Follow the herd?:

Studying herding behaviour in mask-wearing during the COVID-19 pandemic in the Netherlands

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Studying herding behaviour in mask-wearing during the COVID-19 pandemic in the Netherlands

by

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TU Delft

Preface

This thesis concludes my master's study in Complex Systems Engineering and Management at the Delft University of Technology. My great interest in statistics and human behaviour, combined with a curiosity sparked in the midst of the COVID-19 pandemic, has resulted in my final research on the effect of herding behaviour in mask-wearing. It is my hope that this work can contribute to the development of more effective public health policies, for now and in the future. It would have been impossible for me to get through this two-year journey, especially the past six months, without the immeasurable kindness of the people who surrounded me along the way. In these few and limited words, I would like to thank some of them.

I would like to express my gratitude to Caspar Chorus for his tremendous support throughout my graduation process. Thank you for believing in my ideas, gathering amazing people to be on my graduation committee, and guiding me even when I lost belief in myself. I would like to thank Maarten Kroesen for his kind and constant guidance, support, and understanding. Beyond that, you have taught me not to lose sight of how this project is only a small part of the grand scheme of life. To Amineh Ghorbani, thank you for your helpful and sharp feedback. Your words of encouragement have made me more confident in my work. I would like to thank Tanzhe Tang for the valuable discussions and your useful suggestion to join the Spring School for Agent-based Modelling.

I would like to thank my dearest friends, the ones who never cease to bring joy, warmth, and wonderful experiences into my life in a foreign country. Thank you for those ears that listen, those words that comfort me, and those arms that hold me. Without your presence, I might not have been able to finish this journey. Thank you to my parents, who never stop loving and supporting me with such patience and understanding. Lastly, my gratitude also goes to the Faculty of Technology, Policy and Management, which has given me major financial support to study and live here.

It is a challenging journey, but also one that I will cherish forever.

Stella Mulia
Delft, August 16, 2021

Abstract

The absence of medicines to cure COVID-19 calls for preventive strategies, including mask-wearing. Despite its protection against exposure to coronavirus, not everyone chooses to wear a mask. Some studies addressed mask-wearing behaviour from the standpoint of behavioural economics, one being the effect of herding behaviour. This occurs when people base their decision on the decisions of others. After a literature review, it is known that herding can indeed play a role, yet it has only been empirically studied up to a correlational relationship and not a causal relationship. Therefore, this study focuses on quantifying the effect of factors that influence mask-wearing, emphasising herding. Aside from being scientifically relevant by filling the knowledge gaps, this study is also societally relevant. This study can be used in a more realistic epidemic transmission study that involves preventive health behaviours and can also help policymakers simulate the impacts of their policy designs more accurately.

The study comprises two overarching phases: choice and agent-based modelling. Within the choice modelling, identification of possible factors using a systematic literature review is performed. This resulted in four types of factors: Health Belief Model (HBM) related factors, herding-related factors, situational cues, and demographics. Next, after developing a questionnaire and collecting 151 respondents within the population of the Netherlands, a Latent Class Cluster Analysis (LCCA) is performed to identify two underlying clusters that represent the health beliefs of the respondents. The first cluster, HBM Class 1, consists of people who are more risk-averse towards COVID-19 and believe more in the efficacy of mask-wearing. The other cluster, HBM Class 2, is simply the opposite of HBM Class 1. Finally, the choice modelling has confirmed a statistically significant effect of herding, only within friends and/or family and the random people.

To explore the macro-level population dynamics resulting from micro-level individual behaviours, the collective result is obtained by taking an interdependent behaviour between people into account. An agent-based model (ABM) has been formalised, implemented, verified, and validated. The main insight obtained from this ABM is that the herding effect is stronger when the majority is not wearing masks than when the majority is wearing masks. In other words, there is a tendency towards no-mask-wearing, instead of the opposite. These discoveries have brought into the state-of-the-art knowledge base not only a new insight on how herding affects mask-wearing, but also an under-explored way of combining static (choice modelling) and dynamic (ABM) research methods.

This study has several limitations. First, there is an unknown risk of low-quality responses due to the online distribution of the survey. Second, the sample cannot be considered as a representative sample of the Dutch population. Care should be taken in generalising the result to the general Netherlands population. Third, the literature review may be missing important factors that were undiscovered in the previous literature up to April 2021. Fourth, this study generalises the factors in a broad categorisation. Finally, the ABM employs simplified input values. Reflecting on the aforementioned limitations, future studies may also incorporate interviews, a more representative sampling method, and a more fine-grained specification of factors.

Finally, five recommendations are derived for the policy-making process. First, this study recommends policy-makers maintain clarity in communicating mask-wearing policy. Second, enforcement of mandatory policy is recommended, especially in outdoor spaces. Third, mask-wearing can be encouraged through social campaigns, if necessary. Such campaigns may contain figures that people can closely relate to. Another alternative is to increase the importance of policy by putting signs in more prominent places and informing people about how active the policy has been enforced. Fourth, the modellers in the policy-making domain could look at incorporating herding to such research and enrich its realism. Lastly, this study can also be utilised for other policy-making processes outside the mask-wearing context and/or outside the COVID-19 context.

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1 Introduction

1.1. Background

1.1.1. Mask-wearing in the midst of COVID-19 pandemic

It begins in one city in December 2019 and has spread across the world – the coronavirus disease (COVID-19) outbreak is unquestionably one of the most severe global phenomena in modern history. Up to the time of this research, it has caused more than 160 million cases and more than 3.3 million deaths (WHO, 2021). It adversely affects not only global health but also the world economy. The absence of medicines to prevent or cure COVID-19 calls for preventive health behaviour strategies to suppress the transmission, such as social distancing, self-isolation, hand washing, and mask-wearing.

According to Soofi et al. (2020), encouraging these strategies has been the focus of all public health policies to mitigate COVID-19. Among other preventive strategies, the WHO[1] stated that mask-wearing is a key measure to reduce the risk of exposure (WHO, 2020). Worby and Chang (2020) found that although mask-wearing has a limited protective effect, it has the ability to reduce COVID-19 infections and deaths. According to Li et al. (2020), in combination with social distancing, mask-wearing "flattens the epidemic curve". These studies show the high relevance of mask-wearing for the public health policy-making context.

In the Netherlands, however, there have been several incidents where people refused to wear a mask in shops and restaurants (Soetenhorst, 2020). Moreover, CBL[2] reported that at least 40% of shoppers are not wearing a mask (van Gennip, 2020). Despite the Dutch government's advice on wearing a mask in indoor public places, a question arises: why do some people still choose not to wear one? Soofi et al. (2020) tried to address this seemingly less optimal choice from the standpoint of behavioural economics, one of them being the influence of *herding behaviour*. Similarly, van den Broek-Altenburg and Atherly (2020) also touched upon the influence of *motivation to conform* on the choice of mask-wearing.

1.1.2. Herding behaviour in mask-wearing

Herding behaviour refers to basing a decision on what others are doing instead of one's own information (Banerjee, 1992). The tendency to herd is higher, especially under uncertain situations (Eun Huh et al., 2014). In the context of mask-wearing, the uncertainty surrounding mask efficacy makes herding behaviour more likely to influence mask-wearing. Numerous official institutes have provided varying information on mask efficacy. While WHO stated that mask-wearing is a *key* measure, ECDC[3] stated that mask "*may* help reduce the spread of infection" (ECDC, 2020, p. 2). To an even lesser confidence level on mask, RIVM[4] reported that mask protects the wearer only to a *very limited extent* (RIVM, 2020).

[1] World Health Organization
[2] Centraal Bureau Levensmiddelenhande
[3] European Center for Disease Prevention and Control
[4] Rijksinstituut voor Volksgezondheid en Milieu

Several sources have supported the possible herding behaviour in mask-wearing. Firstly, Parham and Hardy (2020) from CEBM[5] postulates that based on their non-participant observation, the rapid adoption of mask-wearing in France may be driven by the *surveillance of others* in the social area. Moreover, Jan Gelech from the University of Saskatchewan, Canada, stated that *conformity* to social pressure might explain mask-wearing behaviour (Mattern, 2020). Lastly, in his commentary article, Bellato (2020) argued that *social influence* through seeing others' behaviour, in adhering to COVID-19 regulations, facilitates the emergence of the behaviour itself.

Sim et al. (2014) pointed out that *social acceptance* plays a key role in mask-wearing behaviour during the SARS epidemic in 2003. The influence of peer pressure was observed when flight passengers in Bangkok airport bought and wore masks after noticing that the staff was wearing masks (Sim et al., 2014). Barile et al. (2021, p. 87) quantified the effect of *descriptive norm* (i.e., the frequency of seeing others wearing masks in public) and found it to be a "key element" to translate the mask-wearing intention to action. Furthermore, the concept of *collectivism* (i.e., a view of an individual being a part of a larger social structure (Triandis, 2018)) was argued by Scerri and Grech (2020) as one of the bases of adherence to public health policies. Similarly, Huang et al. (2020) analysed Chinese micro-blog posts and found that collectivism is correlated with higher intention towards preventive health behaviour.

1.1.3. The scientific and societal need for a study on mask-wearing, while taking herding into account

Despite the aforementioned studies, these analyses justify the idea of herding in mask-wearing only up to a correlational relationship and not a causal relationship. Although the correlation may be interpreted as causation through the use of a behaviour change model as its theoretical foundation, such a study has only been done by Barile et al. (2021). Furthermore, most research on COVID-19 has focused only on its epidemiological and psychological impact and very few on behavioural analysis in COVID-19 prevention (Huang et al., 2020). Lastly, studies on herding in public health are also limited (Lee et al., 2021). Therefore, this study focuses on quantifying the effect of factors that influence mask-wearing, emphasising herding.

Aside from being scientifically relevant by filling the knowledge gaps, this study is also societally relevant. It is important to understand the factors influencing mask-wearing, especially considering herding, to understand better the mechanism of people's decisions to wear masks. As the world is facing an unprecedented pandemic, the modelling and prediction thereof will help in developing more effective public health policies. Such a model can be used in a more realistic epidemic transmission study that involves preventive health behaviours and can also help policymakers simulate the impacts of their policy designs more accurately.

This study is socio-technical and complex in nature. Mathematical models are essentially technical solutions that aid policymakers in crafting effective strategies. These models consider individual behaviour in mask-wearing and how these individuals interact and influence each other at the population level, highlighting how the social element is substantial in this study. Capturing the uncontrollable and unpredictable interactions, and subsequently, the population's emergent mask-wearing behaviour, is how this study attempts to better comprehend the complex problem at hand.

[5]Centre for Evidence-Based Medicine

1.2. Main research question

The main research question of this study is:

How does herding behaviour influence mask-wearing during the COVID-19 pandemic in the population of the Netherlands?

1.3. Sub-questions and research approach

The main research question can be decomposed into several sub-questions (SQ's) as follows:

1. What are the possible factors that may influence mask-wearing behaviour?

   A literature review is conducted to synthesise a collection of factors that may influence mask-wearing systematically. To broaden the search space, articles in health protective behaviour are also included. Furthermore, studies in the context of other respiratory disease outbreaks (e.g., Spanish flu, H1N1, and SARS) are considered relevant in respect of the COVID-19 pandemic.

2. To what extent does herding affect an individual's mask-wearing behaviour, with respect to other factors?

   To measure the effect of herding on mask-wearing, a choice modelling is performed. The choice modelling method is elaborated in Section 2. The data used in the modelling is empirically collected through a survey-based choice experiment on people living in the Netherlands.

3. How does herding influence mask-wearing behaviour at the population level?

   The choice model reflects how an individual makes a mask-wearing decision, considering the effect of herding. To explore the macro-level population dynamics resulting from micro-level individual behaviours, simply averaging over individuals is not enough. Because herding is a phenomenon that essentially occurs through social interaction, the collective result should be obtained while taking this interdependence behaviour into account. Agent-based models (ABMs) allow for an explicit link between the micro and macro level of analysis (Bruch & Atwell, 2015).

1.4. Scope

To delineate this study, several scoping decisions are made:

- The analysis of mask-wearing behaviour is focused only in public places.
- Only non-medical masks are considered.
- The study is conducted assuming the current mask-wearing policy (at the time of writing, it is mandatory at indoor public places, except in fixed seating (RIVM, 2021b)).

1.5. Thesis outline

This report elaborates the methodology used in this study in Chapter 2. Next, Chapter 3 identifies possible factors influencing mask-wearing. These factors were then used in the design of questionnaire in Chapter 4. The questionnaire serves as a tool to collect the data necessary for Chapter 5 that models the influence of herding in mask-wearing. Using the choice model resulted in the previous chapter, Chapter 6 models the aggregate mask-wearing behaviour in an agent-based model. Finally, the conclusion, comprising a reflection on the research questions, limitations, and recommendations, is presented in Chapter 7.

2
Methodology

This chapter describes the methodology of this study.

2.1. Phase I: Research Definition

The first phase aims to systematically comprehend the problem situation and discover the knowledge gap contributing to the scientific and societal domains. This phase resulted in the first chapter.

2.2. Phase II: Choice Modelling

The factors influencing mask-wearing behaviour is analysed through a choice modelling. Understanding factors that influence mask-wearing behaviour, especially in investigating the effect of herding, is an attempt to measure how the individuals make trade-offs between multiple factors. For example, someone might trade comfort for being policy-compliant; or trade the protection for conforming with most non-mask wearers. Discrete Choice Experiment (DCE) is a suitable preference elicitation method for this study because it allows for an analysis of a causation relationship between the factors and mask-wearing, as discussed in Section 1.1.3. It stems from the assumption that certain choices – in this case, mask-wearing – can be described by their attributes/properties. The utility, or one's valuation of this choice, is a function of the utilities of each attribute (Kohler et al., 2017). Furthermore, DCE is commonly used in health economics over the past decade (Ryan, 2004).

2.2.1. Identification of possible factors

Previously, it was mentioned that choice modelling measures the trade-offs between *multiple factors*. This study therefore identifies possible factors that influence mask-wearing through a systematic literature review. The review focuses on scientific articles that perform factor analysis on mask-wearing behaviour. A limitation with this method is that there are few to no recent articles in this regard since the COVID-19 situation is rather recent. To account for this limitation, preventive health behaviours, including past epidemics, are also considered. The articles are gathered using an academic search engine. Although this excludes grey articles, scientific articles ensure a solid base for the rest of this study.

Certainly, since herding is the main focus of this study, factors that characterise herding behaviour are given a particular attention in this step. Aside from herding, a social cognition model called Health Belief Model (HBM) also takes a prominent part. The HBM focuses on individuals' "subjective perceptions of illness and treatment" (Abraham & Sheeran, 2001, p. 29). This model is chosen due to its wide use in studies on health preventive behaviours (Sim et al., 2014; Wong & Tang, 2005; Zhang et al., 2019), and even in the context of COVID-19 (see Shahnazi et al. (2020) and Tong et al. (2020). It comprises six mediating constructs and two explanatory factors as shown in Figure 2.1.

The eight components that influence *Action* were treated as explanatory factors in many studies. In

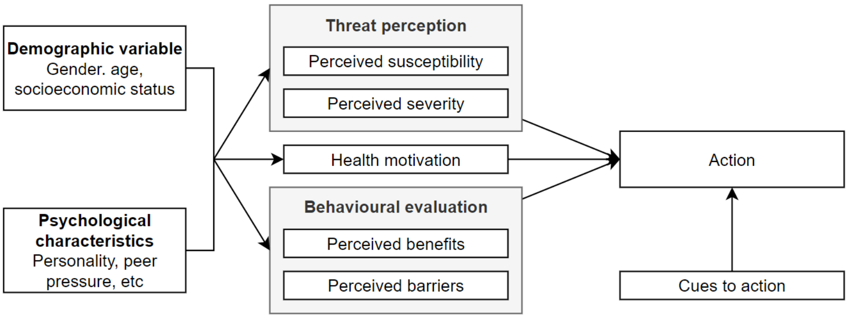

Figure 2.1: The Health Belief Model (Abraham & Sheeran, 2001, p. 31)

different studies, all constructs were operationalised using varying sets of indicators, as they were theoretically left open to debate. In particular, *cues to action* encompass internal and external triggers, such as (perception, presence, or intensity of) symptoms, *social influence*, and mass media campaigns (Abraham & Sheeran, 2001).

2.2.2. Design of choice scenarios

After gathering the possible factors, this study designs a choice experiment using a fractional factorial design. In comparison with the full factorial design, the fractional factorial design only allows for main effects estimation and not interaction effects (Bos et al., 2004). However, this method reduces the number of choice tasks substantially, which is highly beneficial considering time and resource limitation for data collection. Furthermore, an efficient design can actually further reduce the number of choice tasks, but it requires prior parameters. Due to the absence of knowledge in the priors, fractional factorial design is a better method. After all, *blocking* can still overcome the disadvantage of this method if the (already reduced) number of choice tasks is yet deemed too high.

2.2.3. Choice experiment

Modelling the factors that influence mask-wearing behaviour requires empirical data. Train (2009) categorised data into two types: *stated-preference* (SP) and *revealed preference* (RP) data. On the one hand, the RP data provides actual choices but with possible insufficient variation in the relevant factors required for choice model estimation. On the other hand, the SP data allows for experimentally varied factors but with possible hypothetical bias (i.e., the incoherence between what respondents say and do). Nonetheless, considering the lack of RP data in mask-wearing and the need for sufficient variation, the SP data is used.

The SP data is collected through a survey that targets the population of the Netherlands. The survey is conducted through convenience sampling, which means each group in the population has a nonzero probability of being the respondent of this study (Lavrakas, 2013). Moreover, it is administered online, which has the advantage to reach a larger mass in a limited time despite a lack of control over the respondent's attention when filling in the survey. To compensate for this limitation, only surveys completed within a *reasonable* duration are included in the analysis. What is considered *reasonable* is determined after the survey is developed.

2.2.4. Latent class cluster analysis

After the data collection, the analysis starts with identifying clusters in the population. This study assumes that people have varying health beliefs, i.e., perceptions of the pandemic and on mask-wearing as specified by the HBM. These beliefs are subjective to each individual and hence cannot be controlled by the experiment. To account for this heterogeneity, while keeping the model parsimonious, the population is clustered based on their health beliefs. In other words, this study identifies internally homogeneous classes indicated by the health beliefs of the individuals.

In general, there are two approaches in clustering: deterministic and probabilistic (Molin et al., 2016). The different approaches relate to how it assigns an individual to a cluster. Deterministic clustering is considered as the traditional approach (de Haas et al., 2018). However this study employs the probabilistic approach by means of Latent Class Cluster Analysis (LCCA), due to its advantages in reducing misclassification biases and the use of statistical measure to determine the number of classes and the inclusion of parameters (Molin et al., 2016).

The LCCA assumes that a discrete latent variable can explain the correlation between its indicators. As a result, the indicators become statistically independent conditional on the latent variable (Magidson & Vermunt, 2004). In this study, the latent variable is represented by a variable called *HBM class* with the health beliefs (from HBM) as its indicators. By finding the least number of HBM classes that underlies the varying health beliefs, the complexity of this study can be reduced from four types of health beliefs to only one latent HBM class variable.

2.2.5. Choice modelling

After identifying the latent variable *HBM class*, this study then uses a binary logit model with main and interaction effects to model the mask-wearing choice under the possible factors. The model estimation is done in Apollo (a statistical tool in R). The model assumes that a decision is made by choosing an alternative with the highest utility, or referred to as a utility-maximising behaviour (Train, 2009). The term utility is the *weighted* sum of observed factors (X), referred to as the systematic utility (V_i), and an error term (ε_i) that comprises the unobserved factors (Hensher et al., 2005). The weight of each factor m is denoted as β_m. In mathematical terms, if there are M factors, the utility of alternative i (U_i) can be defined as:

$$U_i = V_i + \varepsilon_i$$

where

$$V_i = \sum_{m=1}^{M} \beta_m \cdot X_{im}$$

2.3. Phase III: Agent-based Modelling

To enable a prediction of the emergent mask-wearing behaviour at the population level (using the individual choice model) that considers the influence of herding, this study will perform agent-based modelling. The overall population's mask-wearing behaviour suits the definition of a complex adaptive system by Waldorp (1992). It is a dynamic network of the society, acting and reacting to each other's action in parallel, resulting in the overall behaviour. According to van Daam et al. (2012), agent-based modelling is most suitable for such complex adaptive systems. The choice model from the previous phase serves as the crucial input in model formalisation as the agent's decision rule. This model shall be a tool for deriving public health policy recommendations.

This phase formalises how the Dutch society's behaviour can be translated into an ABM (SQ3). The agents, their states, and properties will be formalised in software data structures. Moreover, the behaviour of agents will also be formalised. The behaviour stands for “which agent does what with whom and when” (van Daam et al., 2012, p. 88). Each agent's behaviour is governed by the decision rule in the form of a utility function obtained from the choice modelling in the previous phase. A simple ABM prototype is developed in NetLogo. Furthermore, after the ABM is verified and validated, experiments are conducted and analysed. Lastly, the contributions of the ABM are discussed.

2.4. Phase IV: Conclusions

This phase reflects this study on its research questions, limitations, and potential future studies.

3

Literature review: possible factors influencing mask-wearing

This chapter explores possible explanatory factors that may influence mask-wearing. To do so, a literature review is performed and presented in this chapter.

3.1. Characterising herding behaviour

Herding behaviour refers to ”doing what everyone else is doing”, regardless of the decision maker’s private information (Banerjee, 1992, p. 798). Lee et al. (2021, p. 3) viewed herding as an irrational and emotional behaviour in ”following the behaviour of the crowd”. An important notion about herding is that the alignment/convergence of behaviours emerges through local interactions and without coercive authority (Raafat et al., 2009). Studies on herding behaviour have been mostly in the domain of economics and finance, for example, herding in stock markets and consumer preferences (Lee et al., 2021). In financial markets, for example, someone is said to herd when their decision to ”not invest” changes to ”invest” after knowing that others are investing, and vice versa (Bikhchandani & Sharma, 2001).

Different fields have captured herding in other similar concepts. In psychology, *conformity* is observed when individuals deflect from their own judgement to yield to the majority (Asch, 1956). As cited by Raafat et al. (2009), a principle of *group mind* was used by Tarde et al. (1903) to explain herd behaviour. In organisational studies, *mimetic isomorphism* is an organisational behaviour to imitate or model themselves on other organisations when their goal, technology, or environment is uncertain (DiMaggio & Powell, 1983). Altogether, these different concepts consider herding under various mechanisms, such as social pressure and uncertainty.

Such mechanisms can be conceptualised as social influence. There are two types of social influence: normative and informational (Deutsch & Gerard, 1955). Normative social influence is “an influence to conform with the positive expectations of another”, and informational social influence is “an influence to accept information obtained from another as evidence about reality” (Deutsch & Gerard, 1955, p. 629). In the context of mask-wearing, a majority of (non) mask-wearers around a decision-maker could be perceived in two ways. In a normative manner, (no) mask-wearing is perceived as the norm. In an informational manner, the majority is perceived to have more information about the pandemic. Because the normative and informational influences are commonly found together (Deutsch & Gerard, 1955), the disentanglement of the two is excluded from this study.

A study by Van den Berg et al. (2018) analysed the effect of herding on the decision to evacuate from a natural disaster. In their study, herding occurs when someone is more inclined to depart after seeing more people depart. The effect of herding is quantified using NDEP (number of people departing) variable, which is used as one of the criteria/attributes that contribute to the choice to depart. Likewise, for this study, herding is quantified using the *proportion of mask-wearers* in a similar manner. The *mask-wearers* in question are based on three reference groups. The distinction between these groups is based on their social proximity with the decision-maker. These groups are the decision-maker’s (1) friends and/or family, (2) random people encountered in public areas (at the neighbourhood level), and

(3) the national population (of the Netherlands).

3.2. Factors influencing preventive health behaviours

A systematic literature review was performed by searching the Scopus database for the title, abstract, and keywords of articles[1] in the English language. The search was aimed at studies in factors influencing preventive health behaviours (including mask-wearing). The search queries and the distinction between them are presented in Table 3.1.

Table 3.1: Queries used to identify possible factors of mask-wearing

Query	Distinction	Articles returned	Articles selected
(mask OR ”mouth cap” OR ”mouth-cap”) AND (behavio*r OR ”mask use” OR wearing) AND covid AND (factor OR driver) AND NOT (”mental health” OR ”psychological distress”)	• In the context of COVID-19 • For any factors • Excluding studies on the impact of COVID-19 on mental health (due to its frequent occurrence)	207	17
(mask OR ”mouth cap” OR ”mouth-cap”) AND (behavio*r OR ”mask use” OR wearing) AND disease AND (factor OR driver) AND (psychosocial OR social OR herding OR conform OR ”social influence”)	• In the context of any diseases • For factors that considers psychosocial aspects	152	7

Due to overlapping search results between the two search queries, in total, there were 278 articles collected. The articles were then selected by excluding unsuitable articles, for example, articles that focus on epidemic transmission and (psychological) impact of COVID-19, evaluate the effectiveness of different public health strategies, or merely describe exhibited preventive health behaviours. Relevant studies on a particular subject group such as health professionals, factory workers, and military forces were also excluded.

Ultimately, the selection resulted in 24 articles. An overview of all reviewed articles is shown in Table 3.2. It presents the authors, year of publication, number of citations, country studied, whether they specifically focus on mask-wearing only (or on preventive health behaviours in general), and the type of factors they found to be influential. The countries are represented using ISO 3166-1 Alpha-2 code (International Organization for Standardization, 2013). By inference, the factors can be grouped into three categories: (1) HBM related factors, (2) psychosocial, and (3) demographics. These types of factors will be discussed in the following subsections.

[1] Only articles with TU Delft university access are considered.

Table 3.2: Overview of reviewed articles to identify possible factors of mask-wearing

Authors (Year)	Cited by	Country*	Only mask	Type of factors discussed		
				HBM	Psychosocial	Demographics
In the COVID-19 context						
Pfattheicher et al. (2020)	18	GB, US, DE			✓	
Galasso et al. (2020)	8	AU, AT, FR, DE, IT, NZ, GB, US				✓
Hutchins et al. (2020)	7	US				✓
Haischer et al. (2020)	7	US	•			✓
Guzek et al. (2020)	7	PL				✓
Tong et al. (2020)	5	CN		✓	✓	✓
Gray et al. (2020)	3	NZ	•	✓	✓	
Cotrin et al. (2020)	2	BR	•	✓	✓	
Stosic et al. (2021)	0	US	•	✓		✓
Hao et al. (2021)	0	US	•		✓	
Campos-Mercade et al. (2021)	0	SE			✓	
Taylor and Asmundson (2021)	0	US, CA	•	✓	✓	
Al Naam et al. (2021)	0	SA	•	✓		✓
Callaghan et al. (2021)	0	US				✓
Rui et al. (2021)	0	CN		✓		
Zhou et al. (2020)	0	CN	•	✓	✓	✓
Barile et al. (2021)	0	US	•		✓	✓
Outside the COVID-19 context						
Chuang et al. (2015)	39	TW			✓	
Tang and Wong (2005)	39	HK		✓	✓	✓
Kuo et al. (2011)	29	TW		✓		✓
Siu (2016)	13	CN	•		✓	
Taglioni et al. (2013)	8	FR		✓		✓
Zhang et al. (2019)	6	HK	•	✓	✓	
Gong et al. (2020)	1	TW		✓	✓	
Total				13	14	13

3.2.1. Psychosocial factors

Fourteen articles (see Table 3.2) found psychosocial factors associated with preventive health behaviour, with half of them specifically focusing on mask-wearing behaviour. The psychosocial factors can be summarised into six main factors:

1. Social capital

   Social capital can be defined as "social cohesiveness and trusting relationships within a community" (Chuang et al., 2015; Jung et al., 2013). Chuang et al. (2015) used three dimensions to categorize this concept: (1) *bonding* as the frequency of neighbourly contact, (2) *bridging* as membership in associations, and (3) *linking* as trust in government. Similarly, Hao et al. (2021) conceptualised social capital as communication and trust with friends, family, and neighbours. The dimension of trust in government was used in Gong et al. (2020) and Tang and Wong (2005). These articles found that a higher social capital is linked to a higher intention to wear a mask.

2. Sociocultural meaning of mask-wearing

   Siu (2016, p. 12) investigated socio-cultural meaning of mask-wearing in terms of "societal ideologies and traditional Chinese cultural beliefs" and how it affects mask-wearing behaviour. The study examined the shift in the sociocultural meaning of mask-wearing shifted from the SARS outbreak (2003) until after the outbreak (2005). There was a *shift* from positive to negative meanings, e.g. from being a social responsibility to a sign of sickness (Siu, 2016). In turn, this shift has diminished the perceived importance of mask-wearing and demotivated people to adopt such behaviour.

3. Prosociality

   Campos-Mercade et al. (2021) defined *prosociality* as the degree of individuals' concern with being socially responsible. They found that higher prosociality predicts higher compliance to preventive health behaviours (Campos-Mercade et al., 2021). This term of prosociality also encompasses the concept of *empathy* for the vulnerable, as considered by Pfattheicher et al. (2020). Moreover, Gray et al. (2020) highlighted individuals' tendency to prioritise the needs of others under (the belief of) a mask shortage. Lastly, Zhang et al. (2019) found that *social responsibility* (i.e., to wear masks for the benefit of others) influence mask-wearing behaviour.

4. Norms

   Studies by Barile et al. (2021) included subjective and descriptive norms as factors that influence mask-wearing. The subjective norm refers to having people who are important to the decision-maker, wanting her to wear a mask. This factor was found to influence both the mask-wearing intention and the actual behaviour. The descriptive norm refers to the frequency of seeing others wearing masks in public. This factor was found to mediate the effect of mask-wearing intention on the behaviour. Similarly, Zhou et al. (2020) also included subjective norm (under a construct of social influence) and found it to influence the mask-wearing intention.

5. Autonomy

   In contrast to prosociality, Zhang et al. (2019) considered the principle of *personal choice* to influence mask-wearing behaviour. This principle entails how an individual perceives mask-wearing as an individual choice rather than a collective choice. In other words, they prefer to decide by themselves, considering whether they are sick or they want to protect themselves. Furthermore, Taylor and Asmundson (2021) included the concept of *psychological reactance* (aversion to being forced). Theoretically, a higher psychological reactance will, in turn, strengthen other anti-mask beliefs (Taylor & Asmundson, 2021).

6. Social cynicism

   Social cynicism is a social axiom considered by Tong et al. (2020, p. 6), which refers to "the belief that human nature and the social world will produce negative consequences". This study found that higher social cynicism is linked to lower adherence to mask-wearing and other preventive health behaviours.

Out of these six psychosocial factors, only the *norms* factor is included in the possible factors. As stated in Section 3.1, this study interprets (descriptive) norm - following Barile et al. (2021) - as the *proportion of mask-wearers*. This factor reflects herding behaviour. The difference between this study and Barile et al. (2021) is that based on how Barile et al. (2021) relied on the self-reflection of study participants regarding how often they see others wearing masks in public (never, rarely, sometimes, often, and always). On the contrary, this study experimentally varies the *proportion of mask-wearers* and assess how this factor affect mask-wearing behaviour.

This study argues that *social capital* and *prosociality* are highly associated with the perceived benefits of mask-wearing (which will be discussed in Section 3.2.2). In this case, individuals – that bond with their community and feel responsible for them – will see a higher benefit of mask-wearing in lowering the risk of COVID-19 not only for themselves but also for their community. Moreover, *autonomy* is associated with perceived barriers. The aversion to being forced can be perceived as discomfort associated with mask-wearing. By excluding these factors, this study prevents over-specification bias from redundant/overlapping factors. Furthermore, this study excludes *sociocultural meaning* and *social cynicism* due to their inherent complexity. Including these factors may blur the subtle effect of herding behaviour.

3.2.2. Health-Belief-Model-related factors

As discussed in Section 2.2.1, the Health Belief Model (HBM) consists of subjective perceptions of illness and treatments, in this case of COVID-19 and preventive health behaviours. Not all articles explicitly use HBM as their theoretical framework. However, thirteen of the reviewed articles found (combinations of) these HBM-related factors to affect preventive health behaviours. *Perceived self-efficacy* is also considered as one of the HBM-related factors because it belongs to the extended-HBM (Abraham & Sheeran, 2001). The prevalence of each variable in the literature is presented in Table 3.3.

The selection of factors to be included in this study is based on Table 3.3. *Perceived self-efficacy* is excluded because this factor is not prevalent in the context of mask-wearing. *Cue to action* is included with adaption, using situational cues such as the type of location (outdoor or indoor), the crowd density, and the mask-wearing policy on the specific location (mandatory or voluntary) (following Zhang et al. (2019)). Due to this adaption, these situational cues are set apart from the HBM-factors.

It is noteworthy that the *cue to action* factor is treated differently from the first four HBM factors (perceived benefits, susceptibility, severity, and barriers). The *cue to action* factor, in this study, is treated as an objective description of the situation, while the rest is a subjective perception of the decision-maker. An element of *cue to action*, which is social influence (Abraham & Sheeran, 2001), is separated from this factor because it is already captured by the *proportion of mask-wearers* factor (see Section 3.1). Subsequently, this study only considers the first four variables as HBM-factors.

3.2.3. Demographic factors

Thirteen articles found demographic factors to be associated with preventive health behaviour. An overview of each factor's prevalence is shown in Table 3.4.

Galasso et al. (2020) investigated gender differences in the perception of COVID-19, attitude towards the public health policies, and compliance thereof. Conducted in eight countries (as specified in Table 3.2), the study found that women are more likely to find COVID-19 critical and to agree and comply with the policies. The prevalence of preventive health behaviours also varies across age groups, as Hutchins et al. (2020) showed that it is the lowest within the 18-29 years group and highest within the >60 years group.

Education level, along with gender, income level, and marital status, were found to be moderating the relationship from mask-wearing intention to behaviour (Zhou et al., 2020). Furthermore, a study by Al Naam et al. (2021) discovered a significant difference in attitude towards mask-wearing between

Table 3.3: Prevalence of Health-Belief-Model-related factors that influence preventive health behaviours

Authors (Year)	Perceived benefits	Perceived susceptibility	Perceived severity	Perceived barriers	Perceived self-efficacy	Cue to action
On mask-wearing						
Gray et al. (2020)	✓					
Cotrin et al. (2020)	✓					
Stosic et al. (2021)	✓					
Taylor and Asmundson (2021)	✓					
Al Naam et al. (2021)				✓		
Zhou et al. (2020)	✓			✓		
Zhang et al. (2019)	✓	✓	✓	✓		✓
On any preventive health behaviours						
Tong et al. (2020)	✓					
Rui et al. (2021)	✓	✓	✓		✓	
Tang and Wong (2005)		✓			✓	
Kuo et al. (2011)			✓			
Taglioni et al. (2013)	✓	✓				
Gong et al. (2020)		✓	✓		✓	
Total	9	5	4	3	2	1

different education levels and nationalities (Saudi and non-Saudi). Lastly, Stosic et al. (2021) found that certain gender, age, race, residence type, and political ideology (female, older adults, black, urban, and liberal) reported more mask-wearing.

Based on Table 3.4, the most prevalent demographic factors are gender, age, education level, and residence type. Therefore, these factors are chosen for this study. Within the less prevalent ones, only nationality is included due to ethical concerns.

3.3. Summary of possible factors

To summarise, the systematic literature review resulted in three major types of factors that may influence mask-wearing (see Table 3.2). The first type is related to HBM, a model that has been widely used for various kinds of health behaviours (Tong et al., 2020). Out of six constructs in HBM, only four are included as HBM-related factors due to their prevalence in the reviewed literature. The *cue to action* is treated as an objective description of the situation (hence referred to as *situational cues*) instead of the subjective perception of the decision-maker. Therefore, this type resulted in two groups of factors: HBM-related factors and situational cues.

The second type of factor encompasses six psychosocial phenomena surrounding preventive health behaviour. As elaborated in Section 3.2.1, only *norms* are used in this study to avoid redundancy between the HBM-related factors and the psychosocial factors and to maintain a manageable level of complexity. The *norms* factor is represented by herding-related factors as defined in Section 3.1. Lastly, five demographic factors are selected based on their prevalence in the reviewed literature and ethical consideration. Finally, four groups of possible factors are considered in this study (see Table 3.5).

Table 3.4: Prevalence of demographic factors that influence preventive health behaviours

Authors (Year)	Gender	Age	Education level	Residence type	Nationa -lity	Income Level	Race	Political Ideology
Galasso et al. (2020)	✓							
Hutchins et al. (2020)		✓						
Haischer et al. (2020)	✓	✓		✓				
Guzek et al. (2020)	✓							
Tong et al. (2020)	✓	✓	✓					
Stosic et al. (2021)	✓	✓		✓			✓	✓
Al Naam et al. (2021)	✓	✓			✓			
Callaghan et al. (2021)				✓				
Zhou et al. (2020)	✓	✓	✓			✓		
Barile et al. (2021)	✓							
Tang and Wong (2005)			✓					
Kuo et al. (2011)	✓		✓					
Taglioni et al. (2013)		✓	✓					
Total	9	7	5	3	1	1	1	1

Table 3.5: Summary of possible factors influencing mask-wearing

Group	Factor	Abbreviation
Herding behaviour	Proportion of mask-wearers within random people	prd
	Proportion of mask-wearers within friends and/or family	pff
	Proportion of mask-wearers within the national population	pnl
Health Belief Model	Perceived susceptibility	sus
	Perceived severity	sev
	Perceived barrier	bar
	Perceived benefit	ben
Situational cues	Location type (indoor/outdoor)	loc
	Crowd density	cwd
	Local policy (voluntary/mandatory)	pol
Demographics	Gender	gnd
	Age	age
	Level of education	edu
	Residence type	den
	Nationality	nat

4
Design of questionnaire

To measure the effect of possible factors (see Table 3.5), a questionnaire is developed. This chapter first presents an operationalisation of a choice model that incorporates the identified possible factors. Then, based on the operationalisation, a choice experiment design is generated using a fractional factorial design in Ngene software. The choice experiment design will be used later to assess the public's mask-wearing behaviour under different scenarios, among other data collected using the questionnaire.

4.1. Choice model operationalisation

Based on the possible factors, the choice model is operationalised. The model consists of two components: a structural model and a measurement model. A graphical representation of the relation between the structural and measurement model is graphically presented in Figure 4.1. To capture the effects of four HBM factors (i.e., perceived susceptibility, severity, benefits, and barriers) in a parsimonious way, these perceptions are assumed to be correlated due to an underlying latent variable. The latent variable will be referred to as *HBM class*. Furthermore, this study assumes that the demographic variable(s) can predict the HBM class membership as its covariate(s). The relationship between the HBM factors, HBM class, and demographic covariates compose a measurement model.

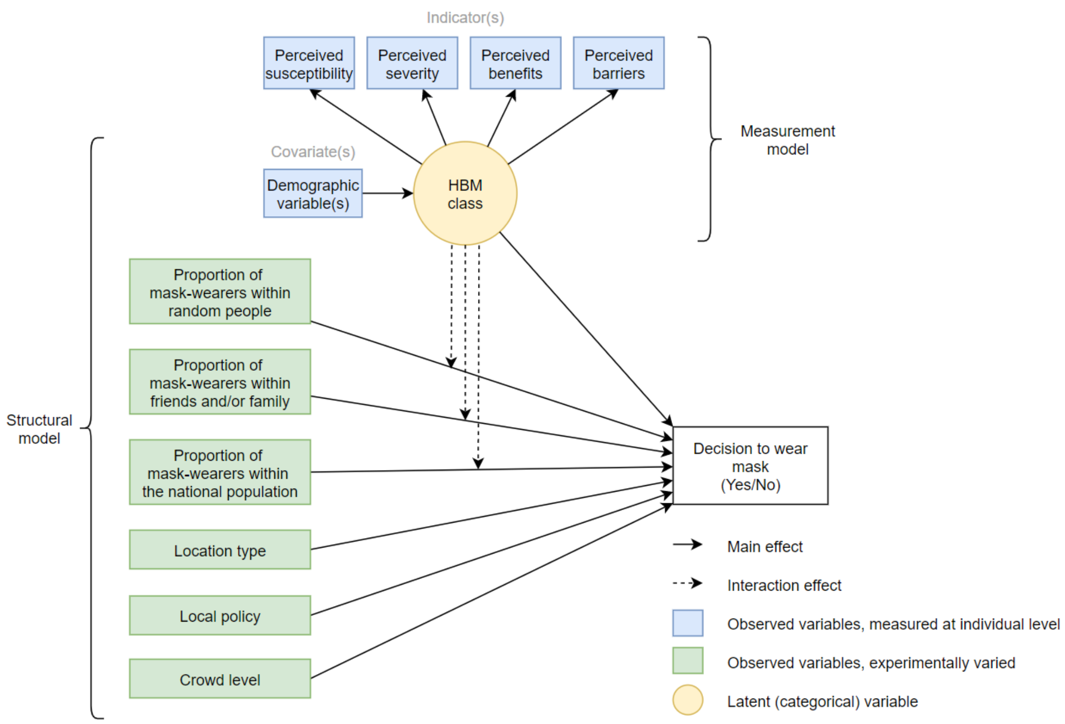

Figure 4.1: Operationalisation of the choice model

The structural model comprises factors assumed to directly influence mask-wearing: herding-related factors, situational cues, and the (latent) HBM class. Herding is said to occur when a higher proportion of mask-wearers within the reference groups leads to a higher probability of mask-wearing. These herding-related factors are weighed against situational cues and internal health belief represented by the HBM class. Furthermore, the effects of herding are assumed to interact with different HBM classes. This assumption is based on an idea that for example, people with a higher (perceived) susceptibility to COVID-19 may be more inclined to wear masks when seeing many others are doing so; or those with a higher (perceived) barrier to wearing masks may be less influenced by the *proportion of mask-wearers* around them.

4.2. Factors operationalisation

4.2.1. Herding behaviour factors

Herding behaviour, as measured by the effect of the *proportion of mask-wearers* within the three reference groups (prd, pff, pnl; see Section 3.1), are specified into four levels:

- Extreme majority: 90% of the people in the reference group wear masks.
- Moderate majority: 60% of the people in the reference group wear masks.
- Moderate minority: 40% of the people in the reference group wear masks.
- Extreme minority: 10% of the people in the reference group wear masks.

4.2.2. Situational cues factors

For model simplicity, the location type (loc) is simplified into two general areas: indoor and outdoor. The place-specific mask-wearing policy (pol) can be either mandatory or voluntary, without specifying the fine for violation under the mandatory policy. Lastly, the crowd density (cwd) can be low, medium, or high with the following specification:

- High: less than 1-meter distance between people
- Medium: 1 to 2-meter distance between people
- Low: more than 2-meter distance between people

4.2.3. Health Belief Model factors

The HBM factors are measured using questions adapted from Shahnazi et al. (2020). In their study, two questions were used for each factor. However, to keep the questionnaire short, only one question instead of two is used. Moreover, some questions are changed to focus on mask-wearing particularly. The questions are as follows:

- Perceived susceptibility (sus): ”I consider myself to be at risk of COVID-19.”
- Perceived severity (sev): ”COVID-19 has a high mortality rate.”
- Perceived barrier (bar): ”Wearing a mask is uncomfortable.”
- Perceived benefit (ben): ”COVID-19 is easily prevented by wearing a mask.”

4.2.4. Demographic factors

Age is measured in four levels following Hutchins et al. (2020): 18 to 29, 30 to 44, 45 to 59, and more than 59). For gender (gnd), respondents can identify themselves as male, female, other, or decide not to say. The levels of education (edu) are based on the classification by Centraal Bureau voor de Statistiek (2021), with equivalent education levels for non-Dutch respondents. The level of urbanisation (of each province of residence; den) is measured in three levels: rural (less than 500 inhabitants/km^2), sub-urban (500 to 1,000 inhabitants/km^2), and urban (more than 1000 inhabitants/km^2). Therefore, the respondents are asked to state their province of residence. Later in the analysis, the level of urbanisation is inferred through the population density data from CBS (2021c). Lastly, the nationality (nat) is differentiated into two groups: Dutch and non-Dutch nationals.

In summary, the operationalisation of factors in the structural model is presented in Table 4.1 and the measurement model in Table 4.2.

4.3. Experimental design generation

A fractional factorial design is used to establish choice sets for the experiment to limit the number of profiles. Ngene software automatically generated the design based on the factors and their levels as specified in the structural model (Table 4.1). Ngene found 24 choice sets to be the smallest possible number of choice sets that allows for an orthogonal design. Because this number of choice sets is considered too exhausting for a single respondent, *blocking* was used to divide the choice sets into three smaller blocks of eight choice sets.

The Ngene syntax and the resulting design are provided in Appendix A and B. To show that the design is orthogonal, the bivariate correlation between the factors are calculated using SPSS. As shown in Appendix C, all factors are significantly uncorrelated (under a significance level of 5%).

Table 4.1: Operationalisation of factors in the structural model

Group	Factor	Levels	Level coding
Herding behaviour	prd, pff, pnl	Extreme majority	90
		Moderate majority	60
		Moderate minority	40
		Extreme minority	10
Situational cues	loc	Outdoor	-1
		Indoor	1
	cwd	Low	0
		Medium	1
		High	2
	pol	Voluntary	-1
		Mandatory	1

Table 4.2: Operationalisation of factors in the measurement model

Group	Factor	Levels	Level coding
Health Belief Model	sus, sev, bar, ben	Strongly disagree	1
		Partially disagree	2
		No idea	3
		Partially agree	4
		Strongly agree	5
Demographics	gnd	Male	0
		Female	1
		Other	2
	age	18-29	0
		30-44	1
		45-59	2
		≥60	3
	edu	Basisonderwijs (Elementary school)	0
		Vmbo, havo-, vwo-onderbouw, mbo1 (Junior high school, Junior college)	1
		Havo, vwo, mbo2-4 (Senior high school, College)	2
		Hbo-, wo-bachelor (Bachelor)	3
		Hbo-, wo-master, doctor (Master, Doctor)	4
	den	Rural	0
		Sub-urban	1
		Urban	2
	nat	Dutch	0
		Other	1

4.4. Questionnaire design

The questionnaire was constructed on Qualtrics[1]. No personal data (information about an identified or identifiable person (ICO, 2021)) is requested. It starts with a consent form that informs respondents about the aim of this study and how their data is handled. Then, a respondent validation page checks whether the respondents are living in the Netherlands. Respondents that do not give their consent and/or do not live in the Netherlands will be immediately directed to the end of the questionnaire.

It consists of three main parts:

- Mask-wearing decision under eight hypothetical scenarios (choice experiment from Section 4.3).

  This part starts with an introduction on what the factor levels mean and asks the respondents to situate themselves under the current national policy of mask-wearing in the Netherlands. They will receive randomly one of the three blocks, which are evenly distributed. Then, for each choice set, they are asked to choose between ”Yes” (they would wear a mask under the situation presented) or ”No” (i.e. they would not).

- Demographics

  The questions are close-ended, except for nationality (nat), for which respondents can state their nationality if they are not Dutch.

- Perception on the COVID-19 pandemic and mask-wearing (HBM factors). All questions (see Section 4.2.3) are answered using a 5-point Likert scale, where 1 represents “strongly disagree”, 2 represents ”partially disagree”, 3 represents “no idea”, 4 represents “partially agree”, and 5 represents “strongly agree”.

A preview of the survey is accessible via this link. To ensure the ethical protection of respondents, this questionnaire (along with the subsequent data handling process) has been approved by the Human Research Ethics Committee of TU Delft.

[1]an online survey development tool for which TU Delft has provided the license

5

Influence of herding in mask-wearing

This chapter first presents the descriptive statistics of respondents that participate in the survey. Next, a Latent Class Analysis will cluster the respondents into *HBM classes* reflected through their perception of COVID-19 and mask-wearing. Lastly, the Binary Logit Model analysis will show the relative effect of possible factors in the structural model, particularly the herding behaviour.

5.1. Description of collected data

The survey was conducted within two weeks through convenience sampling, with 151 respondents completed the questionnaire. For the choice experiment, 52 respondents answered block 1, 50 answered block 2, and 49 answered block 3. Before data analysis, the raw data containing text-based answers was level-coded following Table 4.1 and 4.2. Furthermore, for each respondent, each answer for the choice experiment is treated as a single data record (instead of one record per eight answers), and each record was coupled with the respective choice task and the respondent's demographics and answers to the HBM factors. Therefore, in total there are 1208 data records.

Table 5.1 shows the descriptive statistics of the sample and the Netherlands population for each demographic variable. In comparison with the actual age distribution of the Dutch population from CBS (2021b), the younger age group between 18 to 29 years old is overrepresented. Furthermore, most respondents have a bachelor's or a master's degree, meaning they belong to the highly educated group. Lastly, the majority lives in urban areas. Therefore, this sample cannot be considered as a representative sample of the Dutch population. Nonetheless, this sample is still valuable for a preliminary exploration of the effect of herding on mask-wearing behaviour. Care should be taken in generalising the result to the general Netherlands population.

5.2. Measurement model: Identification of HBM classes

As stated in Section 4.1, different perceptions specified in HBM factors (sus, sev, bar, ben) are assumed to be correlated due to an underlying latent variable referred to as *HBM class*. In other words, people with similar perceptions can be clustered into different HBM classes. LatentGOLD 5.1 software is used for this analysis.

Table 5.1: Descriptive statistics of the respondents

Factor	**Level**	**Frequency**	**Percentage in the sample**	**Percentage in the population**
Age[a]	18-29	109	72%	22%
	30-54	20	13%	27%
	45-59	9	6%	31%
	>=60	13	9%	20%
Education level[b]	Basisonderwijs (Elementary school)	0	0%	9%
	Vmbo, havo-, vwo-onderbouw, mbo1 (Junior high school, Junior college)	1	1%	20%
	Havo, vwo, mbo2-5 (Senior high school, College)	9	6%	40%
	Hbo-, wo-bachelor (Bachelor)	88	58%	19%
	Hbo-, wo-master, doctor (Master, Doctor)	53	35%	11%
Residence type[c]	Rural	14	9%	33%
	Sub-urban	6	4%	29%
	Urban	131	87%	38%
Gender[d]	Male	86	57%	49%
	Female	64	42%	51%
	Other	1	1%	-
Nationality[e]	Dutch	74	47%	-
	Other	77	51%	-

Distribution in the population for each demographic variable is obtained from: [a]CBS (2021b), [b]CBS (2018), [c]CBS (2021c), [d]CBS (2021a), [e]no relevant source was found for this variable.

5.2.1. Determining the number of HBM classes

Two measures of latent class model fit determine the number of HBM classes: Bayesian Information Criterion (BIC) as global model fit and Bivariate Residuals (BVR) as local model fit. A lower BIC value is preferred because it represents higher model fit and parsimony (Magidson & Vermunt, 2004). BVR value of more than 3.84 is not preferred because it represents a significant residual correlation between the indicators (i.e., the HBM factors) (Magidson & Vermunt, 2004).

Three initial models were estimated: 1-class, 2-class, and 3-class models. These models' indicators (HBM factors) are treated as ordinal variables and no covariates are included. All software settings were set to default except for random sets and iterations, which were changed to 100. The performance statistics of the models (as produced by LatentGOLD) and a count of BVR values of less than or equal to 3.84 are presented in Appendix D.

The graphical comparison in Figure 5.1 shows that the 1-class model performs the worst. The low count of BVR ≤ 3.84 means that one latent HBM class is insufficient to explain the correlations between the HBM factors. In contrast, the 2-class and 3-class models are both able to disentangle the correlations. These models only differ in their BIC. Since the 2-class model has the lowest BIC, the respondents are clustered into two HBM classes.

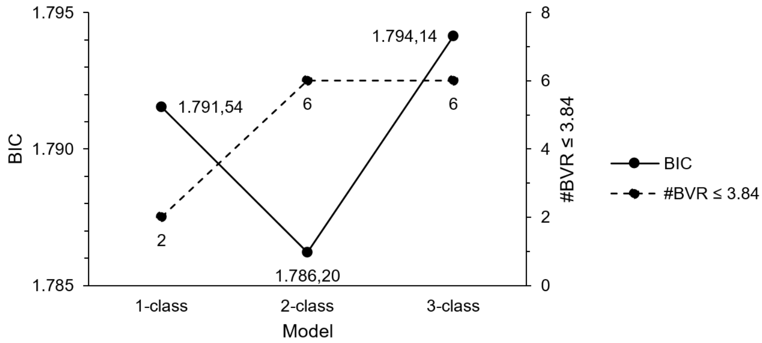

Figure 5.1: Graphical comparison of the three initial latent class models

5.2.2. The 2-class model

The parameters of the 2-class model are shown in Appendix E. Table E.1 and E.2 show the relationship parameters between the HBM class and the indicators. Table E.3 shows the class membership parameter, in which the Wald test shows that the HBM class sizes are not significantly[1] different in the population (with a p-value of 0.57). Furthermore, from Table E.1, the Wald test shows that the relationship between perceived barrier (bar) is statistically insignificant (with a p-value of 0.09). This insignificance means that the relationship between the HBM class and the perceived barriers cannot be generalised into the population, and vice versa for other HBM factors.

Due to its insignificance, bar is removed from the model. Therefore, the 2-class model is re-estimated with only sus, sev, and ben as the indicators. The parameters of this model are shown in Appendix F. As shown in Table F.1 and Table F.2, all relationship parameters between the HBM class and the updated indicators are simultaneously non-zero in the population. The class sizes remain not significantly different in the population (see Table F.3).

This model is further extended by adding demographic factors as covariates. Because the covariates can be defined only as nominal or continuous variables, following the factors operationalisation in Table 4.2, the demographics are treated as nominal. Appendix G shows the relationship parameters between the covariates and the HBM classes. The underlined p-values indicate insignificant covariates. Only nationality (nat) has a relationship with HBM class in the population and thus can predict the class membership. Thus, the other four demographic factors are removed from the covariates.

Finally, the model is re-estimated with only nationality as the covariate. This specification concludes the final measurement model (Figure 5.2 as a further specification of Figure 4.1). This model's parameters are presented in Appendix H. The profile of each HBM class (as clustered by this final model) is provided in Appendix I. The numbers represent the probability of an individual having an indicator/covariate value, given the HBM class. For example, given that an individual is in HBM Class 1, the probability of scoring 4 on COVID-19 perceived susceptibility is 42%.

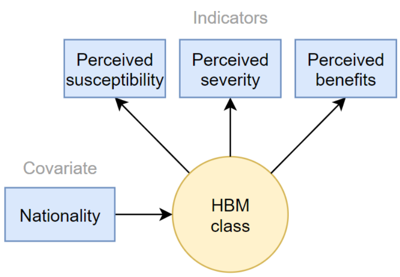

Figure 5.2: The final measurement model

[1] This study employs a confidence level of 95%.

The covariate interpretation in Appendix I (lower part) seems to contradict the measurement model conceptualisation (Figure 5.2), because the covariate is assumed to influence HBM class and not vice versa. Therefore, refer to Appendix J for a more conceptually correct interpretation of the covariate influence: given nat equals 0 (being Dutch), the probability of being in HBM Class 1 is 46% (and 54% in HBM Class 2); and given nat equals 1 (being non-Dutch), the probability of being in HBM Class 1 is 85% (and 15% in HBM Class 2).

A graphical representation of these profiles (Prf-Plot) is shown in Figure 5.3 for an easier interpretation. The Prf-Plot, as generated by the LatentGOLD software, re-scales the class-specific means so that all variable (indicators and covariates) values always lie within the 0-1 range.

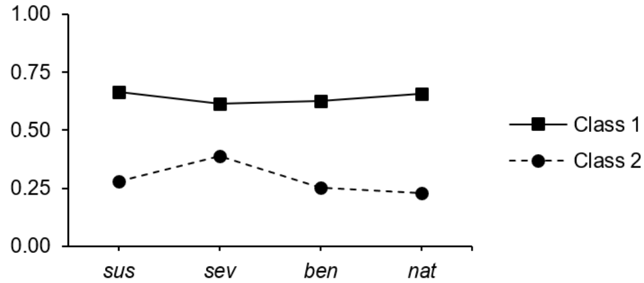

Figure 5.3: Profile for each HBM class

From the Prf-Plot (Figure 5.3), Class 1 is shown to have lower perceived susceptibility and severity towards COVID-19 and lower perceived benefit of mask-wearing (and vice versa for Class 2). Thus, two distinct characteristics can be inferred. Class 1 represents the risk-averse that believe in masks, while Class 2 represents the non-risk-averse and sceptical about masks. Moreover, non-Dutch people are the majority in Class 1, while Dutch people are the majority in Class 2.

It is noteworthy that although the HBM classes differ significantly, their characteristics are not two extreme opposite ends. Instead, both are still at an intermediate level of their respective characteristics. For example, it is incorrect to interpret that people in Class 2 deny the existence of COVID-19 or the efficacy of masks. Table 5.2 shows the mean of the indicators for each profile.

Table 5.2: Summary of HBM class profiles

Indicators	Class 1	Class 2
sus	3.65	2.11
sev	3.45	2.56
ben	3.49	2.00

5.3. Structural model: Factors influencing mask-wearing

As shown in Figure 4.1, the HBM class will be an explanatory and moderating variable assumed to interact with the herding-related factors (prd, pff, pnl). At this point, the HBM class was not part of the raw data because this latent variable is *modelled* (based on the previous Latent Class Analysis) instead of observed or experimentally varied. Therefore, each respondent is assigned an HBM class by matching up their sus, sev, ben, and nat values with the Classification output of the LatentGOLD software (see Appendix K). Since the classification error of the latent class model is relatively low (13%), rather than using the probabilistic classification (the last two columns of Appendix K), the hard classification (column "Modal") is used. For this assignment purpose, the HBM class is effect coded: Class 1 as '1' and Class 2 as '-1'.

After specifying the HBM class for each respondent, choice modelling was performed. A binary logit model was estimated using a choice modelling package called Apollo in RStudio, with no (mask-wearing) being the reference alternative (its systematic utility is equal to zero). Similar to the previous section, the modelling will be performed step by step from the simplest to the more complex models. The complexity is increased by introducing interactions between the HBM class and the *herding-related* factors (see Table 4.1). Interactions within the explanatory factors (herding and situational cues) are not considered because the fractional factorial experiment design only allows for the estimation of main effects (Bos et al., 2004). Afterwards, non-linearity effects are introduced. Along the process, the models are refined by removing insignificant factors and/or levels.

In total, at least 12 model variations were estimated. However, for conciseness, only seven variations are elaborated in the following subsections. Appendix L presents how these models are specified and their model fit measures (Log-Likelihood (LL), BIC, and Rho-square). The bold-faced texts indicate the model change relative to the previous one.

5.3.1. Model 1: simple binary logit model

Model 1 considers only the main effects of *herding-related* factors, *situational cues*, and *HBM class* on mask-wearing. The effect of HBM class, represented by β_{HBM}, can be interpreted as the base utility (or constant) of mask-wearing for each HBM class. The systematic utility functions are defined as

$$\begin{aligned} V_{yes} &= \beta_{yes} + \beta_{HBM} \times HBMclass + \\ &\quad \beta_{prd} \times prd + \beta_{pff} \times pff + \beta_{pnl} \times pnl + \\ &\quad \beta_{loc} \times loc + \beta_{pol} \times pol + \beta_{cwd} \times cwd \\ V_{no} &= 0 \end{aligned}$$

where

V_{yes}	=	systematic utility of mask-wearing
V_{no}	=	systematic utility of no mask-wearing
β_{yes}	=	base utility of mask-wearing caused by unobserved factors
β_{HBM}	=	base utility of mask-wearing for different HBM class
β_{prd}	=	marginal utility of 1% increase in prd
β_{pff}	=	marginal utility of 1% increase in pff
β_{pnl}	=	marginal utility of 1% increase in pnl
β_{loc}	=	marginal utility of the corresponding level of loc
β_{pol}	=	marginal utility of the corresponding level of pol
β_{cwd}	=	marginal utility of the corresponding level of cwd

Referring to Appendix L, Model 1 is statistically superior to the Null model (i.e., Model 1 fits the data better than a model of 'dice throwing'), as the Likelihood Ratio Statistic (Train, 2009) of Model 1 compared to the Null model is 616.49, which is higher than the critical Chi-square value of 15.51 (under 8 degrees of freedom). This provides a good basis for further model variations built on top of this model.

The parameter estimates of Model 1 are presented in Table 5.3 below. The *estimates* (in the second column) are the estimated weights of each factor. The standard error gives a measure of variation of the estimates across the samples. The p-values represent the probability that the estimates are actually zero (no effect) in the population, as obtained from the t-test. Indicated by p-values of higher than 0.05, β_{yes} and β_{pnl} are statistically insignificant. The former means that whatever intrinsic motivation people have to wear a mask is explained fully by the HBM class to which they belong, and there is no residual inclination to wear a mask or not. The latter means that the proportion of mask-wearers within the Netherlands population do not affect mask-wearing choice.

Table 5.3: Model 1 estimates

Factor	**Estimate**	**Std.err.**	**Rob.t-ratio(0)**	**Rob.p-val(0)**
β_{yes}	-0.3017	0.2371	-1.4313	<u>0.1523</u>
β_{HBM}	0.4228	0.0774	3.0150	0.0026
β_{prd}	0.0091	0.0027	3.3858	0.0007
β_{pff}	0.0123	0.0031	3.7097	0.0002
β_{pnl}	0.0003	0.0027	0.1133	<u>0.9098</u>
β_{loc}	0.5325	0.0864	6.6078	0.0000
β_{pol}	0.8770	0.0925	7.2959	0.0000
β_{cwd}	0.7950	0.1061	7.5159	0.0000

5.3.2. Model 2: simple binary logit model without insignificant factors

The insignificant factors in Model 1 were removed, and the model was re-estimated as Model 2. The systematic utility functions for Model 2 are:

$$\begin{aligned} V_{yes} &= \beta_{HBM} \times HBMclass + \\ &\quad \beta_{prd} \times prd + \beta_{pff} \times pff + \\ &\quad \beta_{loc} \times loc + \beta_{pol} \times pol + \beta_{cwd} \times cwd \\ V_{no} &= 0 \end{aligned}$$

Model 2 parameter estimates are presented in Table 5.4 below. Because all p-values are less than 0.05, all factors in Model 2 have statistically significant effects on mask-wearing.

Table 5.4: Model 2 estimates

Factor	**Estimate**	**Std.err.**	**Rob.t-ratio(0)**	**Rob.p-val(0)**
β_{HBM}	0.4118	0.0769	2.9521	0.0032
β_{prd}	0.0072	0.0023	2.8607	0.0042
β_{pff}	0.0098	0.0024	4.2302	0.0000
β_{loc}	0.5123	0.0845	6.3214	0.0000
β_{pol}	0.8574	0.0901	7.5527	0.0000
β_{cwd}	0.7265	0.0922	8.2652	0.0000

A more detailed interpretation of the factors' effects will be further discussed after the final model is selected. For a quick interpretation, Figure 5.4 shows the relative importance of the factors in Model 2. The relative importance is obtained by calculating each factor's maximum utility contribution. Each maximum utility contribution is calculated by multiplying the factor level range (difference between the highest and lowest level) with the absolute value of the factor's estimate. For example, the maximum utility contribution of pol is obtained by multiplying 2 (the pol level range, because pol can take a coded value of -1 or 1), with 0.84 (the pol estimate, β_{pol}), which results in 1.68.

Figure 5.4 shows that herding behaviour is shown to play a role in mask-wearing behaviour. When combined across reference groups, the proportion of mask-wearers around a decision-maker accounts for 26% influence on the overall preference for mask-wearing—as big as the policy factor. Out of the three types of reference groups, the national population is not considered a reference group. The mask-wearing behaviour of family and/or friends influences one's mask-wearing behaviour at a slightly higher level than that of the random people within the neighbourhood does. Furthermore, the mask-wearing policy (i.e., mandatory or voluntary) is found to be the most influential factor.

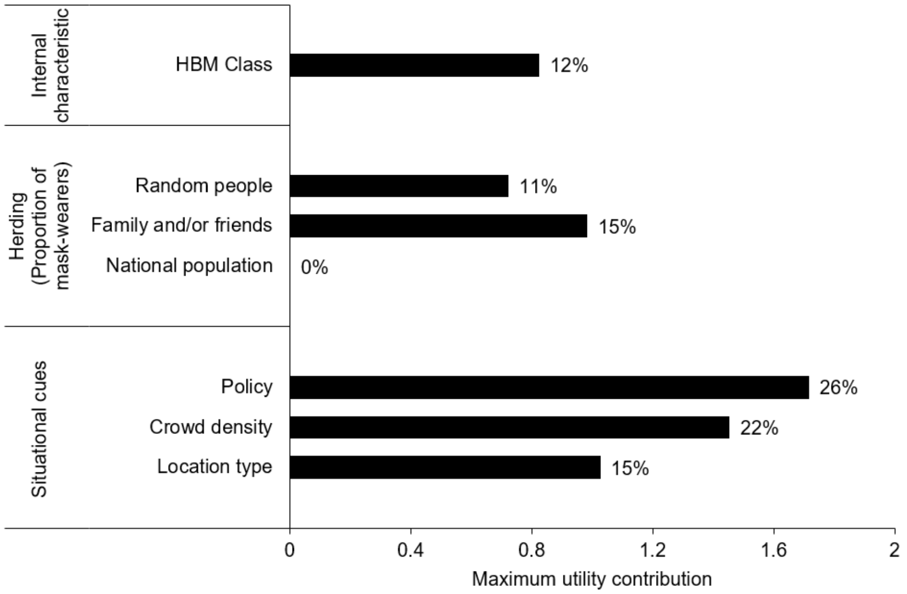

Figure 5.4: Relative importance of factors in Model 2

5.3.3. Model 3: interaction with HBM class

As shown by the structural model (Figure 4.1), the HBM class is assumed to interact with herding-related factors. Therefore, Model 3 includes these interactions simultaneously by making the effect of prd, pff and pnl moderated by the HBM class. In other words, their effects are dependent on the HBM class value. A new parameter for HBM class is assigned for each interaction, coded as *factor*_HBM (e.g., β_{prd_HBM} is an HBM class parameter for its interaction with prd).

The systematic utility functions for Model 3 are:

$$
\begin{aligned}
V_{yes} &= \beta_{HBM} \times HBMclass + \\
&\quad (\beta_{prd} + \beta_{prd\_HBM} \times HBMclass) \times prd + \\
&\quad (\beta_{pff} + \beta_{pff\_HBM} \times HBMclass) \times pff + \\
&\quad \beta_{loc} \times loc + \beta_{pol} \times pol + \beta_{cwd} \times cwd \\
V_{no} &= 0
\end{aligned}
$$

Table 5.5 presents the parameter estimates of Model 3. The parameter size remains relatively the same for factors that are also included in Model 2, except for β_{HBM}. Table 5.5 also shows that HBM class significantly interacts with prd, but not with pff. Moreover, as the effect of HBM class is captured through the interaction relationships, its direct effect (β_{HBM}) becomes insignificant. This is due to significant correlations between the main effect of HBM class and the interaction effects as big as 86% (calculated using SPSS). Therefore, the next model removes the insignificant effects, including the main effect of HBM class.

Table 5.5: Model 3 estimates

Factor	Estimate	Std.err.	Rob.t-ratio(0)	Rob.p-val(0)
β_{HBM}	0.2843	0.1859	1.4561	0.1454
β_{prd}	0.0069	0.0024	2.7474	0.0060
β_{prd_HBM}	0.0059	0.0027	2.3106	0.0209
β_{pff}	0.0100	0.0024	4.2588	0.0000
β_{pff_HBM}	-0.0032	0.0029	-1.1210	0.2623
β_{loc}	0.5106	0.0843	6.3186	0.0000
β_{pol}	0.8599	0.0901	7.5524	0.0000
β_{cwd}	0.7406	0.0928	8.3690	0.0000

5.3.4. Model 4: interaction with HBM class without insignificant factors

In a similar manner as in Model 2, Model 4 is the re-estimation of Model 3 without the insignificant factors. The systematic utility functions of Model 4 are:

$$\begin{aligned}
V_{yes} &= (\beta_{prd} + \beta_{prd_HBM} \times HBMclass) \times prd + \\
&\quad \beta_{pff} \times pff \\
&\quad + \beta_{loc} \times loc + \beta_{pol} \times pol + \beta_{cwd} \times cwd \\
V_{no} &= 0
\end{aligned}$$

Model 4 parameter estimates are presented in Table 5.6 below. All factors are significant, including one interaction between prd and the HBM class (as shown in the first two rows). In comparison with Model 3, the most notable change is the standard error of β_{prd_HBM} that decreases by almost half. This can be explained by the removal of β_{HBM} that reduces correlation, and hence minimises the standard error.

Table 5.6: Model 4 estimates

Factor	Estimate	Std.err.	Rob.t-ratio(0)	Rob.p-val(0)
β_{prd}	0.0069	0.0024	2.7137	0.0067
β_{prd_HBM}	0.0079	0.0014	3.2683	0.0011
β_{pff}	0.0100	0.0024	4.3259	0.0000
β_{loc}	0.5143	0.0843	6.3196	0.0000
β_{pol}	0.8590	0.0899	7.5756	0.0000
β_{cwd}	0.7493	0.0925	8.5138	0.0000

HBM class moderates the effect of prd as follows. Table 5.6 shows that β_{prd} is 0.0069 and β_{prd_HBM} is 0.0079. β_{prd_HBM} indicates a decrease in the utility by -0.0079 for HBM Class 1 and an increase by 0.0079 for HBM Class 2. Therefore, the parameter estimate of prd for people in Class 1 is

$$\beta_{prd} - \beta_{prd\_HBM} = 0.0069 - 0.0079 = -0.0010$$

and for those in Class 2 is

$$\beta_{prd} + \beta_{prd\_HBM} = 0.0069 + 0.0079 = 0.0148.$$

HBM class moderates the effect of prd for HBM Class 1 to be negative, i.e., an increase in the proportion of mask-wearers within the random people in the neighbourhood leads to a decrease in the utility of mask-wearing by -0.0010. This contradicts the main effect of *prd* in Model 2, which indicates a positive effect of prd. Nonetheless, it is noteworthy that the utility decrease is extremely small compared to other factors (with a relative importance of 1%; see Figure 5.5). Moreover, with a 95% confidence level, the true coefficients of β_{prd} and β_{prd_HBM} lie within intervals as follows:

$$\begin{aligned}\beta_{prd} &= 0.0069 \pm 1.96 \times 0.0024\\ &= 0.0069 \pm 0.0047\end{aligned}$$

and

$$\begin{aligned}\beta_{prd\_HBM} &= 0.0079 \pm 1.96 \times 0.0014\\ &= 0.0079 \pm 0.0027\end{aligned}$$

Consequently, $\beta_{prd} - \beta_{prd\_HBM}$ lies within the range of -0.0084 and 0.0064. The lower bound is obtained by subtracting the upper bound of β_{prd_HBM} from the lower bound of β_{prd} and vice versa. Because the zero value lies within this range, the effect of prd for HBM Class 1 can be disregarded.

Similar to Model 2, the relative importance of Model 4 is shown in Figure 5.5. The maximum utility contribution of situational cues factors seems to remain virtually the same as Model 2. The only substantial change is how prd (the proportion of mask-wearers within the random people in the neighbourhood) influences mask-wearing.

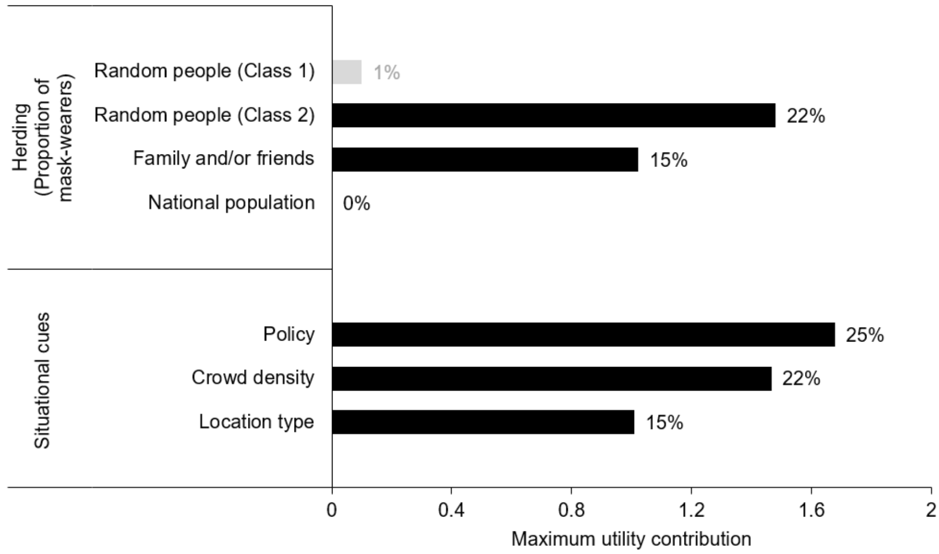

Figure 5.5: Relative importance of factors in Model 4

5.3.5. Model 5: non-linear effect of crowd density levels

Non-linearity refers to unequal utility contribution from each level within a factor. To model such an effect, the factor is decomposed into multiple parameters using dummy coding: the first level is set as the reference level with a utility contribution of zero. In Model 5, the crowd density factor (cwd) is treated as a non-linear factor with the following idea: does the effect of cwd increase (or decrease) as the value of cwd increases? In other words, do people become more (or less) sensitive to crowd density as the crowd gets denser?

The systematic utility functions of Model 5 are defined as:

$$\begin{aligned}V_{yes} &= (\beta_{prd} + \beta_{prd\_HBM} \times HBMclass) \times prd +\\ &\quad \beta_{pff} \times pff +\\ &\quad \beta_{loc} \times loc + \beta_{pol} \times pol +\\ &\quad \beta_{cwd\_med} \times (cwd == 1) + \beta_{cwd\_hig} \times (cwd == 2)\\ V_{no} &= 0\end{aligned}$$

Table 5.7 shows Model 5 parameter estimates. In comparison to Model 4, the parameter size remains the same. β_{cwd} is decomposed into β_{cwd_med} and β_{cwd_hig} (cwd of low is set as the reference level) to account for the non-linear effects. These parameter estimates are statistically significant, meaning that each crowd level does affect mask-wearing in the population. However, looking at the visual representation of each level utility contribution in Figure 5.6, the utility increase is virtually linear. Therefore, cwd remains treated as a linear factor.

Table 5.7: Model 5 estimates

Factor	Estimate	Std.err.	Rob.t-ratio(0)	Rob.p-val(0)
β_{prd}	0.0071	0.0024	2.7361	0.0062
β_{prd_HBM}	0.0079	0.0014	3.2569	0.0011
β_{pff}	0.0094	0.0025	3.7052	0.0002
β_{loc}	0.5141	0.0843	6.3046	0.0000
β_{pol}	0.8557	0.0899	7.6122	0.0000
β_{cwd_med}	0.8656	0.1658	4.3251	0.0000
β_{cwd_hig}	1.4509	0.1909	8.6710	0.0000

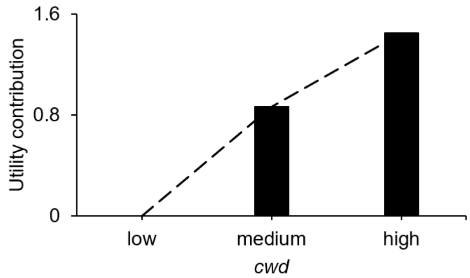

Figure 5.6: Utility contribution of cwd levels

5.3.6. Model 6: non-linear effect of herding-related factors

In Model 6, the proportion of mask-wearers (prd and pff) are treated as non-linear factors: β_{prd} is decomposed as β_{prd_40} and β_{prd_60}, and β_{pff} as β_{pff_40} and β_{pff_60}. As a result, the systematic utility functions for Model 6 are:

$$
\begin{aligned}
V_{yes} \quad &= \quad (\beta_{prd\_40} + \beta_{prd\_HBM} \times HBMclass) \times (prd == 40) + \\
&\quad\;\; (\beta_{prd\_60} + \beta_{prd\_HBM} \times HBMclass) \times (prd == 60) + \\
&\quad\;\; (\beta_{prd\_90} + \beta_{prd\_HBM} \times HBMclass) \times (prd == 90) + \\
&\quad\;\; \beta_{pff\_40} \times (pff == 40) + \beta_{pff\_60} \times (pff == 60) + \beta_{pff\_90} \times (pff == 90) + \\
&\quad\;\; \beta_{loc} \times loc + \beta_{pol} \times pol + \beta_{cwd} \times cwd \\
V_{no} \quad &= \quad 0
\end{aligned}
$$

Table 5.8 shows that the parameter estimates for prd of 40% and 60% are statistically insignificant. This means that there is not enough proof in the sample to say that these level-specific effects are non-zero in the population. Another way to interpret this is that individuals are influenced to wear a mask by prd (the proportion of mask-wearers within the random people) *only* when prd reaches 90%. Meanwhile, all levels of pff are statistically significant.

Table 5.8: Model 6 estimates

Factor	Estimate	Std.err.	Rob.t-ratio(0)	Rob.p-val(0)
β_{prd_HBM}	0.4893	0.0917	3.1904	0.0014
β_{prd_40}	0.3080	0.2025	1.6945	<u>0.0902</u>
β_{prd_60}	0.4806	0.2057	1.7730	<u>0.0762</u>
β_{prd_90}	0.5605	0.2314	2.7724	0.0056
β_{pff_40}	0.4246	0.2109	2.0426	0.0411
β_{pff_60}	0.6023	0.2063	3.4586	0.0005
β_{pff_90}	0.9024	0.2408	3.8482	0.0001
β_{loc}	0.5558	0.0965	5.3920	0.0000
β_{pol}	0.8882	0.0956	7.6823	0.0000
β_{cwd}	0.7816	0.0953	8.6732	0.0000

5.3.7. Model 7: non-linear effect of herding-related factors without insignificant levels

Model 7 then re-estimates Model 6 without the insignificant levels, with the following systematic utility functions:

$$
\begin{aligned}
V_{yes} \quad &= \quad (\beta_{prd\_90} + \beta_{prd\_HBM} \times HBMclass) \times (prd == 90) + \\
&\quad\ \ \beta_{pff\_40} \times (pff == 40) + \beta_{pff\_60} \times (pff == 60) + \beta_{pff\_90} \times (pff == 90) + \\
&\quad\ \ \beta_{loc} \times loc + \beta_{pol} \times pol + \beta_{cwd} \times cwd \\
V_{no} \quad &= \quad 0
\end{aligned}
$$

This resulted in estimates shown in Table 5.9. After removing prd of 40% and 60%, the prd of 90% also became statistically insignificant, hence eliminating the effect of prd as a whole. This result contradicts the preceding models that found a significant effect of prd. Furthermore, a visual representation of the level-specific effect of pff in Figure 5.7 shows that overall, the effect of pff is also virtually linear. Finally, the LL of Model 7 is lower than all previous models despite having more parameters (see Appendix L). Being worse in both LL and model parsimony, this model is disregarded.

Table 5.9: Model 7 estimates

Factor	Estimate	Std.err.	Rob.t-ratio(0)	Rob.p-val(0)
β_{prd_HBM}	0.5429	0.1690	2.8276	0.0047
β_{prd_90}	0.3716	0.2258	1.8791	<u>0.0602</u>
β_{pff_40}	0.4851	0.2038	2.2657	0.0235
β_{pff_60}	0.8356	0.1962	4.6430	0.0000
β_{pff_90}	1.2621	0.1886	6.1614	0.0000
β_{loc}	0.5075	0.0945	5.3459	0.0000
β_{pol}	0.8579	0.0933	7.6757	0.0000
β_{cwd}	0.8582	0.0889	9.3238	0.0000

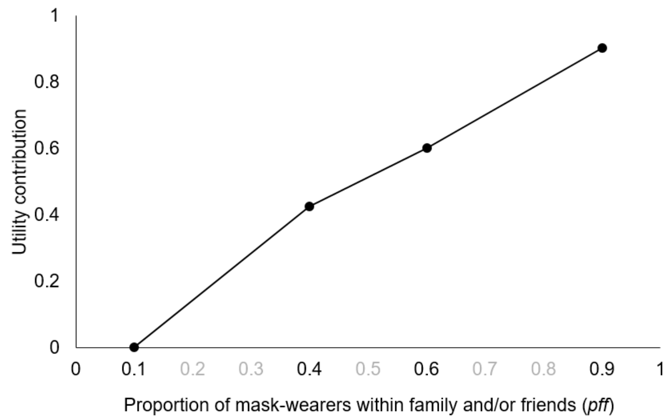

Figure 5.7: Utility contribution of pff levels

At this point, seven choice models have been elaborated. Although each model offers different insights on mask-wearing behaviour, one will be chosen as the model that fits the data best and provides a sound explanation on factors that influence mask-wearing. Aside from these models, other model specifications were also estimated incorporating different combinations of (insignificant) factors and non-linearity effects. For example, the insignificant β_{yes} and β_{pnl} were not removed simultaneously, but sequentially; or β_{HBM} was not included in the simple binary logit model. Nevertheless, due to their inferior model fit and partly redundant specifications, it is not deemed necessary to elaborate on these models in detail.

5.3.8. Selection of the final choice model

From the seven models, Model 1, 3, and 6 are not considered because they are the 'old' versions of Model 2, 4, and 7, respectively. Moreover, Model 5 is unnecessary because the effect of cwd factor is virtually linear. Lastly, Model 7 has been disregarded due to its contradictory and deficient performance relative to the previous models. Thus, Model 2 and 4 are the only remaining options. In Appendix L, although Model 2 has a lower LL and a higher BIC than Model 4, these measures cannot be used for direct comparison because Model 2 and 4 are non-nested models.

Therefore, the Ben-Akiva & Swait test (Ben-Akiva & Swait, 1986) is used. Using the Apollo package, there is a 5% probability that Model 2 is actually the better model in the population. Because this study adopts a 95% significance level, the conclusion to choose Model 4 is borderline. As a last resort, the choice is made following the law of parsimony, or the Occam's razor principle, that says the best explanation is the simplest one (van Daam et al., 2012). Since Model 2 has a simpler explanation, i.e., direct/main- instead of interaction effects, Model 2 is chosen as the final model. Nonetheless, Model 4 is still valuable for further research on interactions within the factors.

In Section 4.1, a proposed operationalisation of the choice model is shown in Figure 4.1. As Model 2 has been chosen, Figure 5.8 below shows the (updated) graph representing the final choice model. The greyed out figures indicate the variables removed from the proposed model.

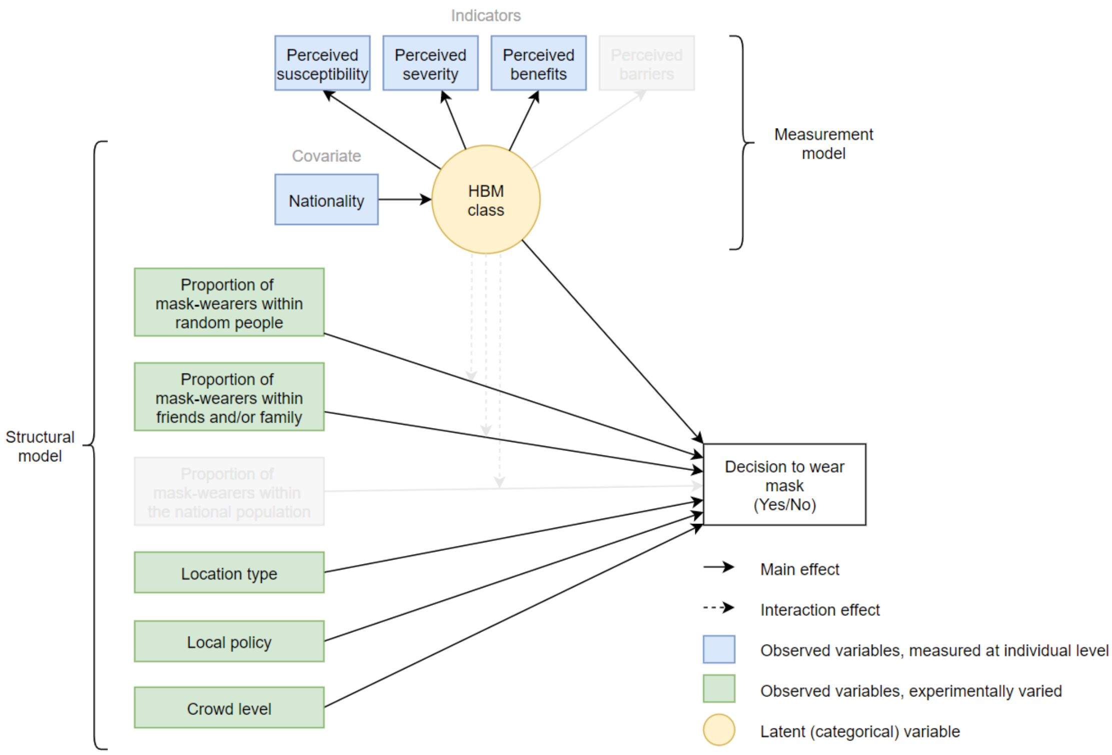

Figure 5.8: Final choice model

5.4. Discussion

Having chosen Model 2, the mask-wearing choice model is simply specified by the parameter estimates in Table 5.4. However, it is noteworthy that these parameter estimates are not point estimates. Rather, they are estimated under a confidence level of 95% and hence lie within confidence intervals of $\hat{\beta} \pm z_{0.025} \times SE$ where $\hat{\beta}$ is the parameter estimate, $z_{0.025}$ is the z-score for a cumulative probability level of 2.5% (1.96), and SE is the standard error of each parameter estimate. As a result, Table 5.10 shows the confidence interval of each factor.

Table 5.10: Confidence intervals of parameter estimates

Factor	Lower bound	Mean	Upper bound
β_{HBM}	0.2610	0.4118	0.5626
β_{prd}	0.0026	0.0072	0.0118
β_{pff}	0.0051	0.0098	0.0145
β_{loc}	0.3468	0.5123	0.6779
β_{pol}	0.6808	0.8574	1.0341
β_{cwd}	0.5459	0.7265	0.9072

In the following discussion subsections, for each factor, the expectation-based validity (Mariel et al., 2021) of the model is evaluated in terms of the factors' sign (direction of effect). Then, their relative importance is discussed. Lastly, their effects on mask-wearing probability are assessed. For this assessment, the parameter estimates are varied within their respective confidence intervals under a *ceteris paribus* context to show how sensitive the choice model is to changes in parameters.

As a default, unless the respective factor is the matter of interest, the context is arbitrarily set as follows: everyone belongs in HBM Class 1, at an outdoor place with a low crowd density level and voluntary mask-wearing policy. The initial prd and pff is set at 76% which is based on the overall percentage of mask-wearers in the Netherlands obtained from Center for Geospatial Information Science University of Maryland (2021, June 20).

5.4.1. HBM class latent variable

The $HBMclass$ serves as a class-specific constant on the utility of mask-wearing. This is the only factor that originates from the decision-makers' internal characteristic, that is their subjective health belief in terms of their susceptibility towards and severity of COVID-19, along with the benefits of mask-wearing. To review, this latent variable classifies people into two classes with profiles as specified in Table 5.2. The HBM class is effect coded as specified in Section 5.3, where HBM Class 1 is coded as '1' and Class 2 as '-1'.

As people in HBM Class 1 are generally more afraid of COVID-19 and believe more in mask efficacy, it is plausible that they are predisposed to a higher utility towards mask-wearing, and vice versa for those in HBM Class 2. The positive sign of β_{HBM} confirms this line of reasoning: a utility *increase* of 0.4118 applies for those in HBM Class 1 because the estimate is multiplied by 1, and a *decrease* of 0.4118 for HBM Class 2 because it is multiplied by -1. Considering the sign being as expected, this parameter estimate is considered valid.

The effect of HBM class on mask-wearing probability across its confidence interval is shown in Figure 5.9. Under the mean estimate, people HBM Class 2 is 13% less likely to wear a mask than those in Class 1. Moreover, the variation of β_{HBM} from its lower to upper bound causes a change in probability by 6% for those in Class 2 (and less for Class 1). In other words, under the confidence level of 95%, the probability is subject to change by $\pm$ 3% if β_{HBM} shifts within its confidence interval.

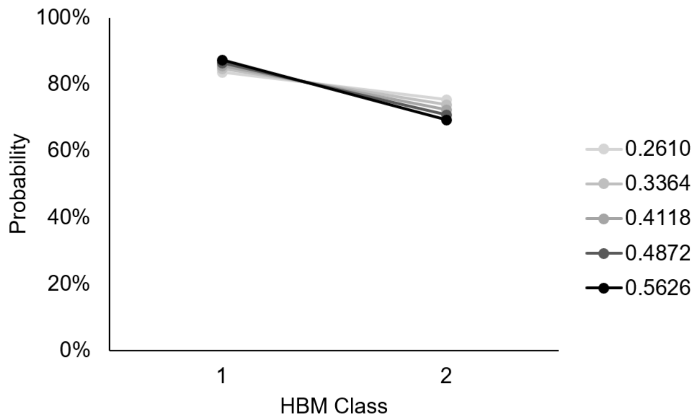

Figure 5.9: Effect of HBM class on mask-wearing probability across confidence interval

Since HBM class comprises three HBM perceptions, one might wonder whether a certain perception affects the basic predisposition to mask-wearing more than the others. Although this is an interesting question, the current model is conceptually and practically incapable of providing the answer. Conceptually, the perceptions are caused by HBM class (which is the basis of the predisposition), and not vice versa. Practically, because the perceptions are intercorrelated without the HBM class (shown by the BVR in Appendix D), an attempt to measure their direct effects will only result in biased estimates.

Lastly, the rapid speed of vaccination against COVID-19 in the Netherlands (Government.nl, 2021b) also sparks another question of whether this influences mask-wearing behaviour. At the individual level, this study argues that the choice model stays the same. With the two HBM classes, vaccination shall not change the parameter estimates. Instead, it shifts more people that were in HBM Class 1 (the more risk-averse class) to Class 2 (the less risk-averse class). Hence, this will certainly affect the overall predicted proportion of mask-wearers, but not the mask-wearing probability at the individual level.

5.4.2. Herding: proportion of mask-wearers

The prd and pff are two factors that confirm the causal effect of herding in mask-wearing. Since the effect of pnl was found to be insignificant in Model 1, the herding behaviour is only limited to a local environment. Since herding is simply defined as ”doing what everyone else is doing” (Banerjee, 1992, p. 798), this study assumes that a higher proportion of mask-wearers shall increase one’s mask-wearing utility (and consequently its probability). The positive effects of prd and pff support this assumption, and therefore both estimations are considered valid.

Looking at their relative importance in Figure 5.4, it is interesting to observe that the importance of friends’ and/or family’s mask-wearing behaviour comes first, followed by one’s personal predisposition, and lastly by the random people’s behaviour. This order is aligned with the high score of the Netherlands on the individualism dimension under the Hofstede cultural framework (scoring 80 according to Hofstede Insights (2021)). In an individualist society, everyone is expected to take care of oneself and their immediate family (Hofstede, 2011). Consequently, the importance of random people is the lowest of all. Ultimately, the alignment between the estimation results and the cultural context of the Netherlands even further validates these findings.

The size of β_{prd} and β_{pff} in Table 5.10 are not to be confused with their relative importance, especially because of their contrasting level range from other factors. For every 10% increase in the proportion of mask-wearers within the random people in the neighbourhood (prd), the mask-wearing utility linearly increases by 0.0720, while within the family and/or friends (pff) it increases by 0.0980. To see how the change in prd and prf affects the mask-wearing probability, refer to Figure 5.10 and 5.11. These figures also show the effects under varying estimates within the confidence intervals.

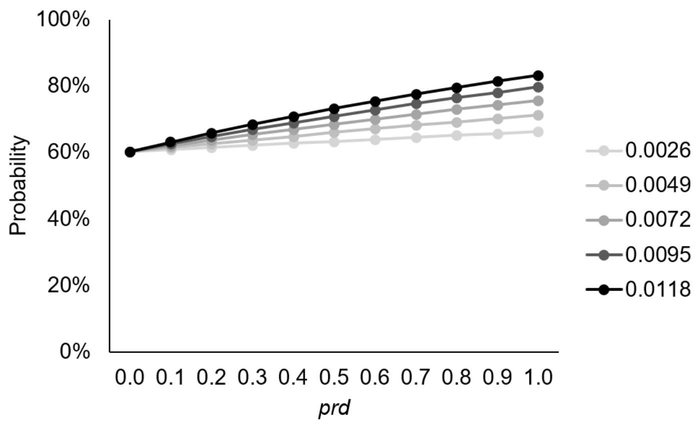

Figure 5.10: Effect of prd on mask-wearing probability across confidence interval

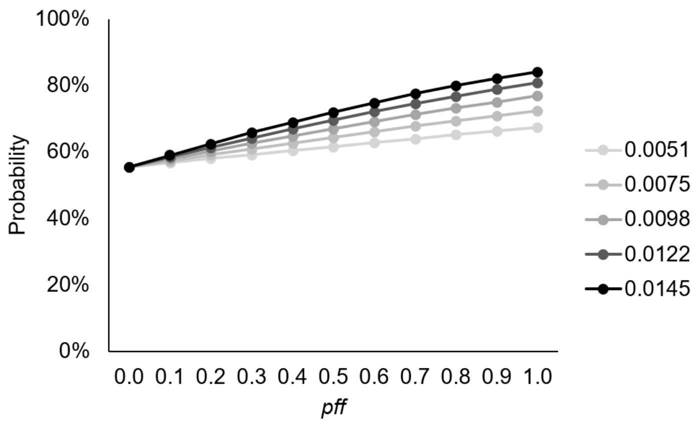

Figure 5.11: Effect of pff on mask-wearing probability across confidence interval

Although the effect of prd and pff on mask-wearing probability is not perfectly linear, as an approximation, an increase of 10% in prd leads to about 1 to 2% increase in the probability, while for pff leads to about 2 to 3% increase under the mean estimates. When compared between the two extremes (0% and 100% of mask-wearers), prd causes an increase by 15%, while pff does by 21%. Looking at the varying size of β_{prd} and β_{pff} within their confidence interval, both impose an about $\pm$10% variation on the probability under an extremely high proportion of mask-wearers. The lower the β_{prd} and β_{pff}, the bigger the variation is, and vice versa.

When the choice model is used to explain the herding mechanism behind mask-wearing, this relatively high sensitivity should be taken into consideration. Mask-wearing probability within 40 to 60% (exclusive) calculated under the mean estimate may be higher or lower than 50% under a lower estimate. In other words, a predicted moderate minority and moderate majority of mask-wearers are subject to possibly an opposite conclusion. Therefore, the choice model is more reliable when dealing with situations that result in more extreme probabilities.

5.4.3. Location type

The location type mainly relates to mask-wearing through how COVID-19 transmission risk differs in indoor and outdoor spaces. According to Rowe et al. (2021), this risk is lower in outdoor than in indoor space by orders of magnitude. Therefore, this study assumes that the utility of mask-wearing will be higher when decision-makers are situated in an indoor space in comparison with when being in an outdoor space. Since the loc factor is effects coded: -1 for outdoor and 1 for indoor, this assumption is supported by the positive sign of β_{loc}. This means that the mask-wearing utility *decreases* by 0.5123 in an outdoor space, and *increases* by 0.5123 in an indoor space.

Furthermore, reflecting on the relative importance in Figure 5.4, the effect of location type (loc) is the same as the herding effect within family and/or friends (pff), both being 15%. It may seem abstract to comprehend an equal effect of two different concepts. Thus, for an illustration, this equality means that a decrease of 100% mask-wearers within family and/or friends has the same effect of the change of location type from indoor to outdoor, and vice versa. This insight may be useful in promoting mask-wearing (or other preventive health behaviours): when a mandatory policy cannot be imposed, convincing people that many others wear masks can remediate the negative effect of outdoor space.

The effect of loc on mask-wearing probability across its confidence interval is shown in Figure 5.12. Under the mean estimate, people in an indoor location is 16% more likely to wear a mask than those in an outdoor location. Moreover, the mask-wearing probability in an outdoor location is more sensitive to variation of β_{loc} than in an indoor location. The variation causes a change in probability by $\pm$4% and $\pm$2%, respectively.

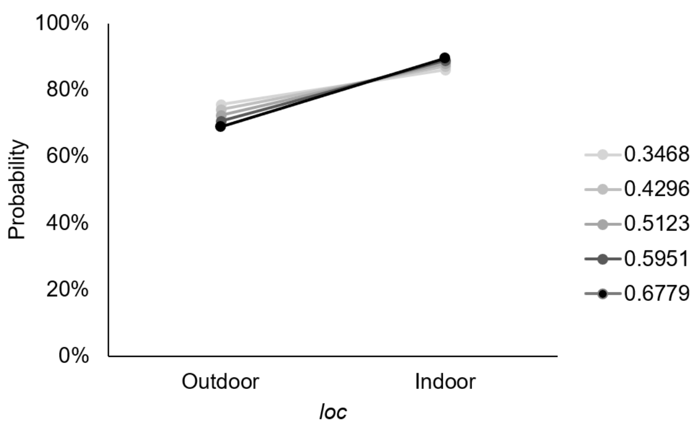

Figure 5.12: Effect of loc on mask-wearing probability across confidence interval

5.4.4. Mask-wearing policy

To interpret the mean estimate of β_{pol}, consider that the voluntary and mandatory policy are coded as -1 and 1, respectively. Therefore, their utility contributions are -0.8574 and 0.8574. In comparison to other factors, the mask-wearing policy (i.e., mandatory or voluntary) is the most important factor. This high, positive effect of policy is reasonable due to the fairly high level of compliance to the mask-wearing policy in the Netherlands (82%) (RIVM, 2021a). Thus, β_{pol} is considered valid.

Figure 5.13 shows how the mask-wearing probability differs across varying β_{pol} within its confidence interval. The graph shows that under the mean estimate of β_{pol}, a change of policy from voluntary to mandatory increases the probability by 21%, and vice versa. For each policy, the varying estimates cause minimal change on the probability of around 4%. Therefore, the model is considered insensitive to changes in β_{pol}.

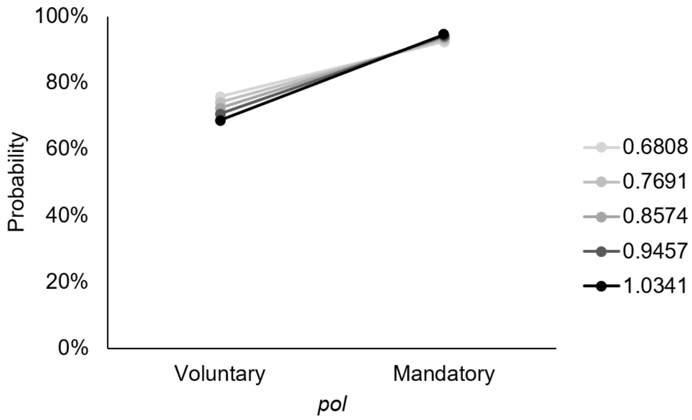

Figure 5.13: Effect of pol on mask-wearing probability across confidence interval

Furthermore, the relative importance graph in Figure 5.4 shows that the combined effect of prd and pff (11% and 15%) are the same as the single effect of pol (26%). This means that the effect of an increase in mask-wearers in *both* reference groups from 0 to 100% is as big as the effect of mask-wearing policy change from voluntary to mandatory. This insight is useful in explaining a drastic change in mask-wearing behaviour when the policy changes from mostly mandatory to voluntary. After the Dutch government dropped the mandatory policy almost in all places (Government.nl, 2021a), the average proportion of mask-wearers has dropped since to as low as 24% (Center for Geospatial Information Science University of Maryland, 2021).

In reality, there might be situations where the policy seems ambiguous: it may be *mandatory* in an *outdoor* schoolyard or *voluntary* in an *indoor* sports facility. Under this ambiguity, the effect of herding may become larger, but this study cannot model such interactions due to the use of fractional factorial design. Nonetheless, the model can show that under these ambiguous situations, the combined effect of pol and loc is reduced by 75% compared to those under non-ambiguous situations.

5.4.5. Crowd density level

The crowd density level relates to mask-wearing through the fact that COVID-19 spread via the respiratory droplets (Senatore et al., 2021). A social distance of 1.5 meters is considered as the safe distance to avoid the virus transmission (Government.nl, 2021a). Nevertheless, some situations may not offer this safe distance, or instead, the opposite where people are sparsely distributed in an area. This study assumes that as the crowd gets denser, the mask-wearing utility should increase. The positive parameter estimate β_{cwd} confirms this expectation: every increase in the crowd density level contributes to a utility increase by 0.7265. Therefore, β_{cwd} is considered valid.

Figure 5.4 shows that the crowd density level (cwd) is the second most important factor after the mask-wearing policy (pol). This observation is plausible because this factor is related to another health preventive behaviour, social distancing, which is also one of the measures imposed by the Dutch government (Government.nl, 2021a). Thus, the importance of maintaining at least a medium density is simply another aspect of policy compliance in general. Therefore, when this cannot be maintained, it affects the utility of another measure, mask-wearing, almost as big as the mask-wearing policy.

Under the mean estimate of β_{cwd}, a change from low to high crowd density level causes a substantial increase in the mask-wearing probability by 34%. The model sensitivity to variations of β_{cwd} within its confidence interval is shown by Figure 5.14. There is a bigger margin of probability change as the crowd density level gets higher, with the margin of $\pm$ 7% for the highest crowd density level. Similar to β_{prd} and β_{pff}, care should be taken under borderline majority and minority.

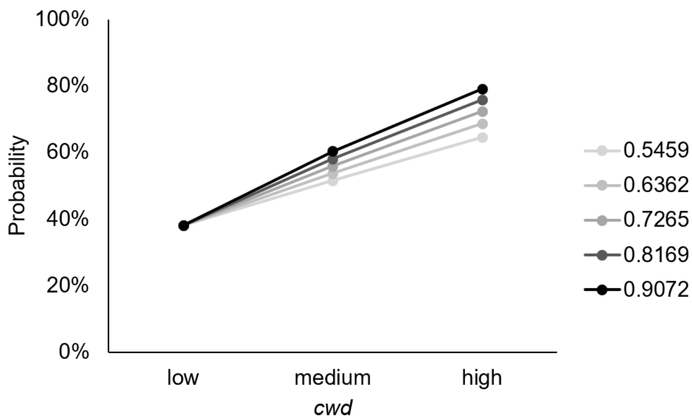

Figure 5.14: Effect of cwd on mask-wearing probability across confidence interval

5.5. Chapter summary

To summarise, the expectation on the directional effect of all factors has been based on logical and theoretical arguments. Using their parameter estimates, especially looking at the signs (positive or negative), and the variable coding as specified in Table 4.1 and 4.2, all factor estimates are able to confirm their respective expectations and hence have a construct validity. Their relative importance (Figure 5.4) is also proven reasonable, by looking at the cultural context and policy compliance level in the Netherlands population.

While the model is sensitive to changes in all parameter estimates, it is more sensitive to β_{prd}, β_{pff}, and β_{cwd}. To account for this higher sensitivity under the current estimates, this study admits that the model is more reliable for explaining mask-wearing behaviour under an extreme majority and minority of mask-wearers. For further research, the sensitivity could be suppressed by collecting a larger sample size, which reduces the standard errors and therefore, the confidence intervals of the parameter estimates.

6 Modelling the aggregate mask-wearing behaviour

The previous chapter has presented a choice model that reflects how an *individual* makes a mask-wearing decision, considering the herding effect. This study argues that simply averaging over individuals is not enough to explore the macro-level *population* dynamics resulting from micro-level individual behaviours. Because herding is a phenomenon that essentially occurs through social interaction, the collective result should be obtained while taking this interdependent behaviour into account. Because agent-based models (ABMs) allow for an explicit link between the micro and macro level of analysis, in this chapter, the ABM aims to provide a better understanding of how herding behaviour affects mask-wearing dynamically at the population level.

6.1. System identification

In this first step, the physical and social entities are defined and structured. The agents in this ABM is simply random people with intrinsic and extrinsic properties. The agents' properties are specified as follows. The agents represent people living in the Netherlands, comprising both Dutch and non-Dutch nationals. Intrinsic properties refer to those that are not directly related to other agents. This study defined three intrinsic properties that characterise each agent:

1. HBM Class (`HBM-class`[1])

   The HBM Class of each agent will be assigned randomly, with a probability of being in Class 1 is denoted by `HBM-class-1-proportion`. The `HBM-class` will determine how the agents react to the proportion of mask-wearers within the random people in the neighbourhood (prd). This property can take an integer value of 1 or 2 for HBM Class 1 and 2, respectively.

2. Mask-wearing decision rule

   The decision rule is based on the previously estimated choice model parameters, as specified in Table 5.4. They are specified as floating-point values and labelled in a straightforward manner: `beta-HBM`, `beta-prd`, `beta-pff`, `beta-loc`, `beta-pol`, and `beta-cwd`. These parameters are used to calculate the utility and probability of mask-wearing, as prescribed by the utility function in Section 5.3.2. An example of the calculation is provided later in Section 6.4.2.

3. Mask-wearing decision (`decision`)

   Each agent will evaluate their environment and make a mask-wearing decision. This property can take an integer value of 1 for mask-wearing and 0 for no mask-wearing. The decision rule governs this decision.

[1] In this section, NetLogo objects such as variables, agents, and procedures are denoted by this font type: `example`.

The extrinsic properties specify each agent's reference group (for pff and prd). The reference groups are simply agent sets. This study defined two extrinsic properties:

1. Friends and/or family of agent (`friends-family`)

   This agent set is defined as a group of agents that are friends and/or family with each other. This group size of five agents was chosen arbitrarily as the minimum size that allows for a sufficient granularity in the proportion of mask-wearers within the friends and family group (pff). No distinction is made on whether these agents are friends or family. Because they are assumed to be in an area as a group, they are always close with each other (see Section 6.3 for how this is modelled). This agent set is static throughout one model run.

2. Random people encountered in the neighbourhood (`random-people-observed`)

   At every time step, this agent set will be updated by choosing the physically nearest number of people specified in `number-of-people-observed`. This agent set is updated continuously because of the constant movement of all agents. People who are not part of the `friends-family` agent set are assigned to the `random-people-observed` agent set.

For agents to update their mask-wearing decision, they must evaluate their environment. In this ABM, the environment is defined as the *context* in which agents are situated. The context is specified by the situational cues used in the choice model: `location` (outdoor or indoor), mask-wearing `policy` (voluntary or mandatory), and `crowd-level` (low, medium, or high). Lastly, the environment keeps track of the current and all-time average proportion.

To summarise, Figure 6.1 shows the schematic overview of the ABM layout.

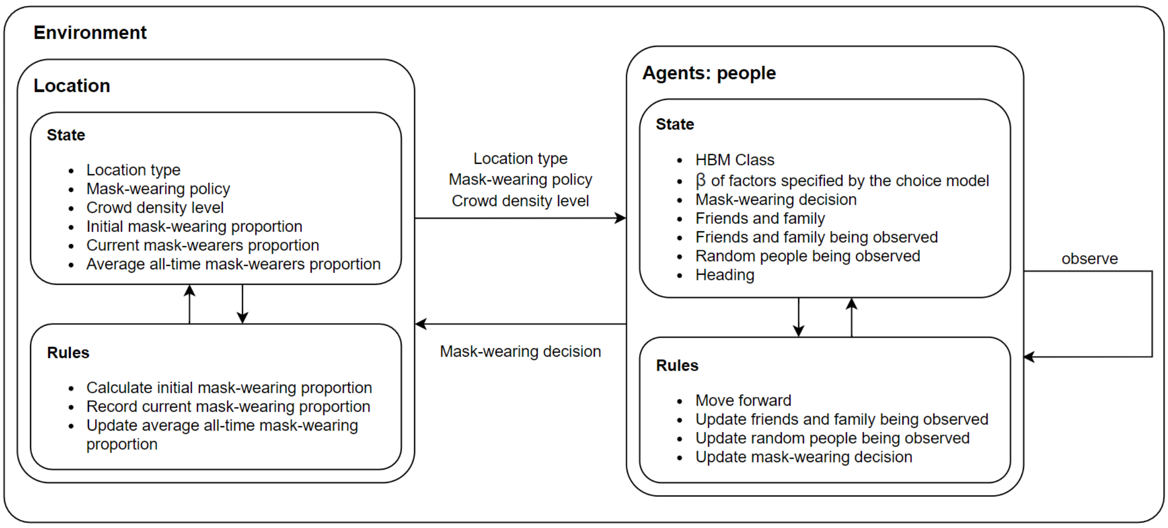

Figure 6.1: Schematic overview of the ABM layout

6.2. Model formalisation

According to van Daam et al. (2012, p. 88), this step specifies the agents' behaviour under a narrative of "which agent does what with whom and when". At each time step, one agent performs these actions:

1. Move forward in their heading by one unit (`forward 1`).
2. Select `people-observed` and separate those who belong in the `friends-family-observed` and `random-people-observed`. In this step, the `friends-family-observed` may be only a part of the `friends-family` because there may be random people who are physically closer than some of an agent's friends/family.
3. Observe the mask-wearing `decision` of agents in both agent sets (these are their reference groups) by evaluating the proportion of mask-wearers in each group.
4. Update his/her mask-wearing `decision` in the following manner. First, the mask-wearing probability is calculated by incorporating the environment's state and the parameters. Next, a random float number between 0 and 1 is generated. If the random number falls below the calculated probability, `decision` equals 1, and vice versa. This mechanism ensures that the non-deterministic characteristic of the choice model is maintained.

Unlike the previous choice model, this mechanism has two advantages. First, it allows for a dynamic feedback loop for the (predicted) proportion of mask-wearers as an input. This feature is important because, as social behaviour, the mask-wearing decision could change over time. Second, the ABM acknowledges local interactions. People are subject to bounded information, i.e., they cannot obtain complete information on the 'global' mask-wearing behaviour of everyone, even within a local public space.

With 1000 people as the agents, everyone performs the actions as mentioned earlier exactly once every 1000 time steps. Each agent within one `friends-family-group` acts in a sequential order without being interrupted by agents from other groups to maintain their physical proximity. Furthermore, it seems unrealistic if people put on and take off their masks every time they move. Therefore to clarify, one time step does not represent one second in time. Instead, after every 1000 time steps, the agents can be considered as being in a new situation, regardless of the time (it can be in the next hour or the next day). A model architecture of this ABM is presented in Figure 6.2.

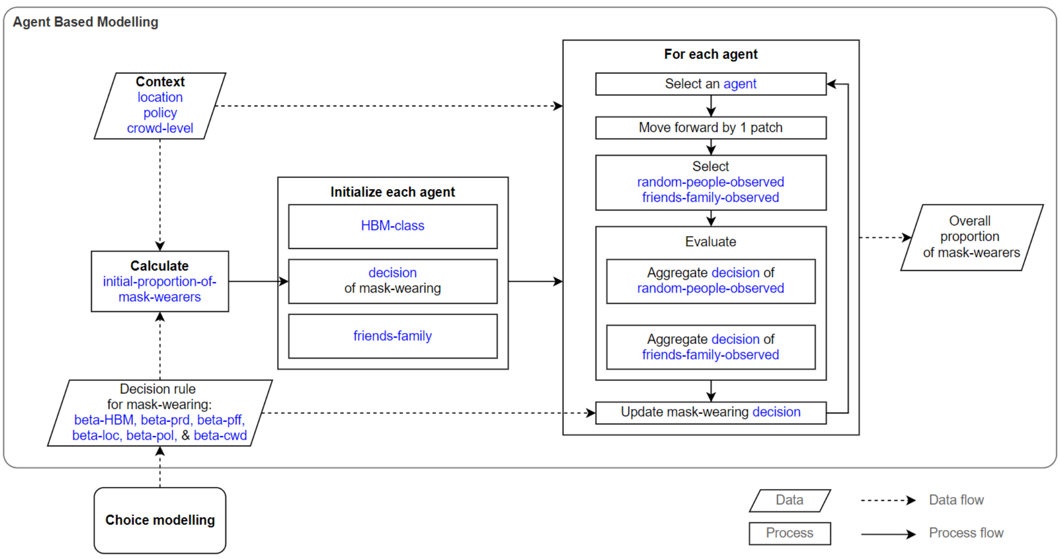

Figure 6.2: ABM architecture

6.3. Model implementation

The model architecture was implemented in the NetLogo software. There are two main features that the ABM exhibits. First, just as in a real public space, the agents encounter random people. Because everyone is moving in a random direction, each agent is surrounded by new people at each time step[2]. Thus, the ABM employs moving *turtles* (NetLogo term) instead of static, patch-based *turtles*. Second, there are always friends and/or family whom an agent observes at each time step. Therefore, the ABM should maintain physical proximity between people in the `friends-family` agent-set. To do so, the initial position of these agents is distributed within a 2.5×2.5 patch area. Moreover, they maintain a uniform *heading* (the agent's direction for their movement).

The ABM consists of a code and an interface. The code can be found in Appendix M. The interface, which is used to set input values and watch the model run (Wilensky, 2021), is divided into three parts: (1) the input panel, (2) the 'world' space, and (3) the plot and monitors.

6.3.1. The ABM input panel

The input panel (Figure 6.3) comprises all location specifications and the decision rule parameters. Furthermore, the other initial conditions such as the proportion of people in HBM Class 1 and 2 (`HBM-class-1-proportion`), the `number-of-friends-family` in a group (this is one number higher than the `friends-family` agent-set, because it includes), the size of `people-observed` agent set, and the `number-of-people` can be modified. However, for the simplicity of the subsequent analysis, the initial values are fixed as follows:

- `HBM-class-1-proportion` = 50%
- `number-of-people-observed` = 15
- `number-of-friends-family` = 5
- `number-of-people` = 1000 (except for minimal testing in the verification step)

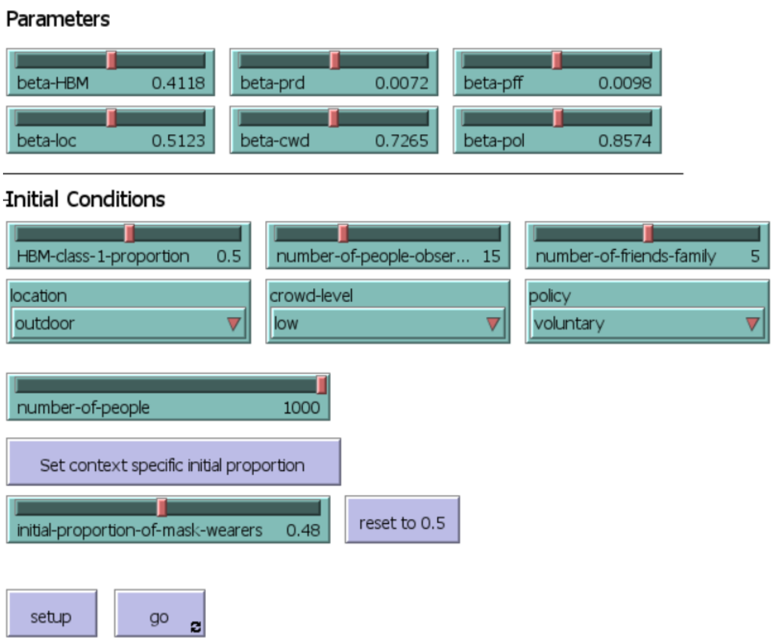

Figure 6.3: The ABM input panel

[2]Each time step is implemented as one `tick` in NetLogo

6.3.2. The ABM 'world'

The 'world' refers to the space in which agents move and interact, as depicted in Figure 6.4. This space wraps horizontally and vertically, i.e., the space is not bounded by 'walls'. The agents are represented by the default NetLogo agent shape, which resembles an arrowhead. The pointy tip indicates their headings, and the colour indicates their current `decision`: *green* for mask-wearing and *red* for no mask-wearing. It is noteworthy that the crowd density level (`crowd-level`) is merely a *conceptual* closeness. Therefore, the physical closeness between agents in this 'world' space (by means of patches) does not affect the crowd density level experienced by the agents.

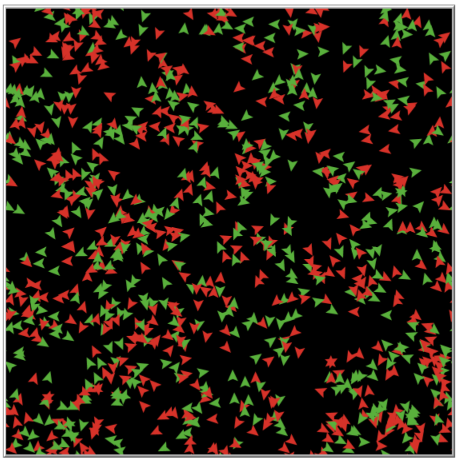

Figure 6.4: The ABM 'world' space

6.3.3. The ABM plot and monitors

Lastly, the plot shows the current and all-time average proportion of mask-wearers, while the monitors print the current values plotted. Figure 6.5 illustrates these metrics after the model was run for 100,000 ticks under initial conditions shown in Figure 6.3. The `initial-proportion-of-mask-wearers` was set as 48%. The plot shows that agents reach a steady state at a much lower overall proportion of mask-wearers after around 10,000 ticks, from 48% to 30%. As this is merely an illustration of the plot and monitors, the specification of the following experiments is to be provided in Section 6.6.

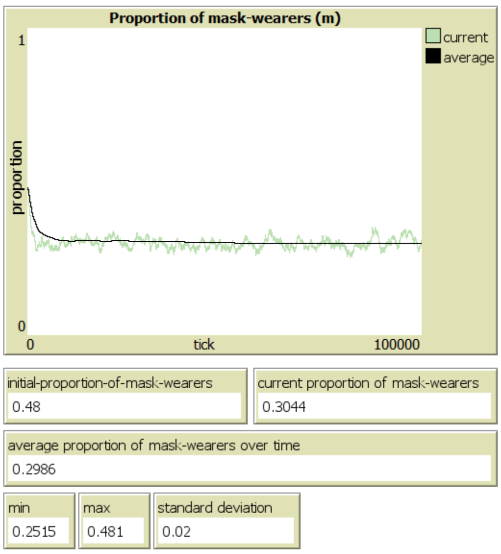

Figure 6.5: The ABM plot and monitors

6.4. Model verification

In this step, two methods are used to check whether the ABM corresponds to its conceptualisation: tracking and interaction testing following van Daam et al. (2012).

6.4.1. Tracking-based verification

For tracking, a 'minimal' model of only 20 agents is used to check whether the family-friends grouping and the agents' movement are expected. This minimal model is for a clearer visualisation than in a model of 1000 agents. Figure 6.6 shows the position of the agents after 20 ticks (left), 100 ticks (centre), and 200 ticks (right). A `friends-family` group as indicated by a white circle is shown to move forward in its heading, remaining in physical proximity within the group. This verifies the desired grouping and movement of the agents.

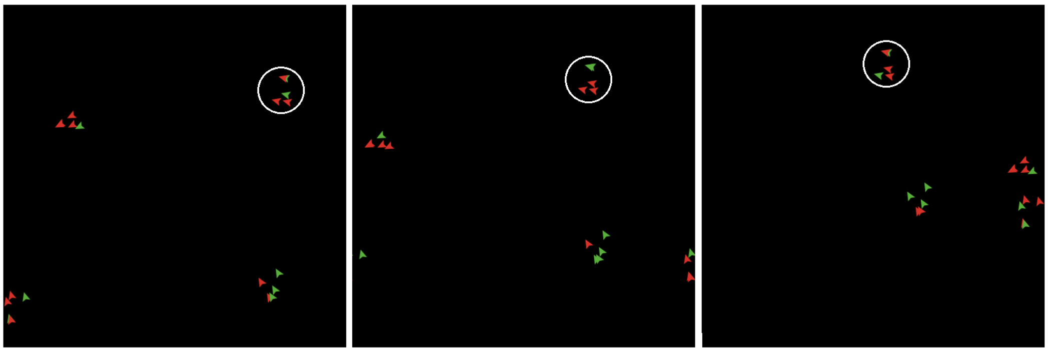

Figure 6.6: Tracking the position of 20 agents after 20 ticks (left), 100 ticks (centre), and 200 ticks (right). The white circle shows one `friends-family` group.

6.4.2. Interaction testing

The model employs 1000 agents for the following verification steps. The interaction testing aims to check whether the interaction occurs correctly (van Daam et al., 2012). This verification is done by observing how an agent (in this case `turtle 999`) interacts with his 15 nearest agents, some of which are his friends and/or family. Figure 6.7 illustrates the `friends-family-observed` and `random-people-observed` by `turtle 999`, each containing 4 and 11 agents, respectively. He appears to wear a mask indicated by the green colour and belongs to HBM Class 2 (checked through inspecting the turtle). This figure is captured after 100,000 ticks.

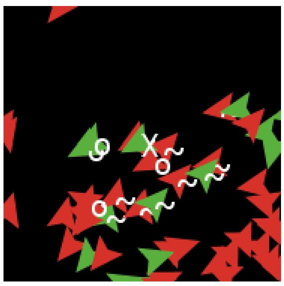

Figure 6.7: Turtle 999 is marked with 'X'. His `friends-family-observed` agent set is marked with 'o' and the `random-people-observed` agent set is marked with '~'.

Afterwards, a manual check of `turtle 999`'s decision is performed. Figure 6.7 shows that two of the `friends-family-observed` and three of the `random-people-observed` are wearing masks. Therefore, pff and pff should be 50.00% and 27.27%. The mask-wearing utility of this agent should then be:

$$
\begin{aligned}
V_{yes} &= 0.4118 \times HBM\ class + 0.0072 \times prd + 0.0098 \times pff + \\
&\quad 0.5123 \times loc + 0.8574 \times pol + 0.7265 \times cwd \\
&= 0.4118 \times 1 + 0.0072 \times 27 + 0.0098 \times 50 + 0.5123 \times -1 + 0.8574 \times -1 + 0.7265 \times 0 \\
&= -0.2715 \\
V_{no} &= 0
\end{aligned}
$$

This utility value translates to a mask-wearing probability of

$$
\begin{aligned}
P_{yes} &= \frac{e^{V_{yes}}}{e^{V_{yes}} + e^{V_{no}}} \\
&= 43.25\%
\end{aligned}
$$

The utility and the probability were confirmed by asking NetLogo to print the values at the end of the model run. Lastly, a random number of 0.1106 was generated. Because the random number is less than the mask-wearing probability, the decision of this agent should be to wear a mask—which the model correctly depicts.

6.5. Model validation

Because an empirically tested choice model governs this ABM, this model already contains a realistic decision-making process. Therefore, this ABM is considered valid to a large extent.

Furthermore, a sensitivity analysis was performed to test the input uncertainty caused by the associated standard errors of the choice model parameters (Bruch & Atwell, 2015). The one-factor-at-a-time (OFAT) method is used since it is recommended by ten Broeke et al. (2016) as the suitable starting point for sensitivity analysis. For this purpose, only β_{prd} and βpff are varied within their confidence intervals by taking five equidistant points between their intervals. These parameters are chosen because this study is mostly interested in how herding affects mask-wearing behaviour—β_{prd} and β_{pff} are the herding-related parameters. As the method name prescribes, one parameter was varied at a time while all other parameters were fixed. Each variation was repeated 20 times under the voluntary policy, outdoor location, and low crowd density.

The results are shown in Figure 6.8. Because the variations of β_{prd} and βpff show an almost identical response, they are discussed simultaneously. Two main observations are apparent: the variations are linear and hence do not contain any tipping points. Furthermore, despite a significant (about 20%) increase of $m_{initial}$ for increasing parameter values, the m_{final} remains relatively stable within a 5% increase. Due to its robustness to changes in herding-related parameters, this model is considered valid.

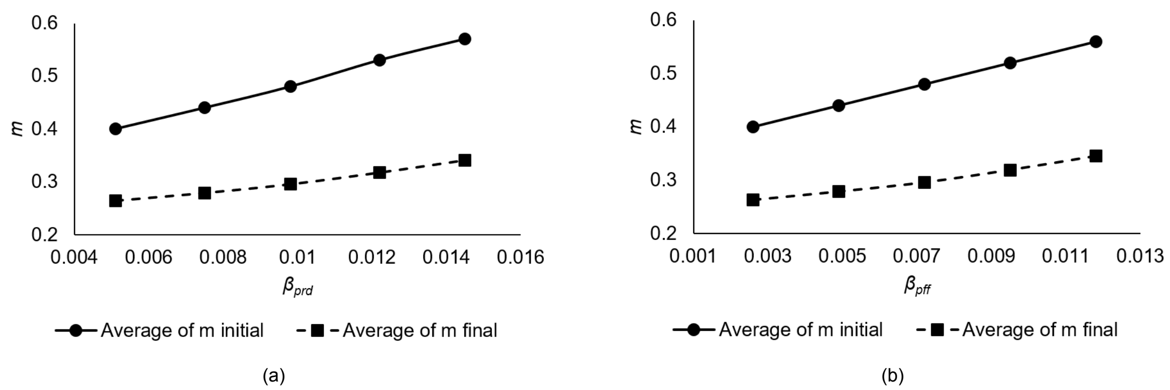

Figure 6.8: OFAT analysis for β_{prd} (a) and β_{pff} (b)

6.6. Experimentation

An experiment was done to see how agents' interactions result in overall mask-wearing behaviour. As explained before, although the choice model can already give an estimation on this matter, it does not consider the feedback effect over time and the locality of interactions. As briefly shown in Figure 6.5, a new steady state of the overall proportion of mask-wearers emerges after at least 10,000 ticks. Therefore, the experiment aims to explore the *proportion of mask-wearers*, from here onwards abbreviated as m, that further highlights the effect of herding.

There are 12 experiments, and each is performed under one of the fully exhaustive combinations of mask-wearing policy, location type, and crowd density level. Each combination is referred to as a *context*. Because there are two types of policy, two location types, and three crowd density levels, the experiment runs under 12 contexts ($2 \times 2 \times 3$). It is noteworthy that the model is stochastic due to the randomness in agents' movement and decision rule. To account for this characteristic, each experiment is repeated 20 times. Therefore, there were 240 model runs in total. In each repetition, the model runs for 100,000 ticks, which is considered sufficient for the model to reach a steady state.

At the start of each experiment, the initial proportion of mask-wearers ($m_{initial}$) is determined considering its context. This is necessary because the $m_{initial}$ should be realistic, i.e., the $m_{initial}$ under a voluntary policy is plausibly lower than it is under a mandatory policy; and the same applies for location type and crowd density level. Therefore, the $m_{initial}$ is first evaluated by utilising the existing choice model as provided in Section 5.3.2. Because the choice model requires the values for prd and pff, the proportion of mask wearers in the Netherlands of 76% (as obtained from Center for Geospatial Information Science University of Maryland (2021) in June 2021) is used. This choice is considered reasonable due to the time scope of this research (as stated in Section 1.4) and the use of the choice model to normalise the value into context-specific $m_{initial}$. The $m_{initial}$ values are shown in the following section. After each replication, the resulting steady-state proportion of mask-wearers (m_{final}) is collected.

6.7. Analysis and discussion

For each experiment, the average $m_{initial}$ and m_{final} across 20 replications are shown by Figure 6.9. On the one hand, the $m_{initial}$ essentially depicts how the choice model estimates m in a *static* manner. On the other hand, the m_{final} shows m after the agents dynamically interacted and produced a new equilibrium. This shows that the non-linear link between micro-level interaction and macro-level m results in a different output than what a choice model would. Nonetheless, it is noteworthy that the ABM preserves the probabilistic nature of the choice model: the m_{final} does not exhibit a tendency towards a consensus on mask-wearing, i.e., extreme values of m.

By comparing the average m_{inital} and m_{final} for each experiment, it is apparent that the m_{final} values are mostly lower than their corresponding $m_{initial}$ values, in particular under the voluntary mask-wearing policy. The difference between $m_{initial}$ and m_{final} is referred to as Δm. It seems that the lower the $m_{initial}$ is, the more negative the Δm is—with an exception for $m_{initial}$ values above 90%. Figure 6.10 plots these differences more clearly for each experiment.

From Figure 6.10, the Δm can be interpreted as the magnitude of the herding effect. Several insights are present. First, it can be inferred that herding behaviour affects the proportion of mask-wearers, especially under the voluntary mask-wearing policy, especially in outdoor places. Furthermore, the lower the crowd density, the herding effect is also stronger. This means that when being in a situation that results in a minority of mask-wearers affects others to also not wear masks; more than being in the opposite situation affects people to also wear masks. Lastly, the negative values of Δm show a tendency towards a no-mask-wearing, even under a majority of mask-wearers situation below 90%.

This study suggests two possible explanations for this observation. First, because of the locality of interactions, agents are not fully aware of the global majority. Meanwhile, there may be local clusters

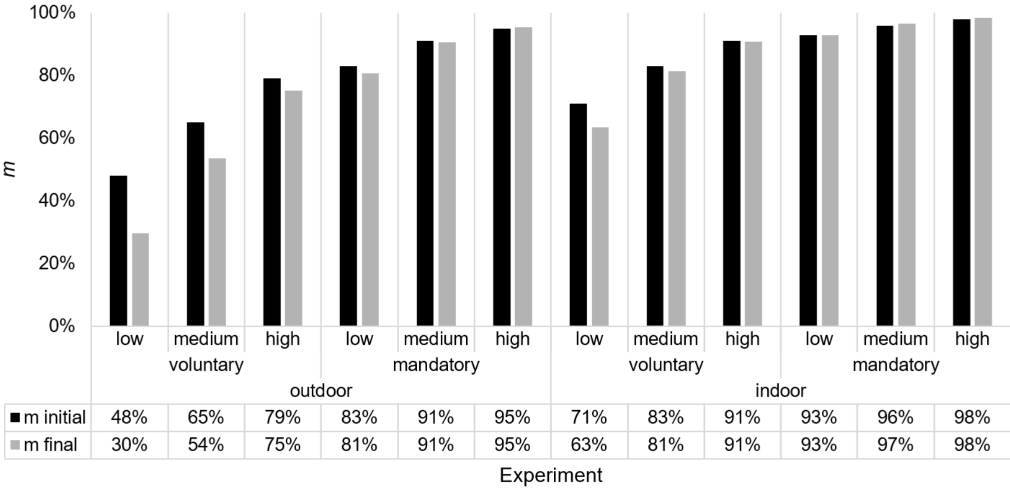

Figure 6.9: Average m_{inital} and m_{final} across 20 replications for each experiment

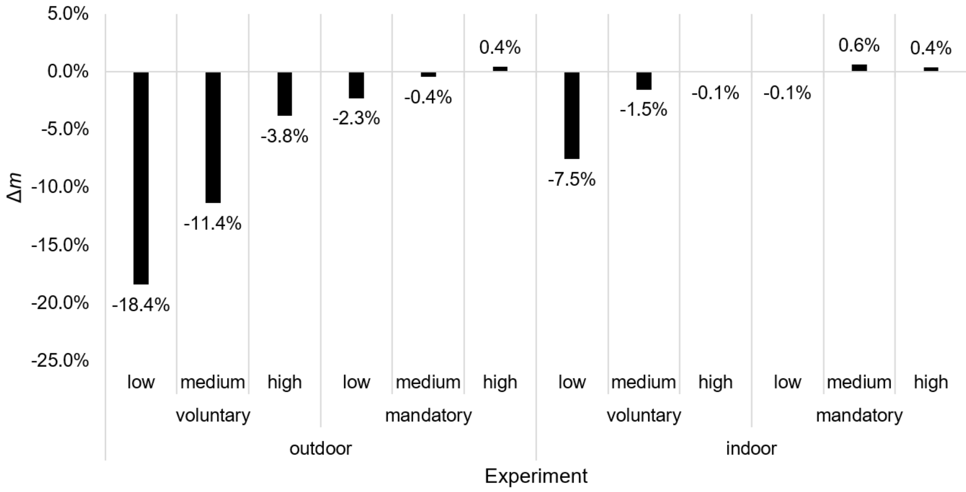

Figure 6.10: Average Δm for each experiment

of non-mask-wearers caused by people moving in friends and/or family groups. The second possible explanation is due to the individual benefit of mask-wearing that decreases with decreasing community mask use (CDC, 2021). Consequently, observing non-mask-wearers decreases the utility of mask-wearing and hence further reduces the proportion of mask-wearers.

6.8. Chapter summary

This study has devised an ABM that allows for local interactions between agents in mask-wearing and shows a more insightful, macro-level understanding of the mechanism behind the effect of herding on mask-wearing behaviour. The ABM is grounded on an empirically validated micro-level decision rule as presented in the previous chapter. The model has been formalised, implemented, verified, and validated. After performing experiments for 12 different contexts, the analysis has allowed this study to understand mask-wearing behaviour even further than the occurrence of herding on mask-wearing: this study unveils an asymmetry in the effect of herding. There is a stronger herding effect towards no-mask-wearing, except under a very high proportion of mask-wearers.

7 Conclusion

This study has analysed the effect of herding on mask-wearing behaviour at the individual (micro) and the population (macro) levels. At the individual level, after conducting a choice experiment, the study has successfully identified clusters in the population-based on their health beliefs and measured the importance of herding along with the health beliefs and situational factors. Then, the choice model was used as an input for the macro-level analysis using an ABM. This analysis has resulted in an enriched understanding of the effect of herding. The following chapter reflects this study on its research questions, limitations, and recommendations for future studies and the policy-making process.

7.1. Reflecting on the research questions

What are the possible factors that may influence mask-wearing behaviour?

A literature review has been conducted to synthesise a collection of factors that may influence mask-wearing systematically. The review resulted in four major types of possible factors. The first and second type is related to HBM, a model that has been widely used for various kinds of health behaviours. This type resulted in two groups of factors: HBM-related factors and situational cues. The situational cues are decomposed into mask-wearing policy, the location type, and the crowd-density level. The second type of factor encompasses psychosocial phenomena, which are represented by herding-related factors characterised by the proportion of mask-wearers within the random people in the neighbourhood, family and/or friends, and the Netherlands national population. Lastly, five demographic factors are selected based on their prevalence in the reviewed literature and ethical consideration.

To what extent does herding affect an individual's mask-wearing behaviour, with respect to other factors?

After collecting a sample of 151 respondents[1] for eight choice tasks (resulting in 1208 observations) on the population of the Netherlands, the effect of herding on mask-wearing is analysed through choice modelling. However, before that, a Latent Class Cluster Analysis (LCCA) was performed to identify two underlying clusters representing the respondents' health beliefs. The first cluster, HBM Class 1, consists of people who are more risk-averse towards COVID-19 and believe more in the efficacy of mask-wearing. The other cluster, HBM Class 2, is simply the opposite of HBM Class 1.

Then, the choice modelling has confirmed a statistically significant effect of herding, only within friends and/or family and the random people. When combined, their effects are as big as the most important factor: the mask-wearing policy. Furthermore, one's personal health belief comes after his/her family and/or friends, but before the random people that he/she encounters. The location type is as important as the proportion of mask-wearers within family and/or friends, and the crowd density level comes in between the location type and the mask-wearing policy. A visualisation of the factors' relative importance is illustrated by Figure 5.4 in Section 5.

[1] The data collection process and the subsequent analysis have been approved by the Delft Human Research Ethics Committee of TU Delft.

How does herding influence mask-wearing behaviour at the population level?

To explore the macro-level population dynamics resulting from micro-level individual behaviours, the collective result is obtained by taking an interdependent behaviour between people into account. An agent-based model (ABM) has been formalised, implemented, verified, and validated. A sensitivity analysis has shown that the model is robust to changes in the herding parameters. Interestingly, the probabilistic nature of the choice model is preserved in this ABM. The main insight obtained from this ABM is that the herding effect is stronger when the majority is not wearing masks than when the majority is wearing masks. In other words, there is a tendency towards a no-mask-wearing, instead of the opposite.

To conclude, the answers to the three sub-questions have built on top of each other the answer to the main research question: *How does herding behaviour influence mask-wearing during the COVID-19 pandemic in the population of the Netherlands?* These discoveries have brought into the state-of-the-art knowledge base not only a new insight on how herding affects mask-wearing, but also an under-explored way of combining static (choice modelling) and dynamic (ABM) research methods.

7.2. Limitations and recommendations for future studies

As mentioned in Section 5.1, the data collection is subject to two limitations. First, due to time limitations, the survey is conducted using an online platform to reach a larger mass of people within a short amount of time. As a result, it was impossible to ensure that all respondents filled in the survey with their utmost attention and honesty. However, the survey is relatively short (can be finished in under five minutes) and provided with simple yet elaborate introductions. Moreover, unfinished surveys were excluded from the analysis. Therefore, the response quality can be considered adequate. Second, the sample cannot be considered as a representative sample of the Dutch population. Nonetheless, this sample is still valuable for a preliminary exploration of the effect of herding on mask-wearing behaviour. Care should be taken in generalising the result to the general Netherlands population.

The identification of possible factors was done using literature published up to April 2021. Since COVID-19 is a major pandemic across the globe, the worldwide research output on this subject keeps increasing. Thus, the literature review may be missing important factors that were undiscovered in the previous literature. Nevertheless, the review is still considered comprehensive and insightful by including literature from previous epidemics such as the SARS, Spanish influenza, and H1N1.

Furthermore, this study generalises the factors based on the situational cues in a broad categorisation—policy only as voluntary and mandatory, and location type as outdoor and indoor. In reality, the amount of fine within a mandatory policy may affect people differently, and there may be a difference between how people behave in two different indoor spaces, such as public transport and the supermarket. Moreover, the duration of visit and other physical conditions (e.g., humidity, temperature) might actually also influence mask-wearing behaviour. However, the current simplification is deemed necessary and reasonable to maintain manageable research within a limited resource and time.

Lastly, the ABM roughly assumes that everyone has an equal capacity and, more importantly, the interest in observing the same amount of people surrounding each agent. In reality, there may be other factors that determine these aspects, such as age and concern for appropriateness (Lennox & Wolfe, 1984). Moreover, other assumptions regarding the model's initial conditions may also influence the final result. Nonetheless, these aspects are considered much less important because of the highly realistic agents whose behaviours are governed using an empirically validated choice model.

Reflecting on the aforementioned limitations, future studies are recommended to also incorporate interviews to confirm the possible factors before conducting a survey. When conducting a choice experiment, the sampling could be done on a municipality that has a set of representative characteristics of the Netherlands population or on a larger sample across the country. Furthermore, a more fine-grained specification of factors may increase the validity of the research.

7.3. Recommendations for policy-making

Direct and indirect recommendations for the policy-making process can be derived from this study.

In a direct manner, this study recommends policy-makers maintain clarity in communicating mask-wearing policy. As discussed earlier, the effect of herding occurs more predominantly under uncertainty (Eun Huh et al., 2014). Due to the observed tendency towards no-mask-wearing, ambiguity in mask-wearing policy shall lead to a low level of mask-wearing. Ultimately, this will reduce the collective protection of mask-wearing when it is necessary. Next, enforcement of mandatory policy is recommended, especially in outdoor spaces. Examples of these spaces are schoolyards and bus and tram stops. When a mandatory policy remains unenforced, the policy may instead be perceived as voluntary. Consequently, the utility of mask-wearing will drop substantially due to the high relative importance of policy. Ultimately, because of the stronger herding effect towards non-mask-wearing, there will be even fewer mask-wearers. Therefore, enforcement through continuous observation and correction is necessary to maintain stability in the proportion of mask-wearers.

Furthermore, this study can also be considered when devising mask-wearing campaigns. The observed effect of herding in mask-wearing presents a way to encourage mask-wearing through social campaigns, if necessary. Due to the importance of family and/or friends compared to the random people and the national population, such campaigns may contain figures that people can closely relate to. Another alternative is to increase the relative importance of the mask-wearing policy. Leveraging the already high importance of this factor may also be an efficient way to promote mask-wearing. The importance of policy can be increased by putting signs in more prominent places, and related to the previous recommendation, by informing people about how active the policy has been enforced.

This study is also useful indirectly when policy-makers are conducting epidemiological research for COVID-19 and other respiratory diseases. Bruch and Atwell (2015) claimed that ABM has been mostly successful for policy-making in the field of epidemiology and urban planning. Such epidemiological research is useful to assess the contagion rate of the disease while taking into account the health behaviour that people may do to protect themselves. In this case, this ABM serves as a part of a bigger whole. This study shows that it is important to consider not only how people exhibit preventive health behaviour but also how this behaviour changes over time under continuous interactions. Therefore, the modellers in the policy-making domain could look at incorporating herding to such research and enrich its realism.

Finally, this study can also be utilised for other policy-making processes outside the mask-wearing context and/or outside the COVID-19 context. Its findings related to herding can be generalised, with caution, into other preventive health behaviours such as social distancing and staying at home. This study can even apply to health behaviours outside the COVID-19 context, for example, smoking and alcohol use. These behaviours are similar to a certain extent—more similar for those within the COVID-19 context—since they all involve social interaction. Moreover, the methods used in this study can be used for policy-makers who would like to consider the effect of herding in other social behaviour such as opinion dynamics in social movements, or even littering and illegal parking.

A

Ngene syntax to generate the experimental design

```
design
;alts = yes, no
;rows = 24
;orth = seq
;block = 3
;model:
U(yes) = b1 * pff [10,40,60,90] +
         b2 * prd [10,40,60,90] +
         b3 * pnl [10,40,60,90] +
         b4 * loc[1,-1] +
         b5 * pol[1,-1] +
         b6 * cwd[0,1,2]
$
```

B

Experimental design

SET	yes.prd	yes.pff	yes.pnl	yes.loc	yes.pol	yes.cwd	Block
11	40	90	60	1	1	2	1
12	60	90	10	1	1	1	1
13	40	10	90	-1	1	1	1
14	60	10	40	-1	1	1	1
15	90	60	60	-1	1	0	1
16	90	60	40	1	-1	1	1
17	10	40	60	-1	-1	1	1
18	40	60	40	-1	-1	2	1
21	10	10	10	1	1	0	2
22	10	90	40	1	1	2	2
23	10	10	60	1	-1	2	2
24	40	10	10	1	-1	0	2
25	90	40	40	1	-1	0	2
26	60	90	90	1	-1	0	2
27	60	40	90	-1	-1	2	2
28	60	60	60	-1	-1	0	2
31	90	10	90	1	1	2	3
32	90	40	60	1	1	1	3
33	10	40	40	-1	1	0	3
34	40	90	90	-1	1	0	3
35	60	60	10	-1	1	2	3
36	10	60	90	1	-1	1	3
37	40	90	10	-1	-1	1	3
38	90	40	10	-1	-1	2	3

See Table 3.5 for the list of factors’ abbreviations.

C

Correlation of factors in the experimental design

		yes.prd	yes.pff	yes.pnl	yes.loc	yes.pol	yes.cwd
yes.prd	Pearson Correlation	1	0.000	0.000	0.000	0.000	0.000
	Sig. (2-tailed)		1.000	1.000	1.000	1.000	1.000
	N	24	24	24	24	24	24
yes.pff	Pearson Correlation	0.000	1	0.000	0.000	0.000	0.000
	Sig. (2-tailed)	1.000		1.000	1.000	1.000	1.000
	N	24	24	24	24	24	24
yes.pnl	Pearson Correlation	0.000	0.000	1	0.000	0.000	0.000
	Sig. (2-tailed)	1.000	1.000		1.000	1.000	1.000
	N	24	24	24	24	24	24
yes.loc	Pearson Correlation	0.000	0.000	0.000	1	0.000	0.000
	Sig. (2-tailed)	1.000	1.000	1.000		1.000	1.000
	N	24	24	24	24	24	24
yes.pol	Pearson Correlation	0.000	0.000	0.000	0.000	1	0.000
	Sig. (2-tailed)	1.000	1.000	1.000	1.000		1.000
	N	24	24	24	24	24	24
yes.cwd	Pearson Correlation	0.000	0.000	0.000	0.000	0.000	1
	Sig. (2-tailed)	1.000	1.000	1.000	1.000	1.000	
	N	24	24	24	24	24	24

D

Comparison of performance between the three initial latent class models

Model	LL	BIC	Number of parameters	L^2	Degrees of freedom	p-value	Class error	#BVR ≤ 3.84
1-class	-855.63	1791.54	16	341.06	135	8.30E-20	0%	2
2-class	-840.42	1786.20	21	310.63	130	8.10E-17	17%	6
3-class	-831.84	1794.14	26	293.48	125	1.40E-15	15%	6

E

Parameters of the 2-class model

Table E.1: Model for indicators: class-dependent parameter

Indicator	Class 1	Class 2	Wald	p-value	R^2
sus	0.41	-0.41	10.40	0.00	0.23
sev	0.43	-0.43	9.92	0.00	0.24
bar	-0.24	0.24	2.82	0.09	0.07
ben	0.42	-0.42	10.20	0.00	0.22

Table E.2: Model for indicators: class-independent parameter

Indicator	Level	Overall	Wald	p-value
sus	1	-0.10	16.04	0.00
	2	0.14		
	3	-0.22		
	4	0.54		
	5	-0.36		
sev	1	-0.31	44.51	0.00
	2	0.72		
	3	-0.96		
	4	0.84		
	5	-0.29		
bar	1	-0.72	72.86	0.00
	2	0.49		
	3	-1.18		
	4	1.43		
	5	-0.01		
ben	1	-0.05	56.28	0.00
	2	0.74		
	3	-0.63		
	4	0.93		
	5	-1.00		

Table E.3: Model for clusters (intercept)

Class 1	Class 2	Wald	p-value
0.17	-0.17	0.32	0.57

F

Parameters of the 2-class model without *bar* as an indicator

Table F.1: Model for indicators: class-dependent parameter

Indicator	Class 1	Class 2	Wald	p-value	R^2
sus	-0.46	0.46	7.39	0.01	0.27
sev	-0.41	0.41	7.81	0.01	0.22
ben	-0.42	0.42	9.16	0.00	0.22

Table F.2: Model for indicators: class-independent parameter

Indicator	Level	Overall	Wald	p-value
sus	1	-0.35	15.74	0.00
	2	0.03		
	3	-0.18		
	4	0.68		
	5	-0.18		
sev	1	-0.49	43.56	0.00
	2	0.60		
	3	-0.97		
	4	0.94		
	5	-0.08		
ben	1	-0.25	56.29	0.00
	2	0.63		
	3	-0.62		
	4	1.05		
	5	-0.81		

Table F.3: Model for clusters (intercept)

Class 1	Class 2	Wald	p-value
0.05	-0.05	0.01	0.90

G

Covariate parameters of the 2-class model without *bar* as an indicator and with covariates

Covariates	Level	Class 1	Class 2	Wald	p-value
age	0	-0.38	0.38	4.79	0.19
	1	-0.89	0.89		
	2	0.04	-0.04		
	3	1.22	-1.22		
gnd	0	-1.03	1.03	1.12	0.57
	1	-0.68	0.68		
	2	1.71	-1.71		
edu	1	-0.01	0.01	3.09	0.38
	2	-0.38	0.38		
	3	0.76	-0.76		
	4	-0.36	0.36		
den	0	0.85	-0.85	3.18	0.20
	1	-0.33	0.33		
	2	-0.52	0.52		
nat	0	-0.95	0.95	6.87	0.01
	1	0.95	-0.95		

H

Parameters of the 2-class model without *bar* as an indicator and with only *nat* as covariate

Table H.1: Model for indicators: class-dependent parameter

Indicator	Class 1	Class 2	Wald	p-value	R^2
sus	0.48	-0.48	7.61	0.01	0.28
sev	0.26	-0.26	6.30	0.01	0.10
ben	0.57	-0.57	11.52	0.00	0.31

Table H.2: Model for indicators: class-independent parameter

Indicator	Level	Overall	Wald	p-value
sus	1	0.03	16.85	0.00
	2	0.26		
	3	-0.18		
	4	0.46		
	5	-0.56		
sev	1	-0.17	42.80	0.00
	2	0.69		
	3	-1.06		
	4	0.77		
	5	-0.24		
ben	1	0.10	57.52	0.00
	2	0.92		
	3	-0.55		
	4	0.83		
	5	-1.30		

Table H.3: Model for clusters (intercept)

Class 1	Class 2	Wald	p-value
0.38	-0.38	1.50	0.22

Table H.4: Model for covariates

Covariate	Level	Class 1	Class 2	Wald	p-value
nat	0	-0.46	0.46	7.53	0.01
	1	0.46	-0.46		

Profile of each HBM class for the final latent class model

		Class 1	Class 2
Class size		0.66	0.34
Indicators			
sus	1	0.07	0.40
	2	0.13	0.31
	3	0.14	0.12
	4	0.42	0.14
	5	0.25	0.03
Mean		3.65	2.11
sev	1	0.08	0.22
	2	0.23	0.40
	3	0.05	0.05
	4	0.43	0.26
	5	0.20	0.07
Mean		3.45	2.56
ben	1	0.05	0.35
	2	0.20	0.45
	3	0.08	0.06
	4	0.56	0.13
	5	0.12	0.01
Mean		3.49	2.00
Covariates			
nat	0	0.34	0.77
	1	0.66	0.23

J

ProbMeans output of each HBM class for the final latent class model

		Class 1	Class 2
Class size		0.66	0.34
Indicators			
sus	1	0.21	0.79
	2	0.48	0.52
	3	0.73	0.27
	4	0.82	0.18
	5	0.95	0.05
sev	1	0.38	0.62
	2	0.55	0.45
	3	0.53	0.47
	4	0.76	0.24
	5	0.86	0.14
ben	1	0.22	0.78
	2	0.45	0.55
	3	0.63	0.37
	4	0.90	0.10
	5	0.98	0.02
Covariates			
nat	0	0.46	0.54
	1	0.85	0.15

K
Classification output of LatentGOLD

nat	sus	sev	ben	**ObsFreq**	**Modal**	**Class 2**	**Class 2**
0	1	1	1	2	2	0.01	0.99
1	1	1	1	1	2	0.04	0.96
0	1	1	2	1	2	0.02	0.98
0	1	1	4	1	2	0.17	0.83
1	1	1	4	1	1	0.57	0.43
0	1	2	1	3	2	0.01	0.99
0	1	2	2	3	2	0.03	0.97
1	1	2	2	2	2	0.19	0.81
0	1	2	4	1	2	0.26	0.74
1	1	2	5	1	1	0.87	0.13
0	1	3	1	1	2	0.02	0.98
0	1	3	3	1	2	0.16	0.84
0	1	4	1	1	2	0.03	0.97
0	1	4	2	3	2	0.09	0.91
1	1	4	4	2	1	0.86	0.14
0	1	5	2	2	2	0.15	0.85
0	1	5	4	1	1	0.63	0.37
0	2	1	1	1	2	0.02	0.98
0	2	1	2	1	2	0.05	0.95
1	2	1	2	1	2	0.26	0.74
0	2	2	2	3	2	0.09	0.91
1	2	2	2	3	2	0.37	0.63
1	2	2	3	1	1	0.65	0.35
0	2	2	4	1	2	0.47	0.53
1	2	2	4	1	1	0.85	0.15
1	2	2	5	1	1	0.95	0.05
0	2	4	1	3	2	0.08	0.92
0	2	4	2	2	2	0.21	0.79
0	2	4	3	2	2	0.46	0.54
1	2	4	3	1	1	0.84	0.16
0	2	4	4	3	1	0.72	0.28
1	2	4	4	3	1	0.94	0.06
1	2	5	3	1	1	0.90	0.10
1	2	5	5	1	1	0.99	0.01
1	3	1	1	1	2	0.23	0.77
1	3	1	4	1	1	0.90	0.10

nat	sus	sev	ben	**ObsFreq**	**Modal**	**Class 2**	**Class 2**
0	3	2	1	2	2	0.07	0.93
0	3	2	2	1	2	0.20	0.80
0	3	2	3	1	2	0.43	0.57
1	3	2	4	4	1	0.94	0.06
0	3	3	3	1	1	0.56	0.44
1	3	4	2	2	1	0.82	0.18
1	3	4	3	1	1	0.93	0.07
0	3	4	4	1	1	0.87	0.13
1	3	4	4	2	1	0.98	0.02
1	3	5	4	1	1	0.99	0.01
1	3	5	5	2	1	1.00	0.00
1	4	1	1	1	2	0.44	0.56
0	4	1	2	1	2	0.27	0.73
1	4	1	2	3	1	0.71	0.29
0	4	1	3	1	1	0.54	0.46
0	4	1	4	2	1	0.78	0.22
0	4	2	1	1	2	0.17	0.83
1	4	2	1	1	1	0.57	0.43
1	4	2	2	1	1	0.80	0.20
0	4	2	4	2	1	0.86	0.14
1	4	2	4	7	1	0.98	0.02
0	4	3	1	1	2	0.26	0.74
0	4	3	2	1	1	0.52	0.48
1	4	3	2	2	1	0.87	0.13
1	4	4	1	1	1	0.79	0.21
0	4	4	2	4	1	0.65	0.35
1	4	4	2	2	1	0.92	0.08
1	4	4	3	1	1	0.97	0.03
0	4	4	4	6	1	0.95	0.05
1	4	4	4	4	1	0.99	0.01
1	4	4	5	2	1	1.00	0.00
1	4	5	2	1	1	0.95	0.05
0	4	5	4	1	1	0.97	0.03
1	4	5	4	1	1	0.99	0.01
0	4	5	5	2	1	0.99	0.01
1	5	2	2	1	1	0.91	0.09
0	5	2	4	1	1	0.94	0.06
1	5	2	4	1	1	0.99	0.01
1	5	2	5	1	1	1.00	0.00
1	5	3	4	1	1	0.99	0.01
1	5	4	2	2	1	0.97	0.03
1	5	4	4	7	1	1.00	0.00
1	5	4	5	1	1	1.00	0.00
0	5	5	1	3	1	0.72	0.28
0	5	5	2	1	1	0.89	0.11
0	5	5	4	5	1	0.99	0.01
1	5	5	4	1	1	1.00	0.00
1	5	5	5	1	1	1.00	0.00

Choice model variations

Model	Model specification				Number of parameters	Final-LL	BIC	Rho -square
	Description	Non-linear parameters	Interaction with HBM class	Removed variables				
1	All linear parameters	0	0	0	8	-529.08	1114.93	37%
2	pnl and yes-specific-constant are removed	0	0	**2**	6	-530.04	1102.66	37%
3	prd and pff interact with HBM class	0	**2**	2	8	-527.42	1111.61	37%
4	Only prd interacts with HBM class	0	**1**	**3**	6	-528.62	1099.81	37%
5	cwd as non-linear parameter	**1**	1	2	7	-528.25	1106.18	37%
6	prd and pff as non-linear parameters cwd as a linear parameter	**2**	1	2	10	-529.15	1129.26	37%
7	Insignificant prd levels (40, 60) are removed	2	1	**4**	8	-543.46	1143.70	35%

M

NetLogo syntax

```
extensions [ nw ]

globals [
  loc
  cwd
  pol
  proportion-history
]

turtles-own [
  ;; demographic characteristic: nationality
  nationality

  ;; specification of agent's perception on COVID-19 and mask-wearing based on Heatlh Belief Model
  HBM-class

  ;; decision based on the decision rule, considering multiple factors
  decision

  ;; which friends-family group an agent is in
  friends-family-group

  ;; an agent-set of friends and family of an agent
  friends-family

  ;; an agent-set of x nearest agents that is observed by an agent
  people-observed

  ;; specificaiton of which agents are the family-friend
  friends-family-observed

  ;; specification of which agents are random people observed by an agent
  random-people-observed

]


to setup

  clear-all

  let number-of-groups number-of-people / number-of-friends-family
```

```
  let group-number 0

  while [ group-number < number-of-groups ] [
    set group-number group-number + 1
    let member 0

    let direction random 360
    let x random-xcor
    let y random-ycor

    while [ member < number-of-friends-family ] [
      create-turtles 1 [
        ;; if n = number-of-friends-family
        ;; all members are randomly positioned on a n*n area
        setxy x + random-float number-of-friends-family / 2 y + random-float number-of-friends-family / 2

        ;; all members in one group move in the same direction
        set heading direction

        ;; assign group-number to each member
        set friends-family-group group-number

      ]
      set member member + 1
    ]

  ]

  ask turtles [ set friends-family turtles with [ friends-family-group = [ friends-family-group ] of myself ] ]

  ;; set initial mask-wearing decision and HBM Class
  ask turtles [
    set decision 0
    set HBM-class 2
  ]
  ask n-of ( initial-proportion-of-mask-wearers * number-of-people ) turtles [
    set decision 1
  ]
  ask n-of ( HBM-class-1-proportion * number-of-people ) turtles [
    set HBM-class 1
  ]

  ask turtles [ set color ifelse-value ( decision = 0 ) [ red ] [ green ] ]

  set loc ifelse-value ( location = "outdoor" ) [ -1 ] [ 1 ]
  set cwd ( ifelse-value
    crowd-level = "low"    [ 0 ]
    crowd-level = "medium" [ 1 ]
    [ 2 ])
  set pol ifelse-value ( policy = "voluntary" ) [ -1 ] [ 1 ]

  set proportion-history []
```

```
  set proportion-history lput initial-proportion-of-mask-wearers proportion-history

  reset-ticks

end

to go

  ;ask one-of turtles [

  foreach sort-on [ who ] turtles [
    the-turtle -> ask the-turtle [

      forward 1

      ;; set reference groups
      set people-observed min-n-of number-of-people-observed other turtles [ distance myself ]
      set random-people-observed people-observed with [ friends-family-group != [ friends-family-group ] of myself ]
      set friends-family-observed people-observed with [ friends-family-group = [ friends-family-group ] of myself ]

      ;; reference groups' mask-wearing proportion
      let prd ( count random-people-observed with [ decision = 1 ] ) / count random-people-observed * 100
      let pff ifelse-value ( count friends-family-observed = 0 ) [ 0.5 ] [ ( count friends-family-observed with [ decision = 1 ] ) / count friends-family-observed * 100 ]


      ;; evaluate reference groups
      ;; utility
      let v-ext ( beta-prd * prd + beta-pff * pff + beta-loc * loc + beta-cwd * cwd + beta-pol * pol )
      let v ifelse-value ( HBM-class = 1 ) [ v-ext - beta-HBM ] [ v-ext + beta-HBM ]
      ;; probability
      let p ( exp v / ( 1 + exp v ) )

      ;; update decision
      let r random-float 1
      set decision ifelse-value ( r < p ) [ 1 ] [ 0 ]

      ;; DEBUG
      if ticks = 99999 [
        print prd
        print pff
        print v
        print p
        print r
      ]
      set color ifelse-value ( decision = 0 ) [ red ] [ green ]


```

```
    ]
    tick

    set proportion-history lput ( count turtles with [ decision = 1 ] / count turtles ) proportion-history

    if ticks >= 100000 [stop]

  ]



  ;tick

end


to calculate-initial-proportion

;  clear-all

  ;; transform literal to coded values
  set loc ifelse-value ( location = "outdoor" ) [ -1 ] [ 1 ]
  set cwd ( ifelse-value
    crowd-level = "low"     [ 0 ]
    crowd-level = "medium" [ 1 ]
                           [ 2 ])
  set pol ifelse-value ( policy = "voluntary" ) [ -1 ] [ 1 ]

  let prd 76
  let pff 76
  ;https://covidmap.umd.edu/map/results.html

  ;; utility
  let v-ext ( beta-prd * prd + beta-pff * pff + beta-loc * loc + beta-cwd * cwd + beta-pol * pol )
  let v-HBM-1 v-ext - beta-HBM
  let v-HBM-2 v-ext + beta-HBM

  ;; probability
  let p-HBM-1 ( exp v-HBM-1 / ( 1 + exp v-HBM-1 ) )
  let p-HBM-2 ( exp v-HBM-2 / ( 1 + exp v-HBM-2 ) )

  set initial-proportion-of-mask-wearers precision ( HBM-class-1-proportion * p-HBM-1 + ( 1 - HBM-class-1-proportion ) * p-HBM-2 ) 2

end

to reset-initial-proportion

  set initial-proportion-of-mask-wearers 0.5

end
```

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