationale of measures that have a hard impact on the population's social life, improving adherence over time.
The most significant impact of this research is to make aware individuals of the absolute and relative risk of exposure to COVID-19, empowering them to make active choices when they decide to go out.
The study's findings suggest that the new data on the visit duration provided by Google Map can help understand the risk of exposure to COVID-19 associated with the most common activities in our daily life. The empirical determination of risk defined in our study can inform national and local public health policies to contain the pandemic's diffusion. Its simple numerical form can help policymakers effectively communicate difficult decisions concerning our daily lives, justifying their rationale using a language that everyone can understand. Lastly, risk data by location can help us rethinking our daily routine and making informed, responsible choices when we decide to go out.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijerph18094632/s1. All data supporting this study.

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From 15 Minutes to 15 Seconds: How the Delta Variant Changed the Risk of Exposure to COVID-19. A Comparative Epidemiological Investigation Using Community Mobility Data From the Metropolitan Area of Genoa, Italy

Cristina Oliva and Giampiero Favato*

Institute of Leadership and Management in Health (ILMH), Kingston University, London, United Kingdom

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Bambino Gesù Children's Hospital (IRCCS), Italy

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***Correspondence:**
Giampiero Favato
g.favato@kingston.ac.uk

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The Delta variant became dominant during the second wave of the Covid-19 pandemic due to its competitive advantage, the ability to reduce close contact duration from minutes to seconds, and, consequently, increase the risk of exposure to COVID-19. We used game theory to model the most effective public health response to this new threat. We compared the absolute and relative risk of exposure to COVID-19 before and after the emergence of the Delta variant. The absolute risk of exposure was defined as the product of crowding (people within a six feet distance) and visit duration. Our epidemiological investigation used aggregated and anonymized mobility data from Google Maps to estimate the visit duration for 808 premises in the metropolitan area of Genoa, Italy, in June 2021. The relative risk of exposure was obtained by dividing the risk of exposure of each activity by the lowest value (gas stations = 1). The median absolute risk of exposure to COVID-19 increased by sixty-fold in the first semester of 2021, while the relative risk did not significantly differ from the risk of exposure to the ancestral form of Covid-19 (5.9 in 2021 vs. 2.5 in 2021). The Delta variant represents an evolution of the game against COVID-19, but it is not a game-changer. The best response is to commit to our original strategy based on population-wide vaccination and social distancing. Unilateral deviations from the dominant strategy could offer COVID-19 a fighting chance against humanity.

Keywords: delta, variant, risk, exposure, game theory, response, COVID-19

INTRODUCTION

The pandemic spread of a virus in naïve populations can select mutations that alter virulence or transmissibility (1). The ancestral form of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that emerged from China in April 2020 was mainly replaced by the B.1.617.2 mutation, or DELTA variant, first detected in India in late 2020, where it is thought to have contributed to the extremely high number of cases during the country's second wave of COVID-19 (2). As of

June 2021, it had spread to 74 countries worldwide (3). It later contributed to a third wave in the United Kingdom (4), and the WHO warned in July 2021 that it could have a similar effect elsewhere in Europe (5). The Delta variant rapidly replaced all other SARS-CoV-2 variants due to its "fitness", the reproductive rate (R_0), almost double the one observed with the ancestral strain (6).

What was the competitive advantage of the Delta variant? The Delta variant was more transmissible than previously evolved ones (7). Research conducted in the U.K., where the variant accounted for 99% of new Covid cases, suggested that it was about 60% more transmissible than the Alpha variant, which previously dominated (8, 9). Based on CCTV footage, Australian health officials suspect it has been transmitted in "scarily fleeting" encounters of roughly 5 to 10 seconds between people walking past each other in an indoor shopping area in Sydney in at least two instances (10). By reducing the close contact risk from 15 min (10) to 15 seconds, the Delta variant would significantly increase the risk of exposure to COVID-19. Consequently, should public health decision-makers change their response to the Delta variant or commit to the community mitigation measures already in place?

The theory of games can explain how viruses evolve when they compete against one another in a test of evolutionary fitness and predict which strategy will dominate this contest (11).

To understand how game theory might help understand viral mutation when differing strategies are associated with different underlying genetics, we illustrated in **Figure 1** an evolutionary game summarized in three main steps: "*meet, compete and mutate*" (12), graphically represented in **Figure 1**. First, consider a game where a defined population (the residents of the metropolitan area of Genoa, Italy) and the COVID-19 virus always play the same Tit-for-Tat strategy. The success of the population strategy is measured according to the population absolute (μ^1) and relative (μ^2) risk of exposure to the viral infection. Now, suppose that the ancestral form of COVID-19 competes with the Delta variant, which plays the Always Cheat strategy (i.e., they try to cheat everyone they meet). The Delta variant will soon dominate and completely replace the ancestral form, given its competitive advantage on the reproductive rate. The Delta's dominance would increase the population's μ^1, the absolute risk of exposure to viral infection. Should the population adapt its response to the cheater (Delta variant) or maintain the original Tit-for-Tat strategy? If the game is a stable evolutionary game, maintaining the Tit-for-Tat strategy will prove more successful, and the cheaters will eventually lose out (13).

Our working hypothesis was that the Delta variant was a new round of the COVID-19 evolutionary game, a stable form of the "prisoner's dilemma" (14).

The first condition to accept the hypothesis is that the "cheaters" (the Delta variant) must displace the ancestral form of COVID-19 completely. Latest estimates confirmed that by the end of August 2021, the Delta variant represented 90% of all SARS-CoV-2 viruses circulating in the European Union (15).

We needed to confirm the second condition, that the fitness of the Delta variant relative to the ancestral COVID-19 had to be frequency-dependent because the model predicts that cheaters will show their greatest fitness advantage when they are rare relative to the co-operators (16). The primary aim of our study was to confirm the early fitness advantage of the Delta variant. We compared the absolute risk of viral exposure (μ^1) by retail premises estimated in June 2021 with comparable values obtained in December 2020, mainly attributable to the ancestral form of COVID-19. Both sets of data were collected and analyzed following an identical method, which used for the first time mobility data on the average time spent by customers in a given location from a sample of retail premises in Genoa's metropolitan area (Italy). The secondary objective was to compare the population's relative risk of exposure (μ^2), obtained by setting the lowest risk by premise = 1, before

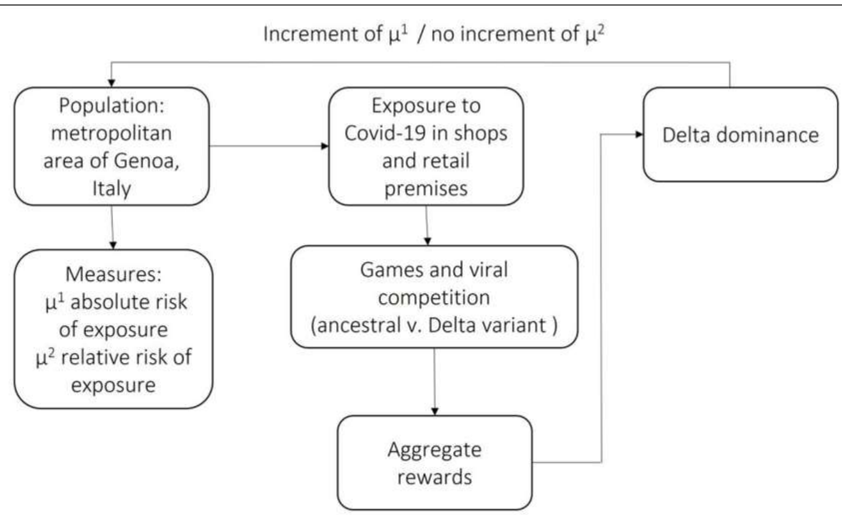

FIGURE 1 | Delta variant evolutionary game.

and after the Delta variant. The dominance of the new variant should not increase the population's relative risk attributable to COVID-19, assuming that the current mitigation strategies (Tit-for-Tat) are maintained.

If these two criteria were met, the Delta variant scenario would be consistent with the prisoner's dilemma. Consequently, the stable evolutionary theory could help us understand the Covid-19 variants' dynamics. Finally, but most importantly, it would confirm that vaccination, mask protection, and social distancing continue to be the dominant public health strategy to mitigate the pandemic's health and social impact.

The selection of the Delta variant is described as a moment of the viral evolutionary game. The process architecture is a simple *meet, mate and mutate* game. The self-contained population (metropolitan area of Genoa, Italy) is defined by two measures (absolute and relative risk of exposure). Exposure to COVID-19 (*meet*) generates random pairs for every encounter between prey and predators (ancestral virus and Delta variant). Delta variant does not co-operate and adopts the "*always cheat"* strategy. The initial reward allows Delta to become the dominant variant (*mutate*). In a stable evolutionary game, the dominance of the cheaters leads to an immediate advantage (increment of μ^1) but does not change the game (μ^2 does not increase).

MATERIALS AND METHODS

The manuscript was prepared in adherence to the STROBE (STrengthening the Reporting of OBservational studies in Epidemiology) reporting guidelines.

New Data: Median Visit Duration Time by Retail Activity

Since June 2020, Google has been showing searchers how long they can expect to be at a specific store or venue based on the crowdsourced data from users who travel to specific stores. Visit duration estimates are based on patterns of customer visits over the past several weeks. Google does not report visit duration for those activities that do not generate reliable daily mobility data.

This new feature shows how much time customers typically spend in a specific store. Visit duration is based on customer visit patterns over the past several weeks and is expressed in units of time (minutes) (17). Some retail stores show the visit duration as a mean value (e.g., 15 min), while others as a range (e.g. 30–60 min). Visit duration times are publicly available on Google Maps.

Since the Delta variant could have reduced the close contact time to just a few seconds, we obtained a univocal measure of visit duration time by including the mean values (e.g., 15 min) or the lower limit of each range (e.g., 30 min) for each retail activity. Then, as input to the risk of exposure, we divided the visit duration (in seconds) by 15.

Google reports median visit duration in minutes as a range (upper and lower limits) for 11 out of 14 retail activities. At the same time, grocery shops, pharmacies and gas stations display only the median average visit duration. Thus, while the dispersion is narrow for in-and-out daily activities (such as grocery shopping or filling up the car at a gas station), the variance of time spent in other activities can be better expressed as a range. For instance, a quick espresso at the counter takes much less than an animated debate about football in front of an aperitive in a coffee shop.

The drastic reduction of time to close contact attributable to the Delta variant imposed a methodological choice regarding visit duration. Rather than a range, we used the shortest visit duration reported by Google as the contact time to calculate the risk of exposure. Consequently, the risk of exposure to the Delta variant by retail activity estimated by this research is fully comparable to the "lower limit of the range" scenario of the risk of exposure to the ancestral COVID-19 reported in the previously published study (18).

During the week from 28/06/2021 to 02/07/2021, we manually collected median visit duration data for all the retail activities, banks and public offices located by Google Maps in the metropolitan area of Genoa, Italy, which reported the visit duration time (n = 808). The sample was then clustered into 14 everyday activities, from grocery shopping to the post office. Data were collected from all the Genoa metropolitan area retail activities visible on Google Maps and reported visit duration times. Google does not report the visit duration for activities that do not generate reliable daily mobility data.

Interpreting mobility data in metropolitan areas requires an in-depth understanding of the urbanism and road mapping of the selected area. The choice of the location was determined by the fact that one of the Authors was born and raised in the metropolitan area of Genoa. The data collected for the study are available in the online **Supplementary Material**.

Ethical Considerations

No data privacy issue is associated with the mobility data used to inform our risk model. Google Map publicly provides the duration of visit data by premise in a strictly aggregated and anonymised form. No personally identifiable information, such as an individual's location, contacts or movement, was made available at any point.

Outcomes

From the CDC's definition of closed contact (19), we derived a working definition of the risk of exposure to the Delta variant for daily activities:

Risk of exposure = [visit duration(seconds)/15] X crowding (1)

At the time of data collection and analysis, the minimum transmission time for the Delta variant was anecdotally estimated to be below 10 seconds: we conservatively used 15 cumulative seconds of exposure at a distance of 6 feet or less (20) as an operational definition for close contact.

Google median visit duration times by individual premise for the sample of n=808 retail premises included in the analysis are reported in the online **Supplementary Material**.

In Italy, crowding standards (the maximum allowable people per square meter) for retail and office premises represented a key social distancing measure, regulated by law since April 2020 (21).

TABLE 1 | Estimated parameter: median visit duration by retail activities.

RETAIL ACTIVITIES (*n* = 808)	**Median visit duration by retail activity in the metropolitan area of Genoa (Italy)**					
	Sample (n)	**MIN visit duration (minutes)**	**MAX visit duration (minutes)**	**Median visit duration (minutes)**	**95% Confidence Interval of the median**	
Fine-dining restaurants	48	15	90	60	60	60
Pubs and wine bars	32	15	90	30	25	45
Hair salons	17	15	60	30	25	45
Shopping centers	21	15	30	25	20	25
Pizza restaurants	78	5	90	20	15	45
Gyms	11	5	60	20	15	20
Food supermarkets	201	10	30	20	15	20
Retail shops (non-food)	91	10	45	20	20	20
Fast-food restaurants	31	10	45	15	15	20
Coffee shops	55	10	45	15	15	20
Banks	50	10	25	15	15	15
Pharmacies	81	10	20	15	15	15
Post offices	65	10	25	15	15	20
Gas stations *	27	10	15	10	10	10

Accordingly, inputs for crowding standards of retail premises were derived from the latest norm in place since June 2021 (22).

We calculated the absolute risk of exposure to the Delta variant as the product of the median visit duration by retail activity expressed in units of time of 15 seconds by the maximum number of people by square meter allowed by the current crowing norm divided by a close contact space of six square feet (approximately 10.4 square meters). We then obtained a relative risk measure by dividing individual exposure risks by a constant equivalent to the lowest risk value observed (gas stations = 1).

The risk of exposure to the Delta variant by retail premises was then compared to exposure to the ancestral form of COVID-19 obtained following the same method but using data collected from the same metropolitan area of Genoa, Italy, in December 2020 (23).

As recommended by CDC, close contact should generally be determined irrespective of whether the contact was wearing respiratory personal protective equipment (PPE) (24).

Statistical Analysis

We calculated the median visit duration using the statistical software MedCalc Version 20.110 (MedCalc Software Ltd, Ostend Belgium). The choice of median values is consistent with Google's method to calculate mobility data changes across different categories of places (25). Data on visit duration by premise were non-randomized (since we collected all visit duration times available for each retail activity in the Genoa metropolitan area) and non-normally distributed. As discussed earlier, the risk of exposure for each retail activity depended on a single variable (the median visit duration time), while all other parameters were constant. Consequently, we tested the following null hypothesis:

H_0: Samples come from the same distribution and have the same median.

Rejecting the null hypothesis would confirm the validity of the estimated parameter (median visit duration) to calculate the absolute and relative risk of exposure to the Delta variant by retail activity.

We used two non-parametric methods to test the fourteen independent, non-normally distributed samples of median visit duration by retail activity.

Firstly, we used the Kruskal-Wallis one-way ANOVA, a non-parametric method for comparing k independent samples. The null hypothesis is that the distributions of k groups are equal. The Kruskal-Wallis test assumes independence of observations, no assumption of normality, and the distributions of the dependent variable must have similar shapes. If these assumptions are met, the test can be interpreted as testing for differences between medians (26).

Secondly, we used the non-parametric Mood's median test as a special Pearson's chi-squared test case. Similarly to the Kruskal-Wallis test, the Mood's test checks whether the medians of two or more groups differ and assumes the same conditions (27). Both tests allow for multiple pair-wise comparisons, which is a desirable feature for estimating the trend of the median visit duration over time. To reduce the risk of type 1 error when making multiple comparisons, *p*-values for pair-wise comparisons were computed using 10,000 Monte Carlo simulations and the Bonferroni correction (significance level: 0.0005) with the aim to reduce the chances of obtaining false-positive results (type I errors) when multiple pair wise tests are performed on a single set of data.

We used both non-parametric tests because the Kruskal-Wallis test is preferable when three or more samples need to be compared. In contrast, Mood's test effectively detects a shift in location for symmetric and heavy-tailed distributions (28).

We then tested the accuracy of the absolute risk of exposure model by using a least square regression of the median visit duration by retail activity against the absolute risk values. Finally, we checked for normality of residuals using the Kolmogorov-Smirnov test for normal distribution with Lilliefors significance correction. Finally, we checked patterns in the scatterplot of standardized residuals v. standardized predicted values for homoscedasticity.

Lastly, we used again both a Bonferroni-adjusted, Monte Carlo resampled, Kruskal-Wallis and a Mood non-parametric method to test the difference in medians of the absolute and relative risk of exposure by retail activity between two different points in time:

December 2020, when the ancestral form of COVID-19 was dominant and June 2021, when the Delta variant was prevalent in Italy (29).

RESULTS

Table 1 reports the median visit duration by retail activity in the metropolitan area of Genoa, Italy, based on store data extracted from Google Maps on June 28, 2021. The distribution of the retail activities for which Google reports the average duration of visit reflects the priorities of our daily life in a metropolitan area, and it is coherent with the published data collected in December 2020. Food supermarkets (*n* = 201), retail shops (*n* = 91), pharmacies (*n* = 81), post offices (*n* = 65) and banks (*n* = 50) were among the most represented locations in the dataset (60% of total compared to 56% in 2020). Social activities, such as pizza restaurants (*n* = 78), fine dining (*n* = 48), pubs (*n* = 32), fast-food (*n* = 31), and coffee shops (*n* = 55), represented 30% of the total locations included in the analysis (24% in 2020), a true testament of the importance of personal contact in our culture. Less habitual activities, such as hair salons (*n* = 17) and gyms (*n* = 11), when the visit duration is more difficult for Google to capture, were also significantly represented in the data set. Since the median was used because visit duration data were not drawn from a normally distributed population, the standard error of the median could not be estimated by multiplying the standard error of the mean by a constant (1.2533). The width of the 95% confidence interval could represent a proxy for the significance level of the estimated parameter (median visit duration) since the width increases as the significance level decreases (30). Most of the median visit duration times by retail activity showed a narrow width of their respective 95% confidence intervals, confirming the accuracy of the effect size measure, the estimated parameter. Pubs and wine bars, hair salons and pizza restaurants showed a wider width of confidence intervals, possibly determined by an insufficient sampling or by the dual nature of their activity. For example, lunch in a pub or pizza restaurant takes significantly less time than dinner. This difference is smaller for fine dining restaurants, which always serve two or three-course meals. Similarly, a simple hair cut requires significantly less time than hair color, styling and salon treatments.

Both the non-parametric methods discussed in the "Methods" section allowed us to reject the null hypothesis that retail activity's median visit duration values were equal. The Kruskal-Wallis two-tailed test on all samples (K value: 2,245.76) rejected the null hypothesis since the computed *p*-value (<0.0001) was lower than the significance level (alpha = 0.05). Hence the samples did not

TABLE 2 | Kruskal-Wallis two-tailed test on all samples of median visit duration time by retail activity: pair-wise significance of the Bonferroni-adjusted P-values according to a degree of evidence.

	Fine dining restaurants	Pubs and wine bars	Hair salons	Shopping centers	Pizza restaurants	Gyms	Food supermarkets	Retailshops(non-food)	Fast-food restaurants	Coffee shops	Banks	Pharmacies	Post Offices	Gas stations
Fine dining restaurants		Medium	High	High	High	High	High	High	High	High	High	High	High	High
Pubs and wine bars	Medium		Low	High	High	High	High	High	High	High	High	High	High	High
Hair salons	High	Low		High	High	High	High	High	High	High	High	High	High	High
Shopping centers	High	High	High		Low	Medium	High	High	High	High	High	High	High	High
Pizza restaurants	High	High	High	Low		Medium	High	High	High	High	High	High	High	High
Gyms	High	High	High	Medium	Medium		High	Medium	High	High	High	High	High	High
Food supermarkets	High	High	High	High	High	High		High	Medium	Low	High	High	Low	High
Retail shops (non- food)	High	High	High	High	High	Medium	High		Medium	High	High	High	High	High
Fast-food restaurants	High	High	High	High	High	High	Medium	Medium		Low	High	High	Medium	High
Coffee shops	High	High	High	High	High	High	Low	High	Low		High	High	Medium	High
Banks	High	High	High	High	High	High	High	High	High	High		High	Low	High
Pharmacies	High	High	High	High	High	High	High	High	High	High	High		High	Medium
Post Offices	High	High	High	High	High	High	Low	High	Medium	Low	Medium	High		High
Gas stations	High	High	High	High	High	High	High	High	High	High	Medium	High	High	

Legend: High (p-values < 0.0001); Medium (0.0001 < p-values < 0.01) and Low (p-values > 0.01).

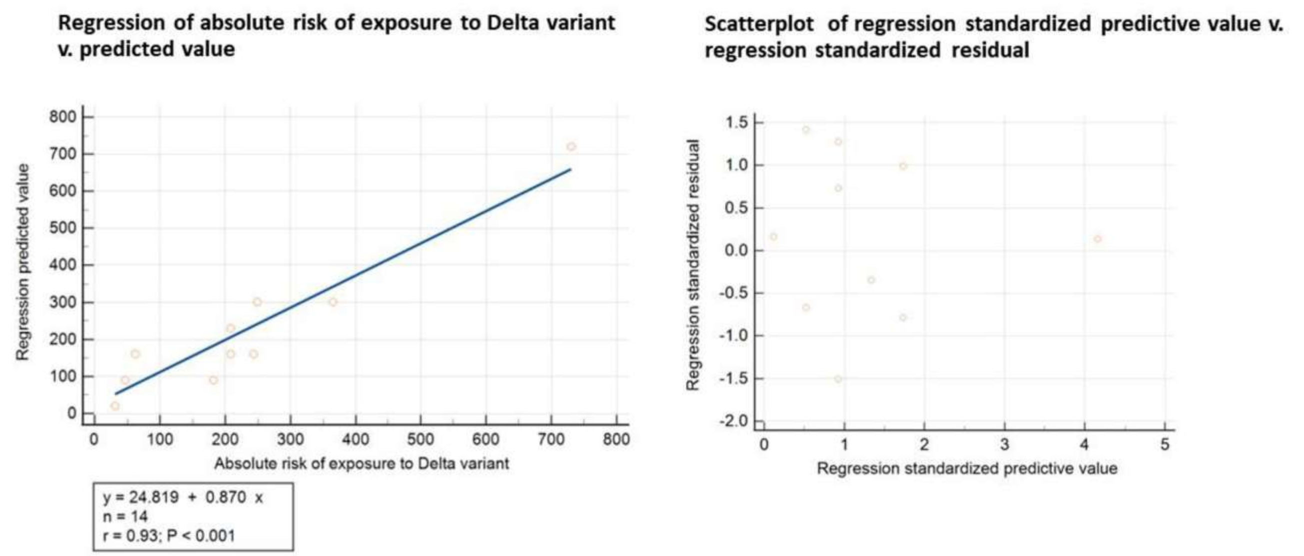

FIGURE 2 | Statistical test of the accuracy of the risk of exposure model.

come from the same distribution. **Table 2** reports the pairwise significance of the Bonferroni-adjusted *P*-values, according to a degree of evidence: high (*p*-values < 0.0001); medium (0.0001 < *p*-vales < 0.01) and low (*p*-values > 0.01). 157 out of 169 (93%) of the pair-wise comparisons resulted highly or moderately significant. The Mood test on all samples (U statistic: 255.851; Critical value: 22.362; Degrees of Freedom: 13) confirmed that the computed *p*-value (<0.0001) was lower than the significance level alpha = 0.05. Hence the null hypothesis should be rejected, and the alternative hypothesis accepted: at least one of the medians was different from the other. The Mood's pair-wise comparisons confirmed the degrees of evidence obtained using the Kruskal-Wallis method. Both statistical tests are reported in full in the online **Supplemental Material**.

We then proceeded to test the accuracy of the risk of exposure model by regressing the median visit duration by store type against the predicted values of risk of exposure to the Delta variant. The Kolmogorov-Smirnov test with Lilliefors significance correction allowed to accept the normality of residuals (D = 0.2252; *p*-value = 0.0526). **Figure 2** below reports the results of the least square regression of absolute v. predicted risk of exposure and the scatterplot of the regression standardized predictive value v. regression standardized residuals. The regression confirmed the model's predictive accuracy (r = 0.93, *p*-value < 0.001), and the scatterplot would exclude homoscedasticity. Regression standardized predictive values, and standardized residuals did not show any obvious pattern, with points equally distributed above and below zero on the X-axis and to the left and right of zero on the Y axis, except for a single outlier to the far right of the distribution. The outlier was represented by the absolute risk of exposure to the Delta variant associated with fine dining restaurants (standardized predictive value = 4.16): the relevance of this finding to public health policy will be better clarified in the following paragraphs.

The least-square regression data are reported in full in the online **Supplementary Material.**

Table 3 reports the risk of exposure to the Delta variant by retail activity based on the latest crowding norms and mobility data compared to the risk of exposure measured in December 2020, when the ancestral form of COVID-19 was prevalent.

Both the Kruskal-Wallis two-tailed test and the Mood test confirmed the statistical significance of the differences in the median between the two observations. The Kruskal-Wallis two-tailed test on the two samples (K value: 20.382) rejected the null hypothesis since the computed p-value (<0.0001) was lower than the significance level (alpha = 0.05). Hence the samples did not come from the same distribution. The Mood test on the same samples (U statistic: 28.0; Critical value: 3.841; Degrees of Freedom: 1) confirmed that the computed *p*-value (<0.0001) was lower than the significance level alpha = 0.05. Hence the null hypothesis should be rejected, and the alternative hypothesis accepted: the median risk of exposure to the Delta variant and the ancestral form of COVID-19 were not equal.

Both statistical tests are reported in full in the online **Supplemental Material.**

The strip plots (**Figure 3**) of the absolute risk of exposure by retail activity showed a significant (*p*-value < 0.0001) variance of risk exposure to the Delta compared to the ancestral form of COVID-19, depending on our choice of activity and time spent on a retail premise. For example, the absolute risk of exposure ranged from a minimum of 31 when we stopped at a gas station to a record high of 730 if we decided to reward ourselves with a meal in a fine dining restaurant. In summary, the observed risk exposure to the Delta variant showed a three-tier risk structure for daily activities:

TABLE 3 | Absolute and relative risk of exposure to COVID-19 attributed to the Delta variant and the ancestral form of Covid-19 by retail activity.

Retail activities	Median visit duration (minutes) Google Maps June 28, 2021	Median visit duration is a fraction of 15 seconds	Max crowding standard (people per square meter) Law 87, June 2021	Close contact area in square meters (CDC, October 2020)	Max number of people in the contact area	Absolute risk of exposure to DELTA variant	Absolute risk of exposure to ancestral form of Covid-19	Relative risk of exposure to DELTA variant	Relative risk of exposure to ancestral form of Covid-19
	a	***(a*60)/15***	***c***	***d***	***c x d***	***(a*60/15) x c x d***	***December 2020 data***	***Gas stations = 1***	
Fine-dining restaurants	60	240	0.293	10.40	3.04	730.1	27.5	23.4	19.8
Pubs and wine bars	30	120	0.293	10.40	3.04	365.0	27.5	11.7	19.8
Hair salons	30	120	0.200	10.40	2.08	249.6	4.2	8.0	3.0
Pizza restaurants	20	80	0.293	10.40	3.04	243.4	27.5	7.8	19.8
Shopping centers	25	100	0.200	10.40	2.08	208.0	2.8	6.7	2.0
Gyms	20	80.00	0.250	10.40	2.60	208.0	9.1	6.7	6.5
Fast-food restaurants	15	60.00	0.293	10.40	3.04	182.5	11.4	5.9	8.2
Coffee shops	15	60.00	0.293	10.40	3.04	182.5	9.7	5.9	7.0
Food supermarkets	20	80.00	0.075	10.40	0.78	62.4	2.8	2.0	2.0
Retail shops (non-food)	20	80.00	0.075	10.40	0.78	62.4	2.8	2.0	2.0
Banks	15	60.00	0.075	10.40	0.78	46.8	2.1	1.5	1.5
Pharmacies	15	60.00	0.075	10.40	0.78	46.8	2.1	1.5	1.5
Post offices	15	60.00	0.075	10.40	0.78	46.8	2.1	1.5	1.5
Gas stations *	10	40.00	0.075	10.40	0.78	31.2	1.4	1.0	1.0
MEDIAN						182.5	3.5	5.9	2.5

*Max crowding standard refers to retail premises of the gas station (convenience store).

(1) HIGH RISK (risk of exposure above 300): fine-dining restaurants and pubs,
(2) MEDIUM RISK (risk of exposure from 100 to 300): fast-food restaurants, pizza restaurants, coffee shops, hair salons, shopping centers, and gyms;
(3) LOW RISK (risk of exposure below 100): retail shops (non-food), grocery supermarkets, pharmacies, banks, post offices and gas stations.

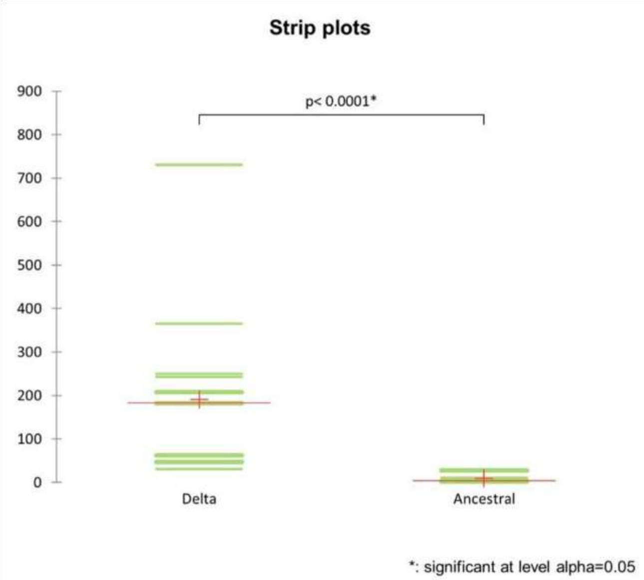

FIGURE 3 | Strip plots of the absolute risk of exposure to the ancestral strain of Covid-19 and the Delta variant by retail activity.

This new evidence should inform future public health policies concerning differential measures of social distancing, crowding and, ultimately, lockdown by retail activity.

Setting the lowest absolute value of the risk of exposure (gas stations) equal to 1, we obtained the relative risk of exposure by retail activity for both samples, as shown in **Figure 4** below.

The comparative analysis of relative risk confirmed the three-tier risk structure observed for the absolute risk of exposure. Two retail activities reported a higher relative risk (fine dining restaurants and pub and wine bars) while the risk decreased in some premises (pubs, pizza restaurants, gyms and fast foods). For most activities, though, the relative risk of exposure remained unchanged, leading to a much smaller difference in median relative risk between 2021 (5.9) and 2020 (2.5) than the one observed for the absolute risk of exposure to the Delta variant v. the ancestral form of COVID-19.

The relative risk of exposure by retail activity in the metropolitan area of Genoa was measured at two distinct points in time:

December 2020 (when the ancestral form of Covid-19 was dominant) and June 2021 (when the Delta variant was prevalent).

Contrary to the absolute risk of exposure, both the Kruskal-Wallis two-tailed test and the Mood test agreed that the null hypothesis (the two medians were equal and came from the same population) could not be rejected. The Kruskal-Wallis two-tailed test on the two samples (K value: 0.119) could not reject the null hypothesis since the computed *p*-value (0.739) was higher than the significance level (alpha = 0.05). The Mood test on the same samples (U statistic: 0.571; Critical value: 3.841; Degrees of Freedom: 1) confirmed that the computed *p*-value (0.701) was lower than the significance level alpha = 0.05. Hence the null hypothesis should be rejected, and the alternative hypothesis

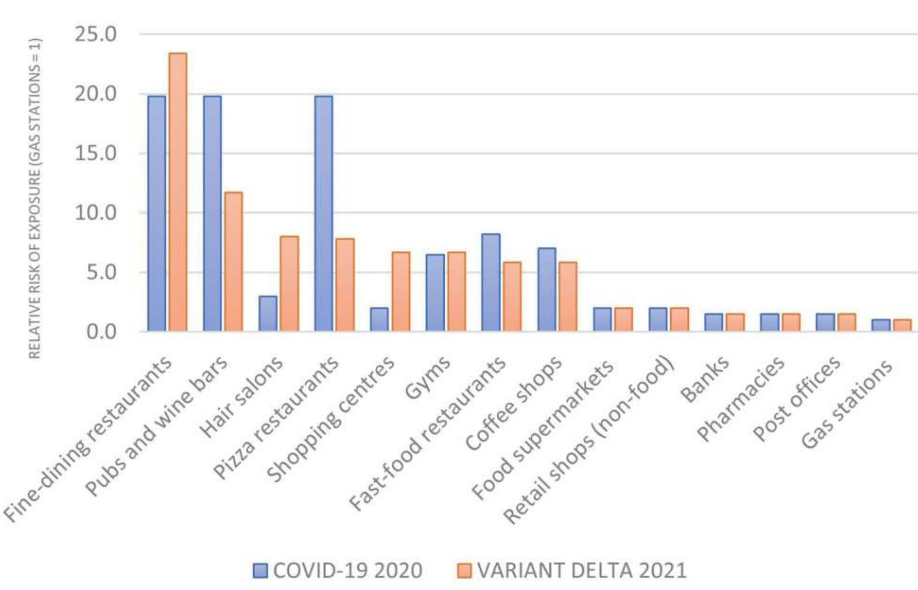

FIGURE 4 | The relative risk of exposure (gas stations = 1).

accepted: the median relative risk of exposure to the Delta variant and the ancestral form of Covid-19 were equal. Both statistical tests are reported in full in the online **Supplemental Material**.

The data analysis and two non-parametric statistical tests confirmed that the absolute risk of exposure to the Delta variant significantly increased compared to its ancestral form due to its shorter time to close contact (competitive advantage). The median relative risk of exposure, though, did not significantly change. The two pieces of evidence satisfy the conditions of our working hypothesis: the Delta variant was not a "game changer" in the COVID-19 pandemic but rather a new round of the viral evolutionary game, a stable form of the "prisoner's dilemma".

DISCUSSION

The analysis of median visit duration data by retail activity confirmed for the Delta variant what we already knew about COVID-19 on the potential risk of exposure when we go out. We spend up to one and a half hours sitting in restaurants, pubs and pizza places. Then, inevitably, remorse comes, and we exercise for 1 h at the gym. Even fast food can be not so fast: a hamburger gobbled up between two appointments takes about 10 min, but if we sit down immersed in our mobile phones, then the duration of the visit can almost quintuple. On the contrary, we are much more efficient in running our daily errands: it takes approximately 20 min to fill a cart at the supermarket, do essential shopping, or go in and out of a bank or post office. Visit duration times provide a clear indication that social activities should be, and are, a key priority for the containment of the diffusion of the Delta variant.

The comparative analysis between the risk of exposure to the ancestral form of COVID-19 estimated in December 2020, and the one attributed to the Delta variant measured approximately 6 months later provided insights relevant to public health policy. The first observation from the data reported in **Table 3** is quite apparent: the median absolute risk of exposure to COVID-19 increased by sixty-fold in the latest semester. New data on visit duration and the relaxed crowding norm had a negligible impact on this dramatic change. Reducing close contact time from 15 min to 15 sec was the only determinant of the incremental, absolute risk of exposure.

The comparative epidemiological investigation of absolute and relative risk of exposure to COVID-19 in crowded metropolitan locations allowed us to accept our working hypothesis that the Delta variant is an evolutionary version of the game against COVID-19, not a game-changer. The shorter close contact time attributed to the Delta variant makes COVID-19 more transmissible, but it does not change the relative risk of exposure when we go out. Consequently, if we do not change our mitigation strategies (Tit-for-Tat), the relative risk of exposure to COVID-19 does not change, irrespective of the Delta variant. In this sense, COVID-19 has no incremental competitive advantage if the Delta variant completely replaces its ancestral form.

The best response strategy in an evolutionary stable game is to commit to the containment strategies already in place, and any competing alternative strategy should not replace them.

Consequently, public health decision-makers should not deviate from the chosen strategies to control the pandemic based on universal vaccination and social distancing (31).

It is the human containment strategy that selected the Delta variant. Viruses have a single, dominating strategic objective: to survive by infecting a host (32). Evolution proceeds by natural selection because the environment dictates which genetic variants favor contributing their genes to the next generation (33). In the game against COVID-19, our strategy to contain the pandemic determines the selection of a variant that is the "fittest" initially, but it will eventually lose out. If we change strategy, we offer the COVID-19 a unique opportunity to benefit from the new environment.

Our data on the risk of exposure to the Delta variant by retail premises confirm the game's evolution against COVID-19. The notion of crowding standards may have contributed to understating social activities' risk. When eating a meal or sipping a coffee, individuals necessarily put their masks down. Considering that face masks may significantly reduce exposure to the virus (34), the risk of exposure to COVID-19 for indoor social activities, such as exercising in a gym, enjoying a drink in a pub or a wine bar, and, most risky, consuming a meal in restaurants of any kind (including fast food), can be higher than expected.

The Delta variant does not seem to change the relative risk of exposure at a population level. Still, our current mitigation strategies might expose some individuals to a higher risk of COVID-19 infection.

Leisure activities are vital in the maintenance of both physical and mental wellbeing. Younger individuals privilege active leisure (social activities, exercising) while the aging population enjoys passive leisure (reading, watching television) (35). National vaccination plans identified elderly and vulnerable individuals as a priority target for immunization to prevent the vast majority of COVID-19 deaths well before herd immunity on the level of entire populations was achieved (36). Data indicates that vaccination may generate more neutralizing antibodies against Covid-19 variants than natural immunity (37).

Consequently, Millennials and Gen Z severely lagged in vaccinations. Vaccine uptake among adults between 18–39 years old has remained alarmingly low since all persons over the age of 16 have been eligible for COVID-19 immunization (38). The indications provided by our study are consistent with early epidemiological data on the "new wave" of Delta variant cases, showing that the majority of infections are among unvaccinated individuals below 40 years of age, who are less likely to fall seriously ill (39).

The empirical determination of the risk of exposure can inform national and local public health policies to contain the pandemic's diffusion. Compared to its ancestral form of COVID-19, the Delta variant puts time pressure on our strategy to contain the COVID-19 pandemic but is not a game-changer. Public health decision-makers should react to the new threat by continuing to play a Tit-for-Tat strategy. Stopping the spread at the source remains critical.

Current measures to reduce transmission – including the vaccination of the younger strata of the population, wearing a mask in crowded premises and physical distancing – should continue to be our dominant strategy against the COVID-19 pandemic (40).

Looking at the global threat of the pandemic from a gaming perspective unlocks a further insight relevant to public health policy. The country's choices that contribute the least determine the outcome of all (41). Therefore, national strategies aimed to mitigate the effects of COVID-19 ought to be coordinated, as an outbreak anywhere in the world puts all other countries at risk. If one country relaxes its control measures and provokes an outbreak, all other countries will be negatively affected (42).

This research presents some limitations. First, the study is subject to a risk of selection bias in the population for whom data is available, limited to smartphone users who have turned on the Location History setting, which is off by default. It is a general limitation imposed by GPS mobility data (43). Spatially and temporally aggregated mobility data also do not capture differences in how individuals use their phones, making unfeasible any further cohort analysis (e.g., by users' age, gender or income). Secondly, the risk of exposure to Covid-19 and its variants can be influenced by many local risk factors, such as pollution (44), climate (45), seasonality (46), temperature (47), wind (48), relative humidity (49) demographics and local management of the pandemic (50). We tried to mitigate the impact of this wide variety of confounders by including in the study only residents of a single metropolitan area (Genoa, Italy) and by reducing the time allowed for data collection to one week, from 28/06/2021 to 02/07/2021.

In conclusion, our study shows that the Delta variant represents an evolution of the game against COVID-19, but it is not a game-changer. The best response to COVID-19 and its variants is to commit to our original Tit-for-Tat strategy based on population-wide vaccination and social distancing. Unilateral deviations from the dominant strategy could offer COVID-19 a fighting chance against humanity.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

CO contributed to conception and design of the study, organized the database, performed the statistical analysis, and wrote the first draft of the manuscript. GF reviewed the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.872698/full#supplementary-material

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EDITED BY
Ibrahim A. Elshaer,
King Faisal University, Saudi Arabia

REVIEWED BY
Marko Ćurković,
Sveučilišta u Zagrebu, Croatia
Patricia Pagan Lassalle,
University of North Carolina at Chapel Hill,
United States

*CORRESPONDENCE
Cristina Oliva
c.oliva@kingston.ac.uk

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An unintended consequence of COVID-19 immunity passports—quasi-experimental evidence of moral hazard observed after implementing the domestic Green Pass policy during the second wave of the COVID-19 pandemic in Italy

Cristina Oliva[1,2]*

[1]Kingston Business School, Kingston University, Kingston upon Thames, United Kingdom, [2]Kingston Business School, Faculty of Business and Social Sciences, Institute for Leadership and Management in Health, Kingston University, Kingston upon Thames, United Kingdom

Objectives: Amidst the second wave of the COVID-19 pandemic, Italian policymakers mandated to exhibit evidence of vaccination or immunity (the Green Pass) as a condition to access retail premises and public offices. This study aims to offer evidence, in a quasi-experimental setting, suggesting that an unintended consequence of this policy was the emergence of moral hazard.

Methods: Google visit duration data measured the time customers typically spend on retail premises or public offices. A pairwise comparison of median visit time per premise was performed at a six-week interval before and after the introduction of the Green Pass.

Results: This study is the first to provide evidence of “ex-post” moral hazard associated with introducing a domestic Green Pass policy. The median visiting time on premises that required digital immunity control significantly increased after introducing the domestic Green Pass policy, contrary to other public premises where access remained free of limitations. The increase in median visit time in premises with faster customer turnaround, such as coffee shops (+49%) and fast-food restaurants (+45%), was lower than the increase observed for fine-dining restaurants (+74%) and pizzerias (+163%). No significant increase in median visit time was observed in premises where the Green Pass was not required, such as food supermarkets, retail non-food shops, post offices, banks, pharmacies, and gas stations.

Conclusion: The evidence of moral hazard highlights the critical issue of unintended consequences stemming from public health policies. This discovery is pivotal for policymakers, indicating that unforeseen behavioral adjustments could offset the intended benefits despite the intent to reduce risk through measures like the Green Pass.

KEYWORDS

public health policy, unintended consequences, moral hazard, COVID-19, immunity certificates, Green Pass policy

Introduction

Public health policies throughout the COVID-19 pandemic were characterized by rapid and decisive actions aimed at combining efforts to contain the spread of the disease and mitigate its impacts. The primary goal was to delay the pandemic's peak, ensure a more level distribution of the demand on limited healthcare resources, and protect vulnerable groups (1). The strict enforcement of policies in this unique situation also uncovered disagreements and showed how these decisions led to opinion differences among policymakers and the general public (2).

Given the significant changes brought about by the COVID-19 pandemic and its profound effects on societal norms, digital proof of immunity rapidly emerged as a contentious point of deliberation within most liberal democracies (3). The Green Pass, as it was commonly called in Italy, was an entry permit to public premises or facilities, a digital proof that an individual had either been vaccinated against COVID-19, received a negative test result, or recovered from COVID-19 (4).

Advocates emphasized that the Green Pass could potentially enhance freedom of movement, stimulate economic resurgence, and facilitate unhindered access to employment and educational avenues without compromising public health. Conversely, concerns abounded regarding their potential to precipitate unequal treatments, accentuate existing societal disparities, infringe on individual privacy rights, and inadvertently jeopardize public health by fostering complacency. An evolving body of academic work has begun to interrogate these ethical dimensions, offering a nuanced exploration of the advantages and pitfalls of such measures (5–7). Unintended responses to public health policies could lead to a maleficent "paradox effect" when riskier behaviors stem from heightened confidence (8).

Under severe epidemiological, economic, and social pressures, Italian policymakers began to explore the idea of a domestic Green Pass policy aimed at increasing the number of activities that could be subject to the possession of proof of vaccination or immunity. Therefore, since August 6, 2021, individuals showing their Green Pass would have complete freedom of access to indoor leisure activities such as restaurants, cafeterias, coffee shops, sports events, shows, museums, cultural exhibitions, swimming pools, gyms, and recreational facilities (9). The introduction of the domestic Green Pass policy was controversial, raising fierce media and political debates about its constitutional validity, practical impact on public health, respect for data privacy, and limitations of personal freedom (10).

The Green Pass domestic policy rests on a single epidemiological premise: individuals vaccinated or previously infected with COVID-19 who produce antibodies to the virus will then be immune to re-infection (at least for some nontrivial length of time) (11). Under this epidemiological condition, limiting access to public premises for Green Pass holders would create a sort of safe "immunity bubble" where the close contact risk of getting infected by COVID-19 would be virtually equal to zero. The Green Pass would implicitly signal to the community that the certificate holders were safe and others would be safe around them.

This study examines how the perceived "immunity" against COVID-19 risks possibly reduced risk-mitigating behaviors (ex-ante moral hazard). In economics, a moral hazard is a situation in which an economic actor has an incentive to increase its exposure to risk because it does not bear the full costs of that risk (12). In the COVID-19 infectious disease context, moral hazard applies where individuals who possess a certificate of immunity, such as the Green Pass, may relax protective behaviors, consequently increasing chances of close contact exposure to COVID-19 (13).

The study's main aim is to provide quasi-experimental evidence of moral hazard determined by the certification of immunity by measuring differences in median visit duration by public premises and the consequent change in protective behavior observed among the holders before and after the introduction of the Green Pass.

The rationale behind the retrospective policy analysis of the domestic Green Pass implementation in Italy hinges on a single pivotal consideration. Understanding how the introduction of the Green Pass influenced individual and collective behaviors, the study seeks to assess whether the Green Pass motivated adherence to health measures or inadvertently led to complacency. The study is positioned to inform future policy adaptations where behavioral choices under moral hazard are rational and can be anticipated "ex-ante."

Methods

Close contact risk of exposure to COVID-19

COVID-19 spreads mainly among people in close contact (14). When defining close contact, factors include proximity (closer distance likely increases exposure risk) and exposure duration (longer exposure time likely increases exposure risk). A working definition of the risk of exposure to COVID-19 for daily activities was developed based on the CDC's definition of close contact (15):

$$\text{Risk of exposure} \quad \text{crowding} \quad \text{visit duration} \qquad (1)$$

As recommended by the CDC, close contact should generally be determined irrespective of whether the contact was wearing respiratory personal protective equipment (PPE).

In Italy, maximum crowding standards are regulated by norms, which set the maximum number of people allowable for design purposes for each square meter of floor area concerning various categories of public offices and retail premises. In March 2020, a decree from the Prime Minister introduced urgent actions to mitigate the impact of the COVID-19 epidemiological crisis. It set a new maximum occupancy limit for all commercial premises based on the requirement to maintain a one-meter distance between individuals for social distancing (16). Consequently, since the introduction of the domestic Green Pass policy in August 2021, Equation (1) could be rewritten as the product of a constant (Kc) and visit duration Equation (2):

$$\text{Risk of exposure} \quad Kc \quad \text{visit duration} \qquad (2)$$

Data collection and inclusion

Google data was used to measure visit duration, the time customers typically spend on a specific retail premise or public office. Google uses aggregated and anonymized data from users who have opted for Google Location History. Data on visit duration indicate the average amount of time (in minutes) customers spend in a particular location, such as a restaurant, coffee shop, or supermarket. These estimates are derived from analyzing patterns in customer visits over the preceding weeks. No personally identifiable information, such as an individual's location, contact, or movement, will be made available at any point (17).

Visit duration data was collected from all the Genoa metropolitan area retail activities visible on Google Maps and reported visit duration times. Interpreting mobility data in metropolitan areas required an in-depth understanding of urbanism and road mapping in the selected area. The choice of location was determined by the fact that the author was born and raised in a metropolitan area of Genoa. This methodological choice was consistent with Google's recommendation to avoid comparing places across regions because of local differences in the data, which might be misleading (18).

Visit duration times (in minutes) for individual premises located by Google Maps in the metropolitan area of Genoa, Italy, were then aggregated into median visit duration time (in minutes) by ten categories according to their primary use: coffee shops, fast food restaurants, pizzerias, fine-dining restaurants, food supermarkets, retail non-food shops, post offices, banks, pharmacies, and gas stations.

Two main factors informed the choice of the time interval between the two observations. The first was the date of introduction of the domestic Green Pass policy (August 6, 2021), which could not be anticipated ex-ante. The second was the availability of a convenience sample of visit duration data dated six weeks before the introduction of the Green Pass policy (June 28, 2021). Visit duration data had been collected following a method perfectly consistent with the one adopted for the second observation, and the data set had been published (19). Based on the date of the first implementation of the domestic Green Pass in Italy and the availability of a convenience sample collected six weeks before, the second sample of visit duration data was collected six weeks after the introduction of the domestic Green Pass (September 13, 2021).

Visit duration data were manually transcribed from Google Maps during two specific working weeks, with data collected within five consecutive days: from Monday, June 28th to Friday, July 2nd, 2021 (Observation 1) and from Monday, September 13th to Friday, September 17th, 2021 (Observation 2). The dates of the two observations spanned the summer season, reducing the bias of seasonality, which could have impacted visit duration and, consequently, changes in customers' behavior. This aspect is particularly relevant to the location of the study: Genoa, a medieval city on the Italian Riviera, is a popular resort rich in art and museums, with an evocative old town, a varied food and wine culture, and a sprawling seafront (Figure 1).

Google determines peak hours, expected wait times, and the length of visits by utilizing aggregated and anonymized data from users who have activated Google Location History. The average visit duration was displayed if a business receives sufficient visits from these users. This data will only appear if enough visitation data is available for that business through Google (20). Due to this limitation, the list of retail premises whose visit duration data were collected in the second observation did not match the list of premises included in the first observation. This discrepancy could lead to a methodological bias since premises grouped in the same cluster can have different features that can significantly impact visit time duration. For example, a coffee shop can have a bar counter and a few tables where the customers quickly consume an espresso or a soft drink. Another coffee shop can have a patisserie and a vast seating area, inviting customers to a significantly longer visit time. Due to this limitation, there were discrepancies between retail premises with visit duration data for the first and second observation. Only retail premises with data for the first and second observations were included for analyses to reduce potential bias and ensure consistency between observations.

In normal distribution, the mean value per cluster would be used as a variable to be compared between observations. In contrast, the median value would have been the variable of choice in skewed distribution since outliers could distort the mean value (21). To reduce the bias of validity when including pairwise samples of premises showing different sizes (e.g., fine dining restaurant $n = 34$, and food supermarket $n = 155$), all mean/median values were resampled with replacement one thousand times (22).

The final sample was then clustered into ten groups of premises: four of which required the Green Pass (fine dining restaurants, pizzerias, fast food, and coffee shops) and six that did not require the Green Pass (food supermarkets, retail stores, banks, post offices, gas stations, and pharmacies).

The data collected for the study, including individual location data and a data dictionary defining each field in the set, are available in the Supplementary material.

Hypothesis testing

As discussed earlier, since the introduction of the domestic Green Pass policy in Italy, the risk of exposure for each retail activity is dependent on a single variable: the visit duration time. Consequently, to test the moral hazard hypothesis, the following null hypothesis was formulated for each retail activity included in the sample:

> H_0: Visit duration times obtained six weeks before and after the introduction of the domestic Green Pass policy have the same means/medians.
>
> H_a: Visit duration times obtained six weeks before and after the introduction of the domestic Green Pass policy have different means/medians.

Suppose the null hypothesis H_0 cannot be rejected for all retail activities or most activities requiring Green Pass; in this case, the conclusion would be that implementing the domestic policy in Italy did not generate moral hazard, as previously defined. If the null hypothesis is rejected, accepting the alternative hypothesis implies that the mean/median visit time duration differed between the two observations. Suppose the mean/median visit duration time related to the premises that required a Green Pass increased. In that case, while the mean/median duration time of the premises where the Green Pass was not required did not change, then moral hazard was the unintended consequence of the introduction of the domestic Green Pass and ultimately resulted in a higher close contact risk of COVID-19 infection for the holders.

Data analysis

The choice of method for comparing mean/median visit duration time between the two observations will be informed by the normality

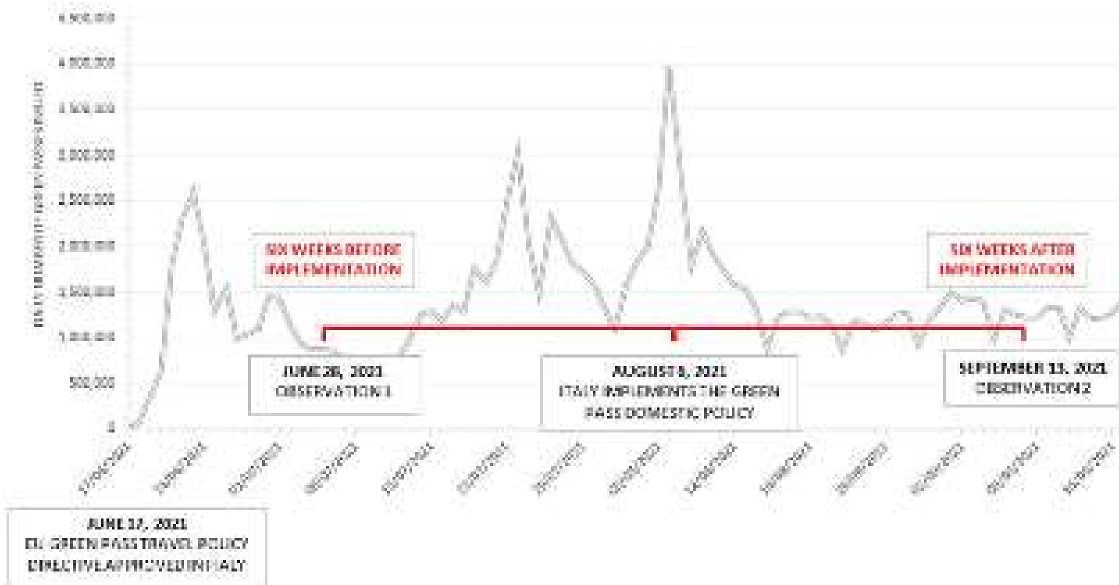

FIGURE 1
The time interval between the two observations. The time chart shows the number of Green Passes daily issued by the Italian Government from adopting the EU directive concerning travel passes (June 17, 2021) to the end of September 2021 (source: Italian Ministry of Health repository). On August 6, 2021, the domestic policy of Green Pass was first implemented. Unlike the travel pass needed to travel abroad, the domestic policy mandated the Green Pass as a condition for all individuals to access crowded retail premises (coffee shops, fast foods, pizzerias, and fine-dining restaurants). The time interval of data collection for the visit time duration for the two observations was set six weeks before and after the introduction of the domestic Green Pass policy in Italy.

test of each sample of data aggregated by premises. In the case of normal distribution of the data, a one-way analysis of variance (ANOVA) will be used to compare whether paired samples' means are significantly different.

In case of skewed data distribution observed in each sample, medians will be first resampled with replacement (1,000 iterations). Then, the Mood test, a special case of Pearson's chi-squared test, will be used to compare pairwise medians. The Mood test is a non-parametric method for comparing k independent samples (23). The null hypothesis is that the distributions of k groups are equal. The Mood test assumes independence of observations and no assumption of normality. If Mood's median test result is significant, a post-hoc test will be conducted to investigate which medians differ (24).

XLSTAT statistical software for Excel by Addinsoft was used for resampling and statistical analysis.

Results

Significance of differences in median visit duration time by premise

The study included a total sample of 506 retail premises and public offices in the metropolitan area of Genoa, Italy. Typical visit duration time (in minutes) was reported by Google Maps and observed at two specific time points during the second half of 2021. The store data was then clustered into ten groups of premises according to their primary activity. A graphical representation of the pairwise comparison of the observed median visit time by premise seemed to indicate a significant increase in the average time spent by customers in the premises where the Green Pass was mandatory compared to the premises that did not require the Green Pass as a condition to access (Figure 2).

Were these differences significant?

The normal distribution hypothesis was rejected for all data samples included in the analysis. Consequently, bootstrapped estimators of median values were obtained by resampling with 1,000 replacements for all samples included in the analysis. Moreover, the non-normality condition justified the choice of non-parametric tests, such as Mood's tests, to compare the bootstrapped estimators of median values.

The four premises with conditional access to the exhibition of the Green Pass (namely, coffee shops, fast foods, pizzerias, and fine-dining restaurants) showed a significant increase in visit duration time compared to the one observed before its introduction (June 28, 2021). On the other hand, the remaining stores or offices that did not require the Green Pass showed no noticeable increase in the typical time spent inside the premises.

Based on the observed data and the results of Mood's statistically significant differences in median values, the null hypothesis (H_0) that visit duration times obtained six weeks before and after the introduction of the domestic Green Pass policy have the same medians can be rejected. The alternative hypothesis (H_a) should be accepted: introducing the domestic Green Pass policy increased the median visit duration observed in the premises where possession was required.

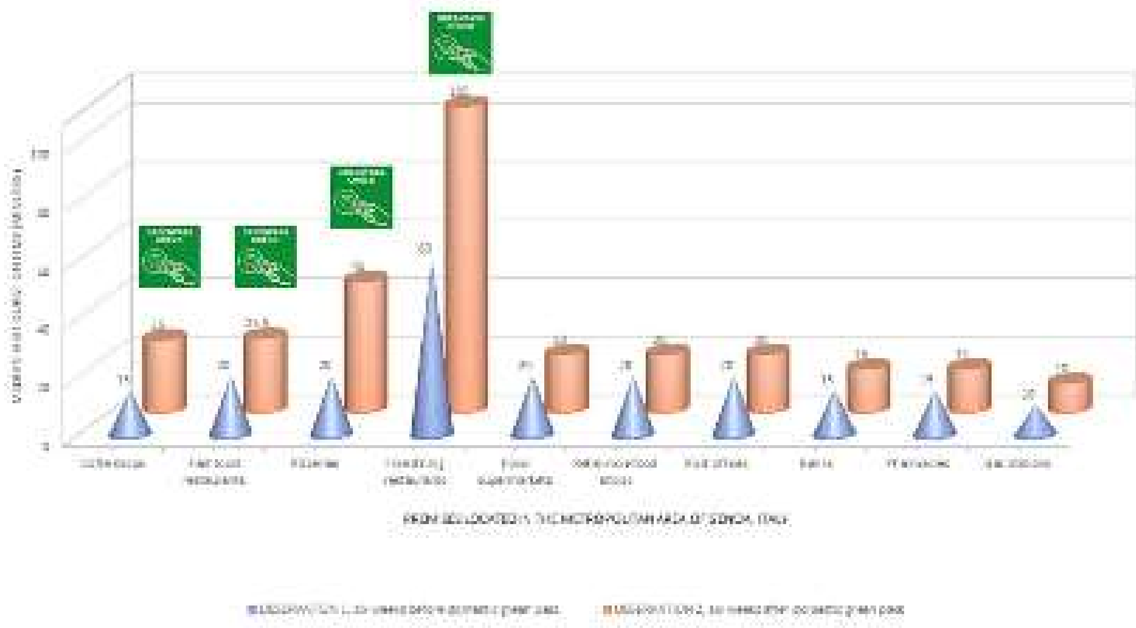

FIGURE 2
Median visit duration time for retail and public premises. The graph shows the median visit duration time (in minutes) obtained by Google Maps for the two samples of premises in the metropolitan area of Genoa, Italy, aggregated by main activity. The cones indicate the median visit time for the first observation (six weeks before the domestic Green Pass policy). The cylinders show the median visit time at the second observation (six weeks after the mandatory Green Pass). The label "Green Pass check" indicates the crowded premises where the pass was mandated as a condition to access (coffee shops, fast foods, pizzerias, and fine-dining restaurants).

Table 1 summarizes this study's main results, while the complete statistical analysis is available in the Supplementary material.

What are the implications of this finding for public health?

Table 2, reported below, shows the horizontal and vertical analysis of the change in visit duration, which provides valuable insights into the incremental risk of exposure to COVID-19 observed after introducing the domestic Green Pass policy in Italy.

A horizontal comparison of visit duration times observed in similar premises at different time intervals showed that by the end of June 2021, just six weeks after the introduction of the domestic Green Pass, the time typically spent by customers in pizzerias more than doubled while the time spent in fine dining restaurants increased by 74.42%. In addition, the duration of visits for more casual and frequent activities in our everyday lives, such as getting an espresso in a coffee shop or grabbing a burger in a fast food restaurant, increased by 48.60 and 45.48%, respectively. The vertical analysis confirmed the relevance of the changes in typical visit time to the risk of close contact in the premises where the Green Pass was required. Relative to gas stations (risk = 1), introducing the Green Pass determined a significant increase in exposure in the four activities already at the highest risk of close contact. The close contact risk increased for restaurants (from 6.01 to 10.48), pizzerias (from 1.82 to 4.78), fast foods (from 1.84 to 2.67), and coffee shops (from 1.54 to 2.28). Restaurants (of any kind), coffee shops, and bars did not require customers to wear facial protection (masks) when having a meal or a drink. Consequently, after introducing the domestic Green Pass policy, individuals paradoxically spent significantly more time on the premises that were most vulnerable to close contact risk.

On the other hand, the incremental and relative risk of exposure remained unchanged for all the premises where the Green Pass was not a condition of access.

Generalizing the outcomes by accepting the alternative hypothesis H_a, this study provided the first evidence of moral hazard observed after introducing a domestic Green Pass policy.

The introduction of the Green Pass indicated that social activities should remain a key priority to contain the spread of COVID-19.

Discussion

The COVID-19 pandemic has imposed an unprecedented social and economic burden on the global population. Although mass vaccination offers a promising exit strategy for the pandemic, limitations in personal freedom and social distancing have been enacted with varying degrees of severity at various points in time to contain the spread of the virus (25).

The benefits and challenges of the Green Pass remain controversial in the infection-acquired and vaccination-acquired immunity framework (26). In August 2021, Italy was the first mover to extend the remit of the Green Pass by enacting a domestic Green Pass policy to allow vaccinated individuals to return to their pre-COVID lives and do so safely. The domestic policy turned the Green Pass into proof of vaccination in a printed personal certificate or a digital version downloaded on a smartphone. As a result, the Green Pass became a

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TABLE 1 Change in median visit duration time by premise after the implementation of the Green Pass domestic policy.

Retail premises and public offices		Sample n = 506	Observation 1 (28 June – 02 July, 2021)			Observation 2 (13–17 September, 2021)			OBS 1 v OBS 2 significance of paired differences
			Median visit duration time (minutes)	Resampled median (1,000 iterations; significance level = 5%)	Shapiro–Wilk test of normality *p*-value two-tailed (α 0.05) (*)	Median visit duration time (minutes)	Resampled median (1,000 iterations; significance level = 5%)	Shapiro–Wilk test of normality *p*-value two-tailed (α 0.05) (*)	Mood test *p*-value (α 0.05) (**)
Green Pass required	Coffee shops	39	15.00	15.35	<0.0001	25.00	22.81	0.001	0.002
	Fast food restaurants	26	20.00	18.36	0.015	25.50	26.71	<0.0001	0.001
	Pizzerias	36	20.00	18.17	<0.0001	45.00	47.82	0.002	<0.0001
	Fine dining restaurants	32	60.00	60.09	<0.0001	105.00	104.81	0.000	<0.0001
Green Pass not required	Food supermarkets	155	20.00	17.98	<0.0001	20.00	18.64	<0.0001	0.877
	Retail non-food shops	44	20.00	20.84	0.001	20.00	20.86	0.000	0.823
	Post offices	60	20.00	18.01	<0.0001	20.00	18.95	<0.0001	0.798
	Banks	37	15.00	15.00	0.000	15.00	14.99	<0.0001	1.000
	Pharmacies	80	15.00	15.00	<0.0001	15.00	15.00	<0.0001	0.634
	Gas stations	26	10.00	10.00	<0.0001	10.00	10.00	<0.0001	1.000

(*) Shapiro–Wilk test interpretation: H0: The variable from which the sample was extracted follows a normal distribution. H_a: The variable from which the sample was extracted does not follow a normal distribution. As the computed *p*-value is lower/higher than the significance level alpha = 0.05, one should reject/accept the null hypothesis H0, and accept/reject the alternative hypothesis H_a. (**) Mood test interpretation: H0: The medians of Observation 1 and Observation 2 are equal. H_a: Medians of Observation 1 and Observation 2 are not equal. As the computed p-value is lower/higher than the significance level alpha = 0.05, one should reject/accept the null hypothesis H0, and accept/reject the alternative hypothesis, H_a.

TABLE 2 Change in relative and incremental risk of exposure by premise after introducing the Green Pass domestic policy.

Retail premises and public offices		Resampled median visit duration time (minutes)			Relative risk of exposure (gas stations = 1)		Incremental risk of exposure after introduction of the Green Pass
		Observation		Significance of paired differences *p*-value (α 0.05) (*)	Observation		OBS 2 v OBS 1(%)
		1	2		1	2	
Green Pass required	Coffee shops	15.35	22.81	0.002	1.54	2.28	49%
	Fast food restaurants	18.36	26.71	0.001	1.84	2.67	45%
	Pizzerias	18.17	47.82	<0.0001	1.82	4.78	163%
	Fine dining restaurants	60.09	104.81	<0.0001	6.01	10.48	74%
Green Pass not required	Food supermarkets	17.98	18.64	0.877	1.80	1.86	4%
	Retail non-food shops	20.84	20.86	0.823	2.08	2.09	0%
	Post offices	18.01	18.95	0.798	1.80	1.90	5%
	Banks	15.00	14.99	1.000	1.50	1.50	0%
	Pharmacies	15.00	15.00	0.634	1.50	1.50	0%
	Gas stations	10.00	10.00	1.000	1.00	1.00	0%

(*) Interpretation of Mood test of difference in paired medians: H_0: The medians of Observation 1 and Observation 2 are equal. H_a: Medians of Observation 1 and Observation 2 are not equal.
As the computed *p*-value is lower/higher than the significance level alpha = 0.05, one should reject/accept the null hypothesis H_0, and accept/reject the alternative hypothesis, H_a.

mandatory prerequisite to attend particularly high-risk events in any indoor setting, whether a dinner in a restaurant, a movie theater, or a sports match.

This study is the first to provide evidence of "ex-post" moral hazard associated with introducing a domestic Green Pass policy. The median visiting time on premises that required digital immunity control significantly increased after the policy was introduced, contrary to other public premises where access remained free of limitations.

COVID Pass's "ex-ante" impact on moral hazard is unambiguous: conceptually, the marginal disutility of risk-mitigating behavior (social distancing) should equal the marginal benefit of self-protection. The marginal benefit of self-protection is simply the marginal change in the probability of infection times the difference in utility between the uninfected and infected states of the world (27). Since the Green Pass certifies immunity, it reduces the marginal disutility of health loss from infection virtually to zero, consequently reducing the incentives for self-protection. This substitution effect would argue that the COVID-19 domestic Green Pass policy should increase ex-ante moral hazard.

Policymakers could have anticipated the behavioral reaction of Green Pass holders to lifting any precaution while dining out or having coffee at a table in a coffee shop. Eating out is an essential part of the Italian lifestyle. Therefore, the prolonged closure of restaurants, followed by a severe limitation of their opening hours (takeaway and delivery only after 6 p.m.), generated a vast dissatisfaction in the population craving social contact after a full year of distancing. It was conceivable that, under the "immunity" premise, Green Pass holders would increase their typical visit duration in these premises since the utility gained from additional time spent in social activities was higher than the perceived risk (close to zero) of incremental close contact risk of COVID-19. Therefore, as shown by comparing median visit duration data, citizens did just that. It was a rational behavioral choice, perfectly predictable.

Limitations

The research aims to establish the impact of the introduction of the domestic Green Pass on the duration of customers' visits to various retail premises and public offices. While the study offers valuable insights into this topic, several potential limitations exist.

The study relies on Google data to measure visit duration, dependent on users opting for Google Location History. The sample may not be representative of the entire population. The data does not account for non-Google users or those who have turned off their location history, which might introduce bias. Only businesses with sufficient Google visitation data are included, potentially excluding numerous other businesses.

Data collection is limited to the metropolitan area of Genoa, Italy. Results might not be generalized to other cities or regions of Italy or countries with different sociocultural or economic contexts.

The two one-week observations took place over 12 weeks in the course of the summer season. Despite the intention to reduce seasonality bias, this timeframe might not fully capture the domestic Green Pass policy's long-term effects or behavior changes during other seasons.

The study assumes that visit duration time directly correlates with exposure risk. However, factors such as airflow, sanitation practices, and individual behaviors during visits could also influence risk.

In summary, while the research provides evidence of the domestic Green Pass policy's unintended effect on consumer behavior in Genoa, Italy, several limitations exist. These should be acknowledged when interpreting or using the results to inform decision-making.

Conclusion

The study provides insight into the effects of the domestic Green Pass on visit durations within certain premises and the subsequent increase in exposure risk provide a critical lens through which to reassess and refine pandemic response strategies. Acknowledging a paradoxical increase in exposure risk despite implementing a safety policy highlights the complexity of managing public health in the context of social and economic activities.

This finding is crucial for policymakers, suggesting that while policies like the Green Pass are designed to mitigate risk, they must also consider potential behavioral changes that could offset their benefits. Policymakers could have foreseen the "ex-ante" moral hazard consequent to implementing the domestic Green Pass policy in Italy and could have observed "ex-post" the unintended behavioral changes determined by the policy. The domestic Green Pass policy depended on the immunological condition of acquired immunity. When this condition was violated, the observed moral hazard significantly increased the close contact risk of infection caused by COVID-19 variants for the entire community. The World Health Organization (WHO) also suggested that the Green Pass could increase the risks of continued transmission because those carrying one would ignore public health advice about physical distancing. Vaccinated people could still be able to spread the virus and put others at risk, so experts have stressed the importance of continuing to distance and wear masks (28).

The balance between economic activity and health safety, as well as the call for continuous monitoring and adjustment of policies, further underlines the ongoing challenges in public health policymaking. These aspects of the study's implications suggest that effective COVID-19 containment requires a multifaceted approach that includes initial policy implementation and continuing assessment and adaptation. To sustain Green Pass' social and economic benefits, the risk of moral hazard could have been mitigated using Google visit duration data to inform the public and potentially influence social distancing decisions during public health crises.

The pandemic has revealed the importance of developing a shared awareness of threats for resilience in interconnected societies. This collective understanding encourages individuals to collaborate on common goals and mitigate shared dangers. A shared understanding of what constitutes a threat versus a desirable outcome may depend on how risk is communicated (29).

The COVID-19 health crisis has led to an unprecedented use of surveillance measures from public health authorities. The acceptance of the use of smartphone location data could mitigate the unintended consequences of moral hazard by helping people self-regulate their behavior to align with societal norms and expectations, essentially surveilling themselves without the need for external oversight (30).

Suppose the public knows the average visit duration for specific locations, such as coffee shops or restaurants. In that case, they can make informed decisions about the incremental risk of exposure of indulging in a conversation while sipping a cappuccino or having a three-course gourmet meal with a large group of friends. Moreover, suppose a store has a notably long visit duration. In that case, some might interpret that as potential inefficiency in social distancing measures and choose to visit at off-peak times or select another location.

In conclusion, the unintended consequences of future public health policies during a crisis can be mitigated by paying closer attention to the data, promoting transparency, encouraging participatory governance, and embracing innovative solutions, all while safeguarding privacy and advancing equity.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethics approval and/or informed consent were not sought for this study. Publicly available Google data were collected to measure the time customers typically spend on a specific retail premise or public office. Google uses aggregated and anonymized data from users who have opted for Google Location History to determine visit duration. No personally identifiable information, such as an individual's location, contact, or movement, will be made available at any point.

Author contributions

CO: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2024.1345119/full#supplementary-material

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