Simulating Dynamics of Institutions

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SIMULATING DYNAMICS OF INSTITUTIONS

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Dissertation

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by

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To my parents..

whose unwavering support and boundless love are cherished beyond words

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Summary

In society, institutions are the foundation that governs human behaviour through rules, norms, and regulations. The actions and interactions of individuals are shaped by these institutions, forming a cyclic system with numerous parameters and factors. Altering any of these factors, triggers the entire system to transition into a new state that comprises new emergent institutions. This process can take anywhere from days to thousands of years.

Employing agent-based models and simulation techniques enables the study of the emergence and transformation of institutions in a shorter timeframe, with reasonable cost, and under diverse parameters and conditions.

The purpose of this dissertation is to enhance institutional theories by generating new insights, testing hypotheses, and offering support to researchers, historians, policymakers, and social scientists who are studying institutional dynamics. The outcomes of this research may assist in the identification of successful institutions and the comprehension of the factors that contribute to their success.

Based on the interdependent relationship between emerging institutions and individual actions, this dissertation addresses the main research question through four distinct parts. Chapter 2 examines the transition between theoretical patterns at the macro-level and the underlying causes at the micro-level. Chapter 3 delves into the role of agents' actions and interactions in the emergence of institutions. Chapter 4 outlines guidelines and best practices for applying machine learning techniques to agent-based models, considering the unique modelling purposes and challenges. Finally, in Chapter 5, the study covers the complete process, exploring the impact of institutions at the macro-level on individuals at the micro-level, their connections, and the effects on emerging institutions, including the triggers that initiate the process.

Reproducing high-level institutional patterns to understand underlying mechanisms better

In numerous historical analyses and studies, there are established institutional trends or patterns that are frequently obtained through data mining techniques from vast datasets or observed in empirical studies. However, the causalities and underlying reasons that resulted in those trends or patterns still have several unanswered questions. In some cases, there are hypotheses on those underlying mechanisms, but in many instances, this causal understanding is lacking. The agent-based model, particularly the proposed framework in Chapter 2 of this research, provides a means to demonstrate how the collective behaviours of individual agents at the micro-level can modify significant emergent phenomena at the macro-level.

In the historical context of common-pool resources, there is a recognized pattern of institutional change; beginning with a phase of initial shifts, followed by stability, and then another phase of frequent changes. However, the micro-level mechanisms driving this pattern remain unknown. To address this, we developed an agent-based model based on hypotheses from literature and historical analysis. Through experiments, the model confirms or refutes these hypotheses, aiding analysts in understanding the plausibility of underlying mechanisms. The results reveal that social shocks can endanger commons, while reduced reliance on sanctions and frequent interactions among commoners positively impact resource longevity by fostering stability through continual adaptations to institutions.

Understanding bottom-up institutional outcomes

Institutional dynamics are shaped by the actions and interactions of individual agents. Chapter 3 of this research demonstrates how an inductive approach utilizing agent-based models can be used to investigate emergent institutions and the triggers that initiate their formation. An abstract agent-based model is developed to explore a common-pool resource management system where appropriators share a resource and collaboratively develop institutions to maintain it. The complexity of this social question, which examines the relationship between wealth inequality and cooperation, necessitates the incorporation of heterogeneous agents and simple learning behaviour. The agents are able to make more conscious choices about the changes they want to make to their actions and toward institutions. We investigated the relationship between wealth inequality and cooperation by focusing on agents' actions and interactions. Subsequently, we analyzed the impact of this relationship on institutional characteristics, population characteristics, and resource characteristics.

The results indicate an inverse relationship between wealth inequality and cooperation, with an increase in wealth inequality corresponding to a decrease in cooperation. Additionally, the findings demonstrate that under conditions of low inequality, common-pool resources exhibit superior performance in terms of both average wealth and resource availability. In similar unequal situations, with increased cooperation, there is a corresponding rise in average wealth and resource abundance. Moreover, elevated levels of cooperation coincide with fewer instances of cheating or non-voting, leading to the later emergence of the initial institution. Furthermore, under comparable cooperative circumstances, the prevalence of cheaters and non-voters diminishes as inequality decreases.

Using institutional data in agent-based models

The aim of Chapter 5 is to investigate how a large set of real-world data from different sources can be utilized in an agent-based model. The COVID-19 pandemic is used as a case study to explore the relationship between institutional change and value change in countries during a crisis. This is a complex problem that involves multiple factors and parameters, making agent-based modelling a suitable tool to examine the relationship between change in values and change in institutions. In this model, agents represent countries that strive to ensure the well-being of their citizens while managing the spread of disease.

To make the agents act similarly to actual countries during the COVID-19 period, they need to be fed with real data. The model which has been built in this chapter is an agent-based model that uses real-world data for crucial parameters. Additionally, the agents are heterogeneous with respect to COVID-19 factors such as infected cases, unemployment degree, freedom degree, and other characteristics. Meanwhile, the real-world data exhibit diversity in terms of sources, types (qualitative, quantitative), and aggregation levels. Therefore, a degree of intelligence is added to the model using a machine learning technique (as a brain of agents), which extracts patterns from the real-world data. The results show an inverse relationship between value change and institutional change. In other words, a global inclination towards greater openness to change values tends to correspond with more flexible institutions, whereas a stronger emphasis on conservation values typically aligns with stricter institutions, on average.

Applying machine learning techniques in agent-based models

Prior to developing the model discusses in Chapter 5, it is crucial to determine the appropriate placement of machine learning techniques within agent-based models. Thus, a literature review is conducted, as details in Chapter 4, to serve as a guide for the use of machine learning techniques in agent-based models based on their specifications and intended purposes. The findings show that machine learning techniques are well-suited for addressing currently overlooked modelling aspects such as social learning and illustration, offering transparency and interpretability in their application. Moreover, the results indicate that Reinforcement Learning algorithms can enhance the precision of behavioural modelling. Additionally, widely used techniques like Decision Trees and Bayesian Networks serve as effective tools for preprocessing agent behaviour data.

In conclusion, this research explores the application of agent-based modelling to understand institutional dynamics, aiming to fill gaps in our understanding of institutional change. Through advanced computer simulations, the study not only enhances our grasp of this complex phenomenon but also provides valuable guidelines for future research. The findings bring insights into how institutions function for research and policy analysis. Using a unique simulation approach, creating, and unraveling patterns, offers potential benefits for diverse simulation inquiries. Additionally, the study advances agent-based modelling by integrating machine learning, enhancing model intelligence and data-driven capabilities. The research's outcomes assist in identifying successful institutions and understanding the factors contributing to their success.

Samenvatting

In een samenleving vormen instituties het fundament dat menselijk gedrag regelt door middel van regels, normen en voorschriften. De acties en interacties van individuen worden gevormd door deze instituties en vormen een cyclisch systeem met talloze parameters en factoren. Het veranderen van een van deze factoren zorgt ervoor dat het hele systeem overgaat in een nieuwe staat die nieuwe, opkomende instituties omvat. Dit proces kan dagen tot duizenden jaren duren.

Het gebruik van agentgebaseerde modellen en simulatietechnieken maakt het mogelijk om de opkomst en transformatie van instituties te bestuderen in een korter tijdsbestek, tegen redelijke kosten en onder verschillende parameters en omstandigheden.

Het doel van dit proefschrift is om institutionele theorieën te verbeteren door nieuwe inzichten te genereren, hypotheses te testen en ondersteuning te bieden aan onderzoekers, historici, beleidsmakers en sociale wetenschappers die institutionele dynamiek bestuderen. De uitkomsten van dit onderzoek kunnen helpen bij het identificeren van succesvolle instituties en het begrijpen van de factoren die bijdragen aan hun succes.

Gebaseerd op de onderlinge afhankelijke relatie tussen opkomende instituties en individuele acties, behandelt dit proefschrift de hoofdonderzoeksvraag aan de hand van vier afzonderlijke delen. Hoofdstuk 2 onderzoekt het verband tussen theoretische patronen op macroniveau en de onderliggende oorzaken op microniveau. Hoofdstuk 3 gaat in op de rol van acties en interacties van agenten bij het ontstaan van instituties. Hoofdstuk 4 schetst richtlijnen en *best practices* voor het toepassen van *machine-learning* technieken op agentgebaseerde modellen, rekening houdend met de specifieke modelleringsdoelen en uitdagingen. Hoofdstuk 5, ten slotte, behandelt het volledige proces, waarbij de impact van instituties op macroniveau op individuen op microniveau, hun connecties en de effecten op opkomende instituties worden onderzocht, inclusief de triggers die het proces in gang zetten.

Reproduceren van institutionele patronen op hoog niveau om onderliggende mechanismen beter te begrijpen

In tal van historische analyses en studies zijn er vastgestelde institutionele trends of patronen die vaak worden verkregen met dataminingtechnieken uit grote datasets of die worden waargenomen in empirische studies. Er zijn echter nog verschillende onbeantwoorde vragen over de oorzaken en onderliggende redenen die tot die trends of patronen hebben geleid. In sommige gevallen zijn er hypotheses over die onderliggende mechanismen, maar in veel gevallen ontbreekt een causaal inzicht. Het agentgebaseerde model, in het bijzonder het voorgestelde raamwerk in hoofdstuk 2 van dit onderzoek, biedt een manier om aan te tonen hoe het collectieve gedrag van individuele agenten op microniveau belangrijke opkomende fenomenen op macroniveau kan veranderen.

In de historische context van gemeenschappelijke hulpbronnen (*common pool resources)* is er een erkend patroon van institutionele verandering; beginnend met een fase van initiële verschuivingen, gevolgd door stabiliteit, en dan weer een fase van frequente veranderingen. De mechanismen op microniveau die dit patroon veroorzaken zijn echter nog veelal onbekend. Om dit aan te pakken hebben we een agentgebaseerd model ontwikkeld op basis van hypotheses uit de literatuur en historische analyse. Door middel van experimenten bevestigt of weerlegt het model deze hypotheses en helpt het analisten om de plausibiliteit van onderliggende mechanismen te evalueren. De resultaten laten zien dat sociale schokken een gemeenschap (*commons)* in gevaar kunnen brengen, terwijl een verminderde afhankelijkheid van sancties en frequente interacties tussen deelnemers aan de gemeenschap een positieve invloed hebben op de levensduur van gemeenschappen door stabiliteit te bevorderen via voortdurende aanpassingen aan instituties.

Institutionele resultaten van onderaf begrijpen

Institutionele dynamiek wordt gevormd door de acties en interacties van individuele agenten. Hoofdstuk 3 van dit onderzoek laat zien hoe een inductieve benadering met behulp van agentgebaseerde modellen gebruikt kan worden om opkomende instituties en de triggers die hun vorming initiëren te onderzoeken. Er is een abstract agentgebaseerd model ontwikkeld om een systeem voor het beheer van gemeenschappelijke hulpbronnen te onderzoeken, waarbij deelnemers (*commoners*) een hulpbron delen en samen instituties ontwikkelen om deze te onderhouden. De complexiteit van dit sociale vraagstuk, dat de relatie tussen ongelijkheid in rijkdom en samenwerking onderzoekt, vereist de integratie van heterogene agenten en eenvoudig leergedrag. De agenten zijn in staat om bewustere keuzes te maken over de veranderingen die ze willen aanbrengen in hun acties en doen dat in het licht van bestaande instituties. We onderzochten de relatie tussen welvaartsongelijkheid en samenwerking door ons te richten op de acties en interacties van agenten. Vervolgens analyseerden we de invloed van deze relatie op institutionele kenmerken, populatiekenmerken en kenmerken van hulpbronnen.

De resultaten wijzen op een omgekeerde relatie tussen welvaartsongelijkheid en samenwerking, waarbij een toename in welvaartsongelijkheid overeenkomt met een afname in samenwerking. Bovendien tonen de bevindingen aan dat onder omstandigheden van lage ongelijkheid, gemeenschappelijke hulpbronnen beter presteren in termen van zowel gemiddelde rijkdom als beschikbaarheid van hulpbronnen. In vergelijkbare ongelijke situaties is er bij toenemende samenwerking een overeenkomstige toename in gemiddelde rijkdom en beschikbaarheid van hulpbronnen. Bovendien vallen verhoogde samenwerkingsniveaus samen met minder gevallen van valsspelen of niet-stemmen, wat leidt tot het later ontstaan van de bijbehorende institutie. Bovendien neemt onder vergelijkbare coöperatieve omstandigheden de prevalentie van valsspelers en niet-stemmers af naarmate de ongelijkheid afneemt.

Gebruik van institutionele gegevens in agentgebaseerd modellen

Het doel van hoofdstuk 5 is om te onderzoeken hoe een grote verzameling gegevens uit de echte wereld uit verschillende bronnen kan worden gebruikt in een agentgebaseerd model. De COVID-19 pandemie wordt gebruikt als casestudy om de relatie tussen institutionele verandering en waardeverandering in landen tijdens een crisis te onderzoeken. Dit is een complex probleem waarbij meerdere factoren en parameters een rol spelen, waardoor agentgebaseerde modellering een geschikt instrument is om de relatie tussen veranderingen in waarden en veranderingen in instellingen te onderzoeken. In dit model vertegenwoordigen agenten landen die ernaar streven om het welzijn van hun burgers te garanderen en tegelijkertijd de verspreiding van ziekten te beheersen.

Om de agenten tijdens de COVID-19-periode op dezelfde manier te laten handelen als echte landen, moeten ze gevoed worden met echte gegevens. Het model dat in dit hoofdstuk werd gebouwd, is een agent gebaseerd model dat gegevens uit de echte wereld gebruikt voor cruciale parameters. Bovendien zijn de agenten heterogeen met betrekking tot COVID-19-factoren zoals besmette gevallen, werkloosheidsgraad, vrijheidsgraad en andere kenmerken. Ondertussen vertonen de gegevens uit de echte wereld diversiteit in termen van bronnen, soorten (kwalitatief, kwantitatief) en aggregatieniveaus. Daarom wordt er een zekere mate van intelligentie aan het model toegevoegd met behulp van een machine-learningtechniek (als een brein van de agent), die patronen uit de werkelijke gegevens haalt. De resultaten laten zien dat een algemene neiging tot meer openheid om waarden te veranderen overeen komt met flexibelere instituties, terwijl een sterkere nadruk op behoud van waarden gemiddeld genomen overeenkomt met strengere instituties.

Machine-learningtechnieken toepassen in agentgebaseerde modellen

Voorafgaand aan de ontwikkeling van het model dat in hoofdstuk 5 wordt besproken, is het cruciaal om de juiste plaatsing van machine-learningtechnieken binnen agentgebaseerde modellen te bepalen. Daarom werd een literatuurstudie uitgevoerd, zoals beschreven in Hoofdstuk 4, om als leidraad te dienen voor het gebruik van machine-learningtechnieken in agentgebaseerde modellen op basis van hun specificaties en beoogde doelen. De bevindingen tonen aan dat machine-learningtechnieken zeer geschikt zijn voor het aanpakken van aspecten van modellering die momenteel minder aandacht krijgen, zoals sociaal leren, en dat ze transparantie en interpreteerbaarheid bieden in hun toepassing. Bovendien geven de resultaten aan dat Reinforcement Learning-algoritmen de precisie van gedragsmodellering kunnen verbeteren. Daarnaast dienen veelgebruikte technieken zoals beslisbomen en Bayesiaanse netwerken als effectieve hulpmiddelen voor het voorbewerken van gegevens over het gedrag van agenten.

Concluderend, dit onderzoek verkent de toepassing van agentgebaseerde modellering om institutionele dynamiek te begrijpen, met als doel om ons begrip van institutionele verandering te laten toenemen. Door middel van geavanceerde computersimulaties verbetert het onderzoek niet alleen ons begrip van dit complexe fenomeen, maar biedt het ook waardevolle richtlijnen voor toekomstig onderzoek. De bevindingen bieden inzichten in hoe instituties functioneren voor onderzoek en beleidsanalyse. Het gebruik van een unieke simulatiebenadering, waarbinnen het creëren en ontrafelen van patronen mogelijk is, biedt potentiële voordelen voor diverse simulatieonderzoeken. Bovendien verbetert het onderzoek agentgebaseerde modellering door machine learning erin te integreren, waardoor de intelligentie van een model en de datagestuurde mogelijkheden worden verbeterd. De resultaten van het onderzoek helpen bij het identificeren van succesvolle instituties en het begrijpen van de factoren die bijdragen aan hun succes.

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Each journey harbors several hidden stories that will always remain attached to our memories. I believe the narratives of growth and transformation into better versions of ourselves are among the most compelling tales to hear.

There is a Persian pattern named Boteh Jeghe or paisley, which I utilized for my cover design. Paisley is a distinctive design featuring curved shapes with intricate details; each element follows a simple pattern, and collectively, they shape a beautiful whole. There is a saying that paisley is the revolution of the circle into a sacred pattern. It is also a reminder of the bent cedar, symbolizing strength and resistance, as it steadfastly endures even on rainy days, yet it embodies modesty and, from another perspective, signifies life and eternity.

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1 Introduction

1.1 Research Rationale

How would establishing sanctioning mechanism influence the longevity of commons? To what extent do crises influence the change of values and strategies of nations? How would wealth inequality between commoners impact their cooperation?

Human behaviour primarily shapes societies and their functioning. A set of shared rules guides this behaviour, and societies have continuously adapted those rules to evolve and survive over many millenniums. Still, the ever-changing environment poses questions, dilemmas, and stress to societies.

As examples of recent questions, the questions raised above are all related to the societal rules established to protect some valuable resources (physical or non-physical) and organize human behaviour. Studying and answering such questions helps develop effective policies and prevent instating conflicting rules. Moreover, the answers to such questions would shed light on structuring effective rules and policies in the future, for example, increasing social well-being.

Rules in society facilitate the functioning of social, ecological, and technological elements in one way or another. The set of rules that influences interactions and decision making in social, ecological, and technical systems are called institutions (North, 1991; Hodgson, 2006). In other words, if life or society is a game, institutions would be the rules of the game (Immergut, 1992). Generally speaking, institutions define a set of incentives that structure human communications and affect individual decisions (North, 1993b). Institutions are the rules-in-use, which emerge via group behaviour of people (Koontz et al., 2015): i.e., it is expected that most individuals recognize, accept and obey institutions, regardless of what they wish to do; otherwise, we cannot call them institutions (Streeck & Thelen, 2005; Koppenjan & Groenewegen, 2005).

Institutions can be formal in the form of regulative rules, political and economic regulations, contracts, or governmental rules, such as policy implementations regarding buses and cars. Alternatively, they can be informal coordination agreements among a group of people in the society to facilitate collective action, such as rules about community gardening or the use of community energy systems, or taboos, customs, and traditions (Jepperson, 1991). Whether formal or informal, these rules, their emergence, and their dynamics play a significant role in how our society functions with all its social, technological, and ecological elements.

Although individuals recognize and may potentially comply with institutions as they are, they also shape and change them within a social system. Institutions shape social interactions, and interactions can lead to new institutions or their change (Giddens, 1986). Individuals or organizations can change their decisions based on new learning and skills (internal triggers) or environmental factors (external triggers), which could lead to institutional change (North 1993bc).

Institutions have different frequencies of change. Some of them change often. For example, operational rules, which include daily activities and interaction between individuals, can change daily. On the other hand, some others have less frequent changes. For instance, collective choice institutions, which determine how operational rules are made, change 5 to 10 years (Agrawal & Ostrom, 1990). Constitutional institutions include the rules, which define collective choice rules, and change in the order of 10 to 100 years. Meta-constitutional institutions, which are cultural rules and values, change in the order of 100 to 1000 years (Agrawal & Ostrom, 1990).

Summing up so far, institutions are dynamic entities, and it is necessary to consider this dynamicity when studying institutions (Parsons, 1990). Like the institutions themselves, the change in institutions can be formal or informal (Koning, 2016).

There are several parameters and triggers to change institutions. For example, environmental changes are exogenous triggers, while new learning and skill can lead to endogenous change (D. C. North, 1993b). Furthermore, the change of institutions is path-dependent, meaning that the starting point of the situation influences how the institutions change (D. C. North, 1993a). Institutions are also context-specific (Ghorbani et al., 2013), and they build the logic of context (Bussey et al., 2012). Additionally, institutions are interconnected, implying that the change in an institution may affect another one (Van Rij, 2008).

1.1.1 Problem Statement

There have been many studies over the years on institutions and institutional change. Yet, they have mainly stayed at the theoretical level or have been carried out as small empirical studies (Van der Heijden & Kuhlmann, 2016).

Although these theoretical insights give us a firm basis to study institutions, studying institutions within their socio-technical-ecological context requires long-term longitudinal empirical studies or advanced tools and methods.

One way to analyse institutions and their changes is through field study (Poteete & Ostrom, 2008; Ostrom, 2009; Poteete et al., 2010). Although field study is a good way to understand how institutions establish, how they work and affect individual decision-making, and how they change, it may take several years to observe the change of institutions and capture all factors that influence this change.

Laboratory experimentation is another way for researchers to observe how institutions are formed and changed in a selected society under certain conditions (Cummings et al., 2004; Ostrom, 2006; Ward et al., 2006; Ostrom, 2007). However, the experimental factors and conditions restrict in a lab setting, and the desired change might not happen in a limited time frame. In addition, volunteers may not feel free under experimental situations to behave exactly as they would in reality.

Another way to study institutions that may also take place in a lab setting is game theory (Gibbons, 1992). It is a useful method for policy analysis due to parameterising problems and comparing before and after situations. However, the limitations of this method are that the number of players (actors) and the number of interactions between them are limited and rational actors with complete information are assumed (Ghorbani et al., 2014).

Simulations and ABM

Given the complex nature of social, ecological, and technical systems and especially considering the institutional dynamics, direct experimentation and observation are impossible in many situations (Bandini et al., 2009). Therefore, researchers use computer simulation as an alternative method to field and lab studies or as a complementary method (Gilbert & Troitzschc, 2005) in order to explore and understand social, ecological, and technical systems, analyse policies, and make informed decisions.

Given these limitations, simulation models, especially agent-based models (ABMs), can be designed to replicate observed patterns and represent an instrument to develop theories and virtually test hypotheses (Edmonds, 2017). More specifically, ABMs allow identifying the specific patterns of individual behaviour at the micro-level that may have resulted in the patterns at the macro-level. ABM allows us to infer whether the hypothesised causalities are actually possible and likely to be true in the best case. ABM is a suitable method to deal with the complexity and ambiguity of social systems (Davidsson, 2000; Goldspink, 2000). In recent years, several models have been proposed using ABM to depict different aspects of socio-technical systems (Macal & North, 2005; Chappin & Dijkema, 2010; Zhang et al., 2010). Modelling multiple factors and parameters under different conditions without being concerned about time or cost is one of the main advantages of using ABMS.

The key benefits of ABM for studying and modelling institutions and their dynamics are as follows:

- Each agent can have specific properties, individual choices and decisions (Macal and North, 2005). This would allow us to model how agents influence and change institutions.
- It is possible to create a natural model of a system consisting of interactions between agents (Poteete et al., 2010) and the effect of their actions on the system (Bonabeau, 2002). This would again allow us to model how actions and interactions result in the change of institutions.
- Emergent patterns can be represented based on individuals' bottom-up actions and communications (Macy & Willer, 2002). The change in institutions can be studied as emergent outcomes and patterns from the simulation.
- ABM is path dependent (Fürstenau, 2013). As mentioned before, the process of institutional change is contingent on the path (North, 1993a); therefore, it can be modelled with ABM.
- ABM can be used as both an inductive approach by purely starting from the bottom-up to extract meaningful patterns and also as a deductive tool by testing specific hypotheses.

The first attempts to analyse dynamic institutions through emerging and evolving modelling rules are made by Smajgl (2008) and Ghorbani (2016). Although these efforts are a good start, institutional dynamics cannot be fully studied because of issues such as path-dependency, complex actor behaviour (e.g. irrationality, incomplete information), time-dependency, and the fact that agents are not intelligent enough to recognise emergent institutions or intelligently change them. In fact, both types of research use random choices and very simple homogenous agents with simple behaviour. Although ABM is a known method for studying social systems, it has not yet been thoroughly studied and exploited as a method to test hypotheses related to the long-term dynamics of institutions.

1.1.2 Research Goal

The goal of this research is to find ways in which the dynamics of institutions can be modelled and studied using ABM in order to explain how institutions change and how certain institutional patterns emerge through individual behaviour and interaction.

1.1.3 Research Questions

To address the goal, we use the Bathtub model of Coleman. Coleman's (1986) boat or bathtub diagram is a tool to analyze complex social processes consisting of two levels: macro and micro. The institutions are located at the macro level; at the micro-level are the individuals with diverse actions and interactions (Coleman, 1986). While the institutions influence and shape individual behaviour, individuals also affect institutions. Figure 1 illustrates institutional dynamics through the bathtub model by also reflecting on learning and environmental change as proposed by North (1993b).

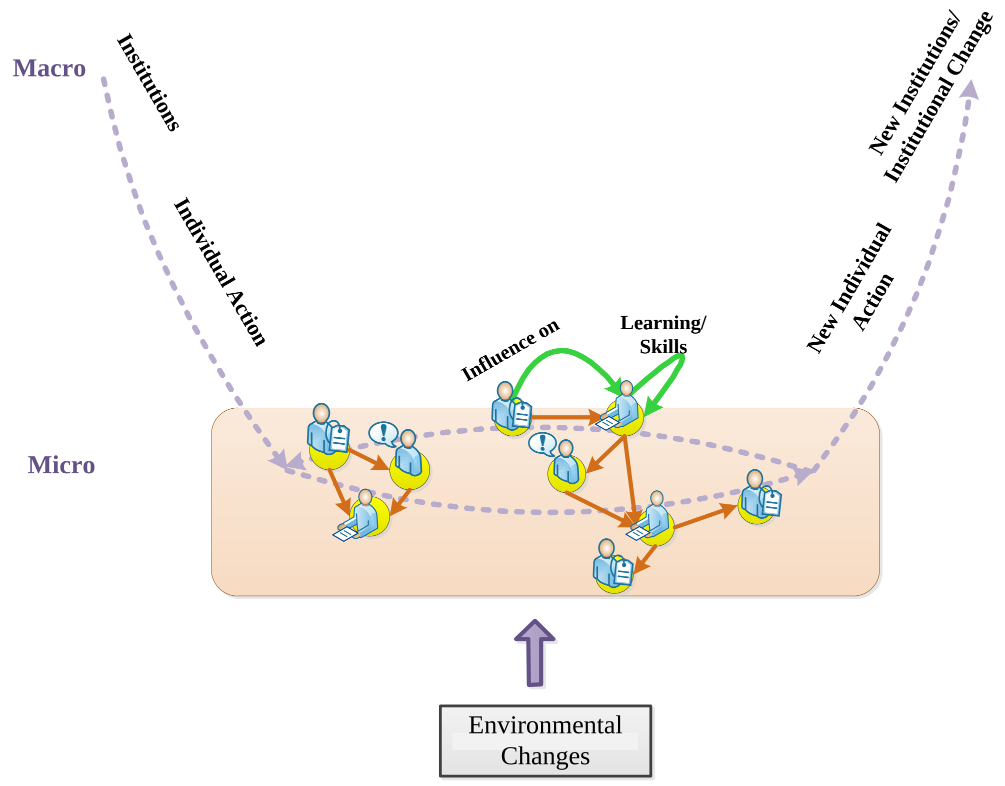

Figure 1. Study the dynamics of institutions, Extended from (North 1993b; Coleman 1986)

In a social context, people act and make decisions based on established institutions. However, over time, environmental factors will change, and individual learning and skills will be improved, which can all potentially trigger new decisions; hence, we will have changes in individual actions, which can change institutions consequently. This institutional change can be sudden, resulting from a shock, force or exogenous trigger (Powell, 1991; Rao et al., 2003). It can also happen incrementally over time (Streeck & Thelen, 2005; Mahoney & Thelen, 2010; Hacker et al., 2013) or be a combination of both (Tang, 2017).

To study the dynamics of institutions, we should look at gradual changes over time (e.g., studying institutional changes over long periods of time) in addition to big changes caused by environmental change (for example, crises). At the same time, we should look closely at individuals' roles in these changes, as individuals are heterogeneous in different ways. The research questions are formulated based on Figure 1:

How can ABM contribute to understanding the dynamics of institutions?

a) How can ABM be used as a deductive approach to test existing hypotheses and theories of institutional change mechanisms found in literature?
b) How can ABM be used as an inductive approach to explain unidentified mechanisms of institutional change?
c) How can real-world institutional data be used for more intelligent and informed ABM for studying institutional dynamics?

The first sub-question considers the left side of Figure 1 by exploring the transition between theoretical patterns at the macro-level and the related underlying causes at the micro-level. The second sub-question covers the bottom and right parts of Figure 1 by focusing on agents' actions and interactions and their role in emerging institutions. The last sub-question covers all parts of Figure 1.

1.2 Research Approach

Based on Figure 1 and the research questions, this research consists of three main parts. Each part refers to a specific perspective and represents a set of typical institutional problems. The first part takes a deductive approach by concentrating on the transition between macro and micro levels (left side of Figure 1) and aims to study existing theoretical propositions on how specific patterns emerge. More specifically, this part will explore how ABM can generate high-level institutional change patterns observed in the real world to explain the underlying mechanisms that led to those changes. The goal is to build an agent-based model that can reproduce institutional patterns observed in the real world and use that model to study whether the model can confirm existing explanations (i.e. theories and hypotheses). An example of such an institutional pattern that we will study is rapid institutional change at the start of collective action, followed by a period of stability and another final rapid change before the collective endeavour ends (Farjam et al., 2020).

The second part of the research is associated with the right side of Figure 1. This part looks at institutions and their dynamics from a bottom-up perspective by exploring how individual behaviour and interaction can lead to potential institutional dynamics. This part of the research will take an inductive approach by allowing unanticipated institutional patterns to emerge from the simulation model. The aim is to see how individual behaviour and interaction lead to such patterns and how the emerging institutions would subsequently change as a result of individual behaviour. An example of a case in the model is the management of common-pool resources and how collective institutions can emerge from the simulation and change over time.

Finally, the fourth part of this research will take a holistic perspective on institutional dynamics. This part aims to apply the lessons learnt from the previous models to a data-driven model. The model will also pay special attention to individual learning, which also implies that there will be a higher degree of intelligence in the agents. As such, the third part of the research will consider how modellers can use Machine Learning to bring more intelligence and learning into our final model.

The following dives into theoretical approach taken in this research, and the specific methods used to address the goal.

1.2.1 Institutional Theory Development and Hypothesis Testing

Based on Bhattacherjee (2012), “theories are explanations of natural or social behaviour, event, or phenomenon. More formally, a scientific theory is a system of constructs (concepts) and propositions (relationships between those constructs) that collectively presents a logical, systematic, and coherent explanation of a phenomenon of interest within some assumptions and boundary conditions”.

ABM can be used to develop, expose (Edmonds, 2017; Squazzoni et al., 2020) or even generate theory (Jaccard & Jacoby, 2019, p.248). Edmonds (2017) defines theoretical exposition as “establishing then characterizing (or assessing) hypotheses, explanations on possible causes (Lawson, 1992), about the general behaviour of a set of mechanisms (using a simulation)”. And Squazzoni et al. (2020) propose that “theoretical exposition is when simulations are used to explore general theories or ideas, without any necessary connection to the real world”.

ABM can be applied as a deductive tool to test institutional hypotheses by explaining underlying mechanisms which have led to already known logics, trends, or patterns or even shed light on hidden unexplored aspects of the theories and eventually extend institutional theories. The ABM that we will use in the first part of this research will be a ‘theoretical exposition’ model (Edmonds et al., 2019), a typical example of this category.

ABM can also facilitate interpreting an institutional observation. Interpreting a phenomenon is a kind of hypothesis testing (Stanford, 2009). Albeit, it does not fully match the traditional definition of a hypothesis: “a hypothesis is a single proposition intended as a possible explanation for an observed phenomenon that is a possible cause for a specific result” (Lawson, 1992). Using ABM in this category supports a deductive approach.

ABM can also be used as an inductive aid by starting from bottom-up micro-level agents’ actions and interactions to extract institutional patterns or trends. The ABM in the second part of this research belongs to this category. An example used in that part is the impact of wealth inequality on cooperation. Such ABM can be categorized in an ‘explanation’ type of modelling purpose as defined by Edmonds et al. (2019).

The ABM, which will be built in the fourth part of this research, will also be an ‘explanation’ model (Edmonds et al., 2019). The model will use an inductive approach to explore the relationship between two variables (institutional change and value change).

1.2.2 ADICO Grammar of Institutions

The theoretical underpinning taken in all models is the ADICO grammar of institutions (IG) (Crawford & Ostrom, 1995). The IG defines institutions as a set of institutional statements. In the IG, A stands for Attributes, specifying the subject to whom an institutional statement applies—such as a 'farmer.' D represents Deontic, determining how an institutional statement is executed, whether it involves prohibition, obligation, or permission. I identifies Aims, identifying the action to which the institutional statement pertains. C indicates Conditions, specifying the circumstances under which an institutional statement applies, including when, where, and how. If no condition is stated, it is implied that the statement holds at all times. Additionally, O denotes Or Else, establishing the consequences of non-compliance with an assigned institutional statement. A common example of 'Or Else' is the imposition of a fine.

For example, for the institution: ‘All people have to keep 1.5 meter distance in any public area whether indoor or outdoor’, A refers to ‘all people’, D indicates ‘have to, I represents ‘keep 1.5 meter distance’, C specifies ‘in any public area’, and there are no associated sanctions (O).

These institutional statements can be rules, norms or shared strategies depending on their syntactic elements. A rule has all five elements of ADICO. A norm contains ADIC elements; it is a rule without any punishment. A shared strategy is a social concept of behavioural patterns which many individuals observe. A shared strategy contains AIC elements. Therefore, it is neither associated with any deontic modality nor having a punishment (Crawford & Ostrom, 1995).

The reason for using the IG is that this grammar is precise and elaborate, making the modelling of institutions traceable and tangible in agent-based models. Furthermore, by providing explicit definitions for norms, rules, and shared strategies, IG enables the modelling of both formal and informal institutions (Ghorbani, 2016). Finally, the use of IG allows building the research on existing research on institutional modelling (Smajgl, 2008; Frantz, 2015; Ghorbani, 2016).

1.3 Case Studies

The first part of the research, which takes a deductive approach, makes use of a historical dataset on European common institutions over seven centuries[1] (De Moor et al., 2016) and the already hypothesized patterns from this dataset (Farjam et al., 2020) to study institutional dynamics. These historical institutional patterns are often general, abstract, and at the macro-level of analysis. They do not include detailed information regarding individual behaviour (Kwok, 2017), which are the primary reasons for shaping those patterns. Therefore, the model that we will develop in this research will contribute to finding underlying causal mechanisms at individual-level behaviour that could have led to these macro-level patterns. We will design the model to replicate observed patterns and, hence, act as an instrument to develop theories and virtually test historical hypotheses (Edmonds, 2017; Romanowska et al., 2019). In other words, by comparing emerging patterns from historical datasets to emerging patterns from simulation models, one can explore the plausibility of the underlying mechanisms that have led to those patterns. **Chapter 2** of this thesis presents this part of the research.

The second part of this research explores how agents and their behaviour and interaction lead to emergent institutional outcomes. Individuals are heterogeneous in different ways. Here, we use wealth inequality as a typical example of heterogeneity. The model that we will develop for this part of the research investigates how wealth inequality shapes individuals’ behaviour concerning cooperation and participation in the collective management of common-pool resources (shared resources among a group of people). **Chapter 3** describes this model.

The third part of this research focuses on the emergence of institutions and, consequently, the effect of those institutions on agents’ behaviours by considering learning and environmental triggers in a data-driven model. Therefore, institutional emergence and changes during the

[1] The dataset is a part of the Common Rules Project (De Moor et al. 2016).

COVID-19 pandemic will be considered as a case study. The disruptions caused by the COVID-19 global pandemic have significantly challenged societal structures and existing institutions. The urge to secure the well-being of citizens has invoked nation-states to deal with numerous dilemmatic situations where vital decisions need to be made in the pandemic situations. Governing the global pandemic, while at the same time being ill-informed about the risks involved, has resulted in heterogeneous institutional responses and challenges (Hull, 2020). This model aims to explore the emergence of institutions as a result of nations' value changes caused by an external environmental change (COVID-19 pandemic in our case). This model is also inductive in nature, as it aims to interpret the relationship between two variables (institutional and value changes). Therefore, in **Chapter 5**, we use ABM as a tool to study this relationship.

ML techniques can provide great potential to bring higher degrees of intelligence and learning into the models, which has also been encouraged and highlighted in the literature (Macal & North, 2010; Rand & Rust, 2011; An, 2012; Kavak et al., 2018).To have a holistic view of this model (i.e., all parts of Figure 2), we will use Decision Tree as a machine learning technique in combination with the ABM. The data that will be used as input is on nations' decisions on COVID-related policies (ACAPS[1] dataset on the COVID-19 government measures and EU COVID-19 datasets[2]). The Decision Tree will bring more learning behaviour and intelligence to the agent's decision making processes using real-world data.

As a pre-requisite to part 3 of this research, to learn how to use ML in ABM, a literature review is conducted, presented in **Chapter 4**.

1.4 Research Outcomes and Scientific Contributions

This research will make contributions to various fields. First, by providing insights into the dynamics of institutions, the main contribution will be in the "Institutional Economics" field of research and policy analysis. In addition, this is one of the first studies that introduce agent-based modelling to historians that study institutions. By complementing their research with modelling, this research can provide additional insights into the course of history. Furthermore, the model that will be built for the first part of the thesis takes a unique approach in simulation as it starts by aiming to generate certain patterns and then backtracks those patterns to find underlying causal mechanisms. This approach may be beneficial for other simulation questions as well. The contributions to the ABM domain, however, are more. The research also contributes ways in which machine learning can benefit ABM by bringing in more intelligence and making agent-based models more data-driven. The literature review that will be conducted as part of the research aims to comprehensively highlight the current state-of-the-art and the directions for future research in this area.

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[1] https://www.acaps.org/covid19-government-measures-dataset

[2]https://data.europa.eu/euodp/en/data/dataset/covid-19coronavirusdata/resource/55e8f966-d5c8-438e-85bc-c7a5a26f4863

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2 Long-Term Dynamics of Institutions: Using Agent-based Modelling as a Complementary Tool to Support Theory Development in Historical Studies[1]

Abstract

Historical data are valuable resources to provide insights into general social patterns in the past. However, these data often inform us only at a macro-level of analysis but do not consider the role of individual behaviour in the emergence of long-term patterns. Therefore, it is difficult to infer 'how' and 'why' certain patterns have emerged in the past. Historians use various methods to draw hypotheses about the underlying reasons for emerging patterns and trends, but since these are the results of hundreds if not thousands of years of human behaviour, these hypotheses can never be tested in reality. Our proposition is that simulation models and specifically, agent-based models (ABMs) can be used as complementary tools in historical studies to support hypothesis building. The approach that we propose and test in this paper is to design and configure models in such a way as to generate historical patterns, consequently aiming to find individual-level explanations for emerging patterns. In this work, we use an existing, empirically validated, agent-based model of common-pool resource management to test hypotheses based on a historical dataset. We first investigated whether the model can replicate various patterns observed in the dataset and second, whether it can contribute to a better understanding of the underlying mechanism that led to the observed empirical trends. We showcased how ABM can be used as a complementary tool to support theory development in historical studies. Finally, we provided some guidelines for using ABM as a tool to test historical hypotheses.

Keywords: institutional modelling, historical data, CPRs, institutional evolution

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2.1 Introduction

Large historical datasets are increasingly being used to reveal social patterns of human behaviour throughout history (Mace, 2000), particularly in the domains of social and economic history. Whether these trends are about migration patterns across continents (Hatton & Williamson, 2005), or the relation between sanctioning and the survival of common-pool resources (CPRs) (De Moor et al., 2020), they all share one common feature: these patterns are the emerging results of the interplay between institutions and other macro-level entities, on the one hand and micro-level individual decisions and behaviour, on the other (Coleman, 1990).

Given the increasing use of large datasets among historians, the description of historiography as “a selection of details from the past, placed in a particular order, to provide a meaningful interpretation of the past” (Noll, 2012) has become too limited. This is because it does not go beyond the primarily descriptive approach of historiography. But even with currently used analytical approaches, often supported by solid statistical methods, insights into recurrent patterns that can be derived from historical data are often general, abstract, and usually only pertain to the macro-level of analysis. In addition, historical data are difficult to use to produce causal explanations about ‘how’ and ‘why’ these patterns occurred in the past due to lack of detailed information regarding individual behaviour (Kwok, 2017). Of course, the data themselves limit any possibilities of retrieving the individual motivations underlying long-term patterns. There simply is too little information available about these motivations, as we can only in very exceptional cases rely on, for example, biographies or interviews that shed light on individual behaviour. Systematic registration of individual biographical events (e.g., births, deaths and marriages,) does not start —until the 19th century, and even then, only in some countries. In terms of methodology, however, there may be more so far unexplored opportunities that could allow us to study causal relationships in more depth, and as such, contribute to our understanding of past evolutions.

Given these limitations, simulation models, and especially agent-based models (ABMs) can be designed to replicate observed patterns and hence, represent an instrument to develop theories and virtually test historical hypotheses (Romanowska et al., 2019; Edmonds, 2017). More specifically, ABMs allow the identification of specific patterns of individual behaviour at a micro level that may have resulted in recorded historical patterns at the macro level. This in turn, allows us to infer whether the hypothesized causalities are actually possible and, in the best of case, likely to be true. In other words, by comparing emerging patterns from historical datasets to emerging patterns from simulation models, one can explore the plausibility of the underlying mechanisms that have led to those patterns.

The goal of this paper is to show how historical hypotheses can be tested with agent-based models. The dataset that we use is a unique historical dataset on CPRs in several Western and Southern European countries from the Middle Ages until the 19th century (De Moor et al., 2016). The dataset includes detailed descriptions of the systems of rules and enforcement mechanisms—i.e., institutions for collective action (Ostrom, 1990a)—that commoners established or modified during the life-cycle of each CPR in order to manage appropriation of resources and to prevent their overuse. On the basis of these data, historians have already suggested hypotheses that can be built upon. For example, De Moor et al. (2016) hypothesized that the reason for the longevity of Dutch CPRs is that they paid more attention to collaboration between commoners rather than sanctioning. Such conclusions can never be tested in reality, as the patterns are the results of hundreds if not thousands of years of human behaviour and any interaction is influenced by numerous parameters (Vahdati et al., 2019).

Here, we extend an existing, empirically validated, agent-based model of CPR management to test hypotheses that were previously generated through the analysis of the above-mentioned dataset. The ABM simulates the emergence of institutions for the management and use of CPRs, where agents collectively exploit a resource using both individual strategies and endogenously generated institutional rules (Ghorbani et al., 2017).

More specifically, we check under which conditions the model can replicate various patterns observed in the dataset of historical CPRs, and whether it can contribute to a better understanding of the causal mechanisms at play in creating specific historical trends. We focus on historical data for CPRs in the UK and the Netherlands for which previous work has already proposed hypotheses that can be tested with our model (De Moor et al., 2016). By configuring the model to represent a particular country, we can compare the generated patterns and trends with the historical ones and hence check whether the hypothesized mechanisms are sufficient to generate the observed pattern.

This article is organized as follows: Section 2.2 describes the literature on using historical data in ABM. Section 2.3 describes our historical dataset. Section 2.4 presents the agent-based model and the specifications. Section 2.5 presents parameter setups. Section 2.6 shows how the model can replicate some patterns and provide explanations. Section 7 provides methodological steps for testing historical hypotheses and Section 8 concludes the article.

2.2 Related Research

Historical data has mainly been used in agent-based modelling practices to either produce more realistic simulation models or to validate them. For example, Carley et al. (2006) base their ABM on historical data in order to build a realistic biological attack (disease outbreak) model, while Bert et al. (2014) validate their land-use ABM by comparing their model output with historical data. Most of this research considers short-term horizons, such as population growth over seven years (Ligmann-Zielinska & Jankowski, 2007) or household and housing information during a 10-year period (Geanakoplos et al., 2012).

Nonetheless, there are also a limited number of articles that have looked into long-term horizons. For example, historical data has been used to calibrate and validate models in order to make them more reliable for testing contemporary scenarios. Sattenspiel et al. (2019), for instance, calibrate an ABM, modelling a specific epidemic event in the early 20th century by using historical data on fishing villages in Newfoundland and Labrador. Historical data is used to calibrate and validate the model, to ensure that the simulated data can reasonably represent real situations, to be used to develop disease transmission scenarios. Historical data is collected from newspaper articles, government reports, photos, and other materials. In addition, the ABM was previously developed using several ethnographic, culture, and historical sources on the specification of the pandemic and early 20th century Newfoundland and Labrador (Dimka et al., 2014). This model presents a small community and its disease transmission during the early 20th century, but not the specific place that provided the data.

In addition to calibrating and validating models, historical data has also been used to replicate and explain historical patterns. Harrison et al. (2002), for example, model the historical trajectory of vowel harmony. They use ABM to reveal how individual changes influence the instability of vowel harmony systems in Turkic (Altaic) languages. The goal was to identify a set of input drivers of this change by systematically varying these inputs and comparing the corresponding ABM output with empirical observations (the process of language change has the shape of an S-curve). In this research, the historical data of a dozen Turkic language corpora were used. The simulation results however were unable to show a downward S-curve. As authors mention, the reason might be the impact of demographic and language contact factors, which have not been implemented in the model.

Furthermore, ABMs have been used to study social phenomena such as cultural evolutions (Derex et al., 2018; Turchin & Currie, 2016; Kandler et al., 2012). Turchin et al. (2018) used ABM as a micro model of individual behaviour and decisions to explain observed patterns and determine why certain conditions result in disruptive emergent events, using data on the social and political organizations of human societies. Turchin et al. (2013) apply ABM to build a cultural evolutionary model to predict under which conditions large-scale complex societies appeared in history. They compared the results of the model with a dataset consisting of spatiotemporal information of societies in Afroeurasia between 1,500 BCE and 1,500 CE.

Likewise, ABM has been applied in the archaeology field (Romanowska et al., 2019; Saqalli & Vander Linden, 2019; Wurzer et al., 2015; Cioffi-Revilla, 2014; Kohler et al., 2005). For example, Axtell et al. (2002) use ABM to reproduce spatial and demographic parameters of the Anasazi community in Long House Valley from A.D. 800 to 1300. The agents in the model represent households and are able to decide where to locate their settlements and fields. Households derive their demographic and nutritional characteristics from ethnographic studies of historic Pueblo groups. The goal was to generate “the history” to explain observed spatiotemporal characteristics of the ancient society. Its focus lies in the environmental account of the development of this society, which in fact goes a long way towards explaining its rise and fall (Axtell et al., 2002).

Additionally, Bowles and Choi (2013) present the evolution of property rights during the Holocene. They model the characteristic of Pleistocene ethnolinguistic period using an ABM, where individuals are in groups and the model has three phases: production, distribution and cultural updating. The goal of the model was to study the emergence of farming systems and property right and cultural evolution to create private ownership during the early Holocene period. The data (climate, archaeological, etc.) is used to calibrate the model and the model outcomes are checked to see whether they replicate the known patterns of the emergence of farming.

More recently, Frantz et al. (2014) used agent-based simulation to model the informal interactions of cheating merchants between Genoese traders, based on game theory. They used several data sources of Genoese perspectives in the 12th century. Different topologies of trust-based networks and two communication modes are used to test their model. The result showed that the communication between the Genoese is not sufficient to detect cheating merchants.

Our work builds on the limited account of research that make use of long-term historical data to explain social phenomena (Sattenspiel et al., 2019; Axtell et al., 2002). Here, we focused on the emergence and dynamics of "institutions as rules" and not cultural evolution of societies. Our goal was to generalize and extend the practices and show the value of ABM for historians and scholars interested in studying historical patterns. By showing how ABM provides insights into the patterns found in our dataset, we aim to provide guidelines for using ABM in historical studies.

2.3 A Historical Dataset of Common-pool Resources

2.3.1 Common-pool Resources and their Management

The dataset used in this article covers the management of CPRs in European countries over seven centuries. CPRs are resources shared among a group of people. These resources are often large enough that many individuals can use them simultaneously (Ostrom, 2002), and they risk depletion as a result of over-use. In this situation, where CPRs are not governed well and individual interests are not properly balanced with the optimal use of the resource, they may be over-used, resulting in the "Tragedy of the commons" (Hardin, 1968). To avoid this, users can collectively build management institutions: systems of rules and enforcement mechanisms (Ostrom, 1990b).

The set of rules defining a socio-ecological system can be formal or informal (Hodgson, 2006; D. North, 1991). Formal rules include political and economic regulations, contracts, and governmental rules; informal rules include norms, taboos, customs, and traditions (Ostrom, 2000; Jepperson, 1991). Generally speaking, institutions define a set of incentives that structure human communications and affect individual decisions (D. C. North, 1993). Institutions for the management of CPRs are the rules-in-use that commonly emerge through people's collective behaviour (Koontz et al., 2015; Ostrom, 2000). For CPRs to be successful, most individuals have to recognize, accept and abide by institutional rules even when they conflict with their self-interest (Koppenjan & Groenewegen, 2005; Streeck & Thelen, 2005).

2.3.2 A Dataset of Common-pool Resource Management over Seven Centuries

In this study, we used a subset of a dataset[1] including an extensive collection of management institutions (5000 rules) of 900 CPRs (i.e., the CPR and the social system surrounding it) across several countries in Europe (Belgium, Germany, Italy, the Netherlands, Spain, and the United Kingdom) between 1283 and 1972 (De Moor et al., 2016), all coded and translated into English. The dataset consists of information on the use, governance and management of these CPRs. It captures the institutional rules which commoners established, updated, or changed during the life span of each CPR to foster cooperation and to protect natural resources from over-exploitation. The commoners had regular meetings, often once per year, where they developed and amended the institutional rules to facilitate the maintenance and use of the resources they

[1] The dataset is a part of the Common Rules Project (De Moor et al., 2016).

held collectively. More information about the dataset can be found in De Moor et al. (2016) and Forsman et al. (2021).

This dataset was analysed by Farjam et al. (2020) to extract long-term historical patterns of institutional rules. They extracted cases that included extensive and reliable information and selected the CPRs that were functional for at least 200 years. This subset of the dataset, which will be used as a reference in this paper, includes 3,775 institutional rules for ten Dutch CPRs and eight UK CPRs across six centuries. The Dutch CPRs were recorded from 14th century to the early 20th century; the United Kingdom CPRs were recorded from 16th century to the 19th century. On average, the CPRs survived for 245 years across this subset of dataset.

2.3.3 Extracting Historical Patterns from the Dataset

Farjam et al. (2020) found that the pattern of institutional change in the CPRs follows a U-shape for both the UK and the Netherlands (Figure 1). This implies frequent institutional changes at the beginning of the establishment of the CPRs, followed by a period of stability, and finally another burst of changes right before the dissolution of the CPRs.

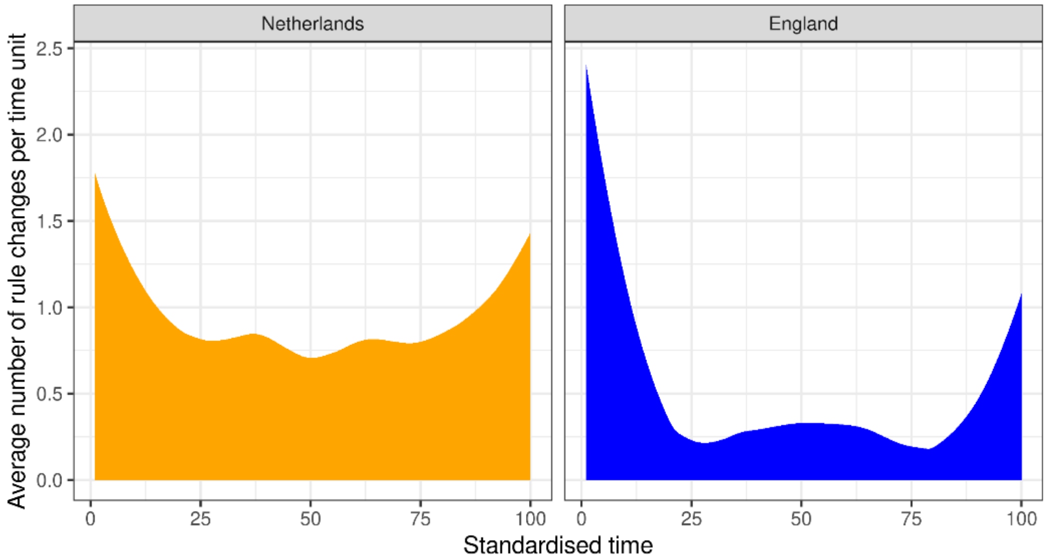

Figure 1. Average number of institutions during the life span of a CPR. Reprinted from Farjam et al. (2020)

We can consider the first period of rapid changes a “training phase”, where the users of the CPRs try to discover, possibly by trial-and-error, rules that are well adapted to local conditions (Ostrom, 1990b) This is often followed by a period of stability, where the institutional rules seem to work in preserving the resources from overuse, organizing their maintenance and guaranteeing the longevity of the CPRs in general.

This period of stability often ends with another burst of changes in the rules, and finally the dissolution of the CPRs. De Moor et al. (2016) advanced an explanation for the latter pattern. During the 19th century, and especially in the period between 1830 and 1850, when most CPRs were dissolved, the governments modification of regulations, legislation and incentives for privatization put pressure on the commoners, who often faced financial difficulty as well. Commoners often tried to react to these pressures and to adapt to the new situation by changing their rules, even if their efforts were not always sufficient to prevent the dissolution of the CPRs. At the same time, historical accounts suggest that environmental pressures (e.g., droughts) could also be determining factors for the dissolution of CPRs and the collapse of entire societies

(Diamond, 2005; Axtell et al., 2002). To summarize, the reasons behind a U-shaped pattern observed in the institutional change of historical CPRs can be hypothesized as below. Note that H2 is not based on the historical dataset that is the subject of this paper but a more general historical account.

H1. The U-shaped pattern of institutional change in the 19th century is the result of an institutional learning phase based on trial and error, followed by a period of stability during which commoners are satisfied with the current institutional setting, and a final period of rapid change as a result of a social shock, such as increased external pressure on commoners through escalating taxation.

H2. The U-shaped pattern of institutional change in the 19th century is the result of an institutional learning phase based on trial and error, followed by a period of stability during which commoners are satisfied with the current institutional setting, and a final period of rapid change as a result of an environmental shock, e.g., a drought.

On another account, De Moor et al. (2020) observed that Dutch CPRs have had a much longer life span than those in the UK. They claim that longer-lived CPRs are associated with fewer rules, including formal sanctions and, vice-versa, that CPRs with short life spans tend to focus more on providing sanctions with the rules. The third hypothesis therefore, focuses on the relation between CPRs' life spans and the number of institutions including formal sanctions.

H3. Less focus on sanctioning has had a positive effect on the CPRs' longevity.

A fourth pattern in the dataset worth further investigation is the link between the CPRs longevity and the frequency of meetings between commoners. De Moor et al. (2016) claim that longer-lasting CPRs are the ones that made incremental institutional changes by meeting frequently to adjust previously formulated rules. They highlight the importance of members' involvement, rule internalization, and the frequency of meetings to establish such institutions. This leads to our fourth hypothesis.

H4. Having frequent meetings among commoners has had a positive effect on CPRs' longevity.

In this paper, we explore these four hypotheses using an ABM to check which ones can emerge in a simulated CPR's setting that confirm the observed historical patterns.

2.4 An Agent-Based Model of Common-pool Resource Institutional Dynamics

2.4.1 Model Overview

The model presented here was initially developed by Ghorbani and Bravo (2016) and validated with extensive contemporary data on irrigation, fishery and forestry cases in (Ghorbani et al., 2017). The model represents a CPR management setting consisting of one resource, a set of agents who exploit it, and endogenously generated institutional rules. Here, we briefly present the model; a full description is available in Appendix and the model is available on CoMSES[1].

Agents in the model represent commoners. There are two independent sets of possible actions and possible conditions that agents use to define their individual resource-exploitation strategies. At the beginning of each run, agents randomly select an action-condition pair as their strategy and follow the strategy to extract "yield" from the resource. If agents are not satisfied

[1] https://www.comses.net/codebase-release/10eeafa9-f5d4-4534-8109-ffeae0d00b5d/

with their yield (i.e., their yield balance is negative), they change their strategy in subsequent rounds. This change of strategy can be completely random (representing innovative behaviour) or done by copying successful neighbours. At specific points in time determined by a parameter specifying frequency of meetings; if a majority of agents are unsatisfied, they “meet” to vote on an institutional rule, which was basically the most common individual strategy. Once in place, all agents have to comply with the institutional rule, although under certain settings they can “cheat” and follow their own individual strategy instead. During the “meeting”, agents also decide on monitoring intensity and fines for any agent caught cheating.

Figure 2 provides an overview of the model. In the initialization phase, the agents are created, the network is set up and agents are initialized with a random action and random condition pair (a.k.a. strategy). The agents consume resource units based on their individual strategy. For example, an individual strategy might look like this: eat 5 units of resource every 2 ticks. In addition, agents gain a fixed amount of yield in each tick, representing their needs. The resource is renewed in each time step according to a logistic growth function. The simulation stops if there are no resource units left, the portion of agents with very low is higher than a certain threshold, or simply after a certain number of ticks.

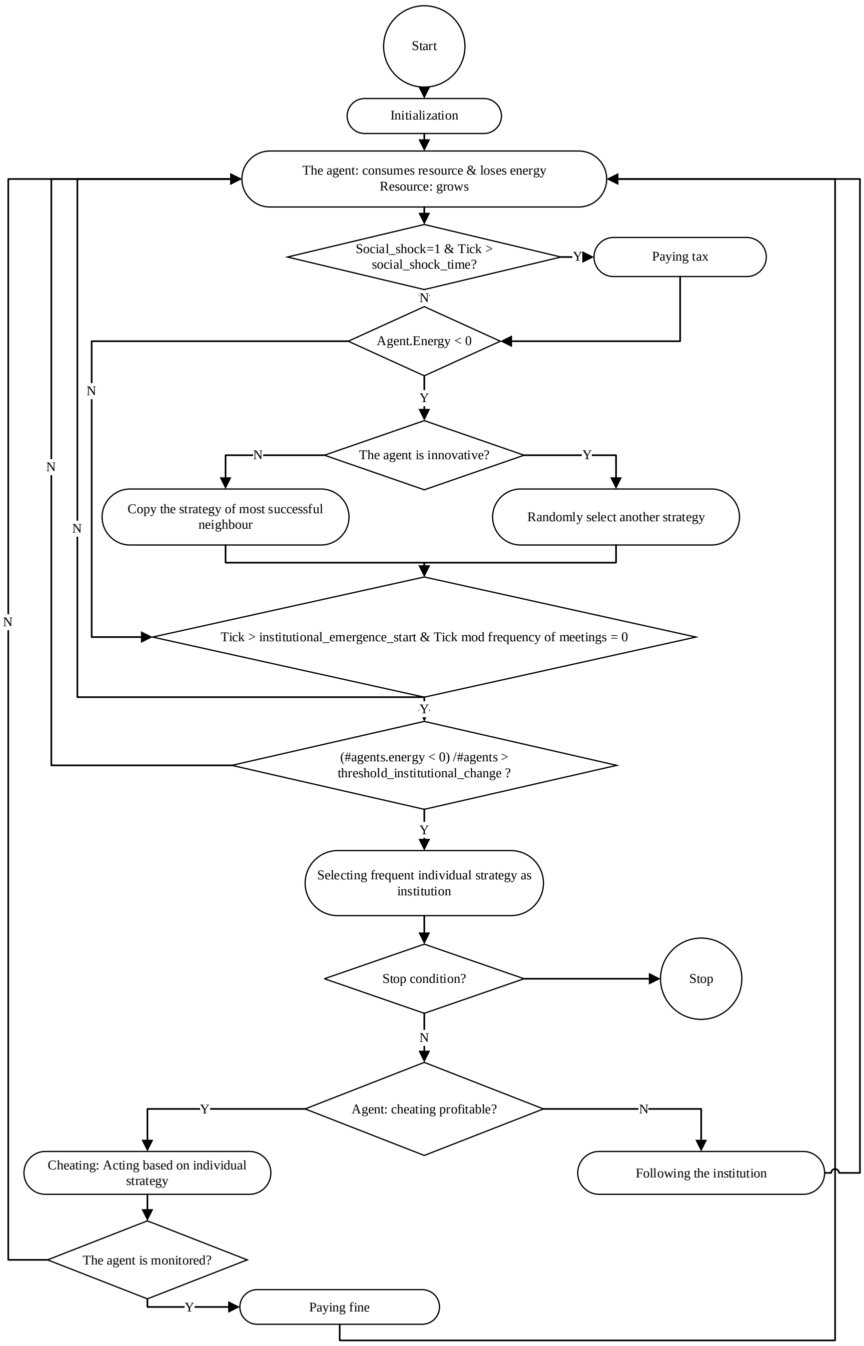

Figure 2. Model overview

2.4.2 Conceptualization

The CPR-model consists of four main components: agents, institutional rules, social and environmental shocks and the resource.

- **Agents**: An initial yield value (resource unit) is assigned to all agents. Each agent records its current strategy, neighbours, and the yield level.
  - <u>Individual strategy</u>: Any possible combination of an *action* and a *condition* shapes a strategy, and agents only have one strategy at a time. An action represents how many units of resource the agent can consume, and each condition shows when or under which condition the agent can gain that amount of yield (‘true’ means at every ticks). At the

beginning the individual strategy[1] is chosen randomly and assigned to the agents. For example, an individual strategy might look like this: eat 4 units from the resource every 3 ticks (i.e., when ticks mod 3 = 0).

- Strategy change: When the agent's yield is below a certain threshold the strategy changes according to one of the two following procedures and the innovativeness of the agent (a parameter of the model): 1) when the innovativeness is less than a certain threshold: copy from the most successful neighbour who currently has the maximum amount of yield, or 2) when the innovativeness is greater than a threshold: randomly select a new combination of action and condition as new strategy.

- **Institutional Rules**: Institutions have the same structure as individual strategies (i.e., action and condition). In addition to that, each institutional rule also specifies the intensity of the monitoring and the amount of the fine the cheaters must pay.
  - Cheating: The agents do not all comply with the institution. If they have the propensity to cheat, and their own individual strategies provide more gain for them than the current institution, they will follow their own strategy instead of following the institution. The management of the resource also includes monitoring activities, where a certain percentage of cheaters are sanctioned.
  - Voting: Agents vote on institutional rules. The most frequent individual strategy is chosen as the institutional rule. After the institutional rule is established, agents must obey it. Besides the action-condition pair, the agents also vote on the monitoring intensity and the amount of the fine.

- **Social and Environmental Shocks:** There are two types of shocks that can take place in the system. An environmental shock is when a large amount of the resource is suddenly lost during some time interval and a social shock is when the agents lose more units per tick (yield is increased). The former represents environmental incidents such as diseases that destroy natural resources and the latter represents taxation where agents pay more for the same number of units they previously received.
- **Resource:** The resource grows according to $\Delta R = rR\left(1 - \frac{R}{K}\right)$, where K is the carrying capacity and r is the reproduction rate.

2.4.3 Model Validation

The model was implemented in NetLogo. A dataset consisting of 66 irrigation, 56 fishery, and two forestry cases and one sea vegetable case[2] were used to empirically inform the model (Ghorbani et al. 2017). To conduct this empirical information, the relationships between the outputs of the model were compared to the relationships between representative variables in the dataset. For instance, the institutional component has negative coefficients on individual income in both the ABM and the dataset, which means that, on average, the agents gain less yield when the frequency of institutional change is higher. Overall, the analysis of Ghorbani et

[1] To define individual strategies, we use ADICO grammar (Crawford & Ostrom, 1995). In the ADICO grammar of institutions A denotes Attributes: specifies subject to whom a strategy, norm or rule applies; D refers to Deontic: determines how an action is done (prohibition, obligation, and permission or, in other words must not, may, and must (Frantz et al., 2013)); I represents Aims: identifies the actions toward which Deontic applies; C indicates Conditions: under which conditions or, in other words, when, where, and how a strategy, norm or rule applies; and O denotes Or Else: determines specific punishments to be applied when an agent acts in violation of the institutional rules.

[2] This dataset used in Ostrom's (1990a) book.

al. (2017) shows that the model was able to reproduce the observed institutional patterns in the data to a great extent.

2.5 Experimental Setup

The experiments were designed to test the hypotheses presented in Section 3.3. For Hypotheses 1 and 2, regarding patterns of institutional change, the model was calibrated to mimic the UK setting (right side of Figure 1).

For Hypothesis 3 and Hypothesis 4, related to the longevity of the CPRs and its correlation with meeting frequency and sanctioning, the Dutch setting was used for calibration. The reason for that was that the Dutch CPRs survived substantially longer than UK CPRs (De Moor et al. 2021). Therefore, by extending parameter ranges for sanctioning, varying the frequency of meetings in the simulation, and relaxing the conditions for the end of the simulation, we were able to model experiments that were similar to the Dutch setting.

For all experiments, we first calibrated the model to produce the desired historical pattern and then tried to identify the limits of parameter space able to reproduce such a pattern. This procedure allows us to establish whether the underlying reasons for an observed historical pattern are consistent with the ones (i.e., parameters) that determine the same output from the simulation. This process will be better illustrated in Section 6. We take each simulation run as representing one CPR and each time step, one month of its life span in order to cover five to seven centuries for a simulation run. Each experiment includes 500 independent simulation runs.

The shared parameter setups across all experiments are shown in Table 1, similar to those in Ghorbani et al. (2017). Note that the values used for the parameters were based on sensitivity analysis of the model.

Table 1 Shared Parameter Setups.

Parameter	**Value(s)**
Actions	consume [0, 2, 4, 6, 8, 10, 12, 14, 16, 18], [-5] (negative value stands for loss)
Conditions	true, (ticks mod 250) = 0, (ticks mod 2) = 0, (ticks mod 3) = 0, yield <= 0, (ticks mod 20) = 0
Social influence	0.9 – 1 (uniform random float)
Monitoring cost weight	50 – 60 (uniform random integer)
Carrying capacity (K)	10000 – 20000 (uniform random integer)
Growth rate (r)	0.25 – 0.35 (uniform random float)
Number of agents	100 (fixed)
Consumption unit	1 (fixed)

(personal) Innovation rate	0.01 – 0.2 (uniform random float)
Threshold for institutional change	0.5 – 0.75 (uniform random float)
Rewire prop	0.1 (fixed)
Type of network	Random network (fixed)
Institutional_emergence_start	500 – 1000 (uniform random integer)

2.5.1 Experiment 1: Impact of Environmental and Social Shock on Institutional Change Patterns.

The first experiment included three scenarios. The primary scenario did not have any shock throughout the simulation. The second scenario included a social shock, and the third an environmental shock (Table 2). Each of these scenarios encompassed 500 independent simulation runs. For all these scenarios, the stop condition (which is adjusted from the original model in Ghorbani et al. [2017]) is shown in Algorithm 1:

```
If {resource = 0 OR
  {((count agents with [energy < average-energy] / number-of-agents) > Threshold)
  AND institutions exist AND ticks > 5000   }   OR ticks > 6000}
          Stop Simulation
Else
          Continue
```

Algorithm1 Stop condition for Experiment 1

Since the United Kingdom CPRs were recorded from the 16th to the 19th century (Farjam et al., 2020), and as we assumed one tick to be one month, we choose the stop condition in the range of 5000-6000 to be sure it covered the life span of the UK CPRs.

In the second scenario, the social shock was modelled in the form of “taxation”, i.e., a certain amount of extra yield subtracted from the agents’ budget in each tick. This happened at ticks greater than “Social shock time” (Table 2). The rationale behind choosing a relatively high number for this parameter was to allow the system to reach a stable state ahead of the introduction of the shocks. The shock was introduced once in the model and continued to the end of the simulation to represent the historical incidence.

In the third scenario, we modelled environmental shock as a sudden change in the amount of the resource stock. This happens at each “Environmental shock interval”, in the range of 1000-2000 ticks. In other words, in each “Environmental shock interval”, the amount of resource decreased based on the “Resource loss percentage”.

Note that for all three scenarios, we looked at full parameter ranges to see whether the U-shape pattern can emerge from the simulation.

Table 2 Parameter Setups for Experiment 1

Parameter	Scenario 1	Scenario 2	Scenario 3
Individual cheating propensity	0.1 – 0.35 (uniform random float)	0.1 – 0.35 (uniform random float)	0.1 – 0.35 (uniform random float)
Max fine	20 (fixed)	20 (fixed)	20 (fixed)
Frequency of meetings	12	12	12
Environmental shock	False	False	True
Social shock	False	True	False
Environmental shock interval	_	_	1000 – 2000 (uniform random integer)
Resource loss percentage	_	_	20 – 70 (uniform random integer)
Social shock time	_	4000 – 4500 (uniform random integer)	_
Taxation amount	_	5 – 10 (uniform random integer)	_

2.5.2 Experiment 2: Impact of Sanctioning on the Longevity of the Common-pool Resources

A remarkable feature of the Dutch data is that, unlike other countries where sanctioning was extensively used, nearly half of the existing institutional rules did not have any sanction attached to them. This suggests that a no-sanction condition can also be sustainable in the long run, contradicting the current literature that assumes sanctioning to be the primary method to avoid freeriding (De Moor et al. 2016). Therefore, we set the probabilities in the model in such a way that at least half of the institutions emerge without any sanctioning attached to them, and the other half follow the same algorithm for choosing a sanction as described in 4.2. The stop condition is based on Algorithm 2:

```
If {resource = 0
   OR rule-compliance < Threshold
   OR ticks > 7000
}
            Stop Simulation
Else
            Continue
```

Algorithm2 Stop condition for Experiment 2 and Experiment 3

We used the Dutch parameter settings for this experiment with the same parameter setup of Experiment 1, but expanded ranges for cheating and fining-related parameters (‘Individual cheating propensity’: a uniform random float in the range of 0.1 – 1, and ‘Max fine’: a uniform random integer in the range of 20 – 100) and also extended the simulation period to 7000 ticks.

This allowed us to better test our fourth hypothesis (H4) by increasing the agents' opportunity to cheat, which better mimics the condition of Dutch CPRs.

Additionally, since commoners usually met at least once annually, we chose the frequency of meeting as 12 (ticks), similar to the previous experiment.

2.5.3 Experiment 3: Impact of Meeting Frequency on the Common-pool Resources' longevity

To analyze the impact of meeting frequency on the CPRs' longevity (H4), we designed four scenarios, each one including 500 independent runs, with frequency of meetings in {6, 12, 18, 24} ticks, i.e., meetings every six months, every year, every one and a half years, and every two years, respectively. The reason behind choosing these periods is the fact that the commoners usually met at least once a year. At these meetings, agents could change their managing institutions, provided that a certain percentage of them (parameter: institutional change threshold) were unsatisfied (i.e., had negative yield).

2.6 Results

2.6.1 Testing H1: Social Shock and Institutional Change Trends over the Lifetime of the Common-pool Resources

The goal here is to test whether it is possible to obtain a U-shaped pattern of institutional change in our abstract model and if so, under which parameter settings and in which scenario. The recorded outcome is the frequency of institutional changes over time, which is compared with the one in Farjam et al. (2020), reported in Figure 1.

In the first scenario of Experiment 1 (without environmental or social shocks) the pattern of institutional change in the simulation shows a high level of activity at the beginning, followed by a long period of low activity, hence forming something similar to an L-shape (Figure 3), in contrast to the U-shape observed empirically.

Based on (Farjam et al. 2020), we used standardized time $t_{c,a}$ by changing the tick in which a given institution emerged ($y_{c,a}$) using the formula:

$$t_{c,a} = \frac{y_{c,a} - y_c^F}{y_c^L - y_c^F}$$

For each institutional change a and CPR c (a simulation run represents one CPR), y_c^F refers to the time when the first institution for the corresponding common emerged (the minimum tick in the simulation run) and y_c^L to the one when the last institution emerged (the minimum tick in the simulation run). In other words, the standardised time = 0 marks the point y_c^F in time at which a CPR comes into being and 100 marks the point y_c^L in time at which it comes to an end.

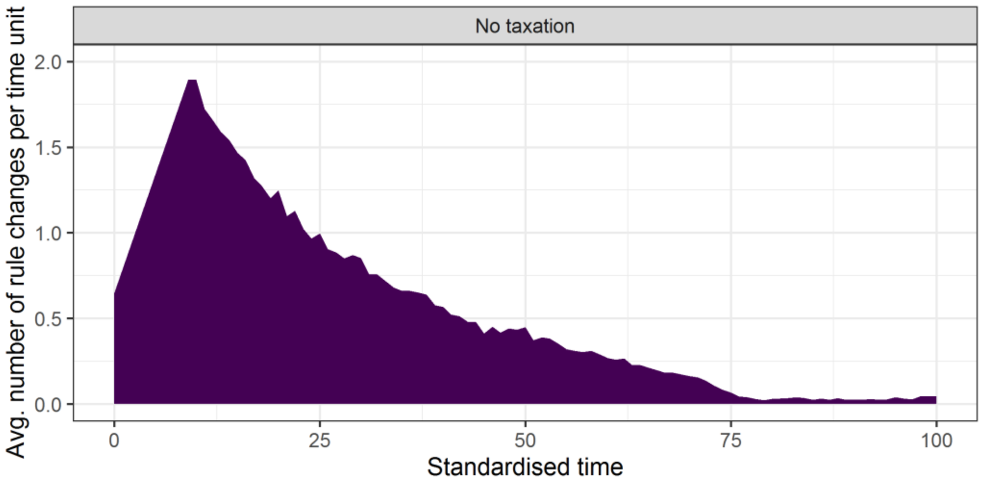

Figure 3. Without environmental shock, without social shock

The second scenario introduced a social shock. Recall that the goal here is to mimic the historical conditions where commoners had financial issues in the 19th century due to the new taxes introduced in the country. Our goal is to see whether having a social shock (i.e., tickly taxes) results in institutions rapidly changing after a period of stability. This can indeed be observed in Figure 4. This outcome primarily depends on the fact that the yield balance of the agents is now more often negative (due to paying "taxes" every tick), making them more prone to changing the existing institution. Consistent with the historical data (De Moor et al., 2016), despite the commoners attempt to adapt, their average yield becomes lower than the stopping condition for the simulation, leading to the dissolution of the CPRs.

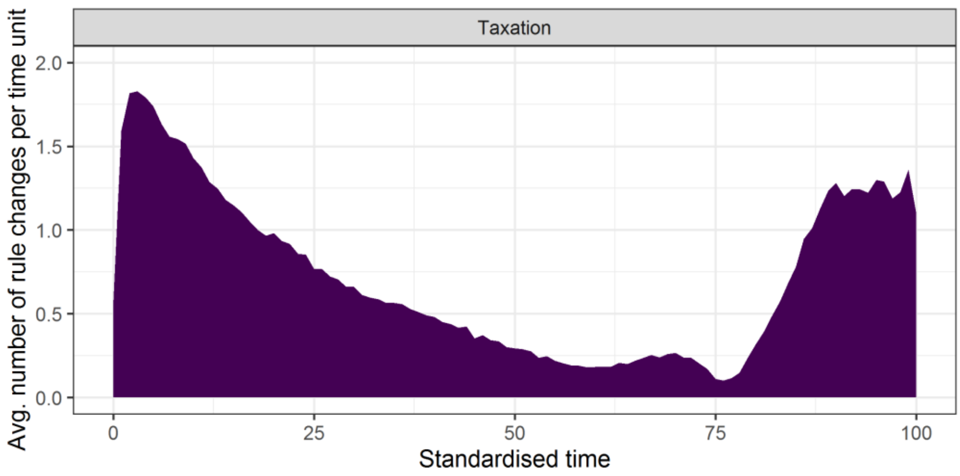

Figure 4. Institutional change pattern with social shock

2.6.2 Testing H2: Environmental Shock and Institutional Change Trends over the Lifetime of the Common-pool Resources

Another hypothesis could be that environmental shocks may have an impact similar to that of social shocks (H2). The goal here was to reproduce the historical U-shaped pattern of institutional change by introducing an environmental shock (in the form of sudden resource scarcity) into the system (Scenario 3). The result of the model with environmental shock (and without social shock) is shown in Figure 5. Similar to the no-shock setting, we observed an L-shaped pattern of institutional change, implying that the sudden loss of a resource does not really cause agents to enter the final phase of the CPR's life (rapid institutional change) that is empirically observed.

Surprisingly, the time of the environmental shock was not even observable in the institutional change diagram (Figure 5): it seems that the agents only changed the institution to a limited extent to compensate for the loss, but the average yield of the agents was eventually not low enough for the CPR to dissolve. In fact, previous model outcomes showed that at times of resource scarcity, the agents tended to extend the time intervals between their consumption of the resource to allow it to be replenished (Ghorbani & Bravo, 2016). Therefore, considering the full parameter range, we can conclude that environmental shock did not result in agents entering a period of rapid institutional change followed by the dissolution of the CPR, which does not support H2.

It is interesting to note here the main difference between a social shock and environmental shock. For the former, the agents continuously require more energy (demand) per time interval, while for the latter, the agents are not able to take from the resource at a certain moment in time, making them temporarily unsatisfied with the situation. This dissatisfaction will however diminish as the resource replenishes over time. This situation is similar to a resource scarcity situation (Ghorbani & Bravo, 2016), where the agents adapt to the environmental shock by taking less resource units over longer intervals of time (e.g. every 100 ticks, this is emergent from the model). Another reason to observe L-shaped pattern is the fact that the agents were not aware of the state of the resource. They are only conscious about their yield level and act accordingly. Therefore, when there was an environmental shock, the agents did not react significantly. Although in the case of sudden reduction of the resource (as an environmental shock), we have indirect impact on the yield level of agents, it seems that they can adapt themselves with the sudden changes of the resource and the impact is not as much as when their yield level have been continuously reduced (social shock). However, when we had a social shock, since their yield continuously reduced and they sensed the changes, their reacted by repeatedly changing the institutions and U-shaped pattern has been emerged.

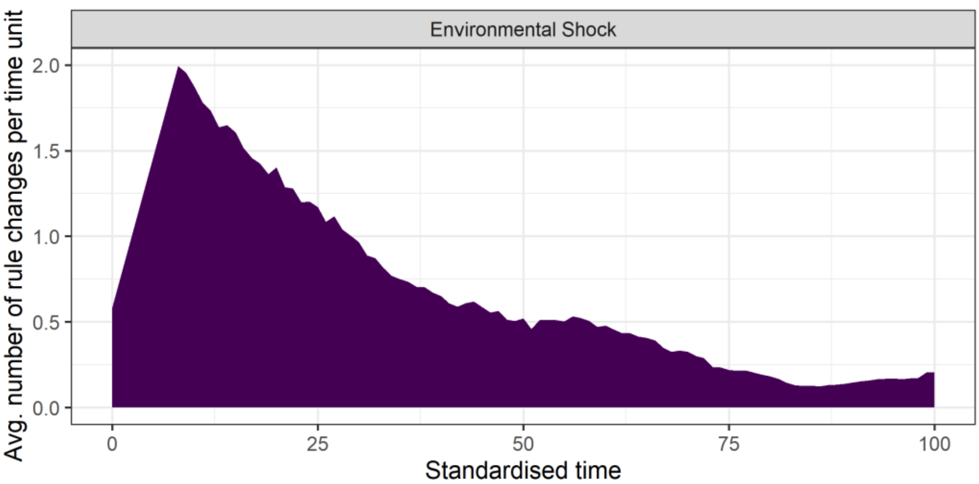

Figure 5. Institutional change patterns with environmental shock

It is worth mentioning that Figures 3 to 5 show a short "warming-up phase", which cannot be found in Figure 1 (i.e., in the dataset). Since the institutions in the model are emerging from agent behaviour, this warm-up period allows the agents to select their individual strategies which eventually become the collective strategy. The time for the institution to emerge is also conditioned on the satisfaction of the agents and therefore varies between simulation runs and also in the diagrams.

By comparing the implementations of environmental and social shocks, one may argue that the two shocks are related in the sense that one is a decline in the availability of the resource, while the other is simply increase in metabolisms (see Blom, 2019) This makes the results even more insightful as they do not lead to the same outcome in terms of institutional change. The reason behind the difference is in the way the shock continues to affect agents: after the environmental shock, the resource gradually recovers, while in the social shock situation there is a continuous burden on the agents.

2.6.3 Testing H3: Sanction-oriented Institutions and Longevity of the Common-pool Resources

To test H3, we tested whether having no sanctions in the modelled institutions significantly affected the simulated CPRs life span. As shown in Figure 6, a significant positive correlation exists between the number of institutions without sanctioning in one run (representing one CPR and standardized based on the total number of institutional changes) and the age of CPR ($r = 0.68$), which supports H3. In other words, the figure shows the relation between the number of institutions without sanctioning (normalized based on the number of institutions) and the age of CPR. The cluster of observations at age_common = 7000 is due to the stop condition of the simulation where all runs that have not finished yet are terminated.

This suggests that institutions lacking sanctions have a positive impact on the longevity of commons. This implies that the CPRs which lasted longest mostly had many institutions with fine=0 (and therefore the ratio is close to 1). Although the amount of a sanction is relatively low compared to the income of agents per tick, and the probability of sanctioning is also low. The explanation behind this may be related to agents losing more yield per tick and therefore, being more frequently unhappy with the institution in place, thus attempting to change it.

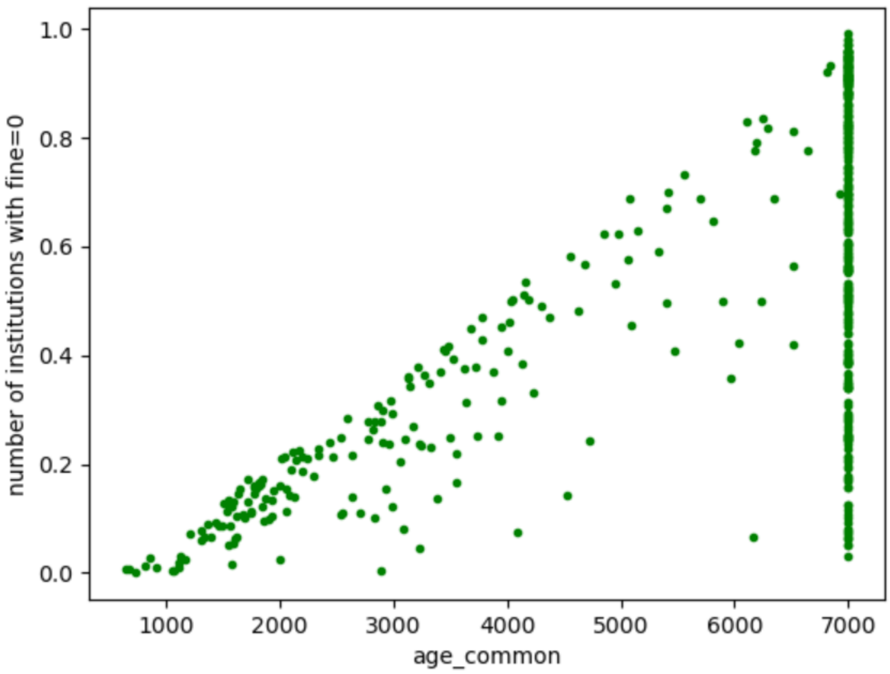

Figure 6. Number of institutions (having fine = 0) normalized based on the number of institutions per CPR age (when stop condition (max common age) is 7000, the total number of runs with this age is 317. Among these runs, 211 have above 0.6 of their institutions without sanctions and 141 runs have above 0.8 of their institutions without sanction; when stop condition is 10000, the total number of runs with this age is 50. Among these runs, 43 have above 0.6 of their institutions without sanctions and 31 runs have above 0.8 of their institutions without sanction.)

2.6.4 Testing H4: Frequency of Meetings and Longevity of the Common-pool Resources

To test H4, we ran four experiments, each including 500 independent runs, with frequency of meetings in {6, 12, 18, 24} ticks.

Given that the data were right-censored— i.e., simulations that were still running after 7,000 time steps were stopped—we analysed the effect of the frequency of meetings using maximum likelihood estimation of censored regressions (Messner et al. 2016). We considered the predictor variable as ordinal, since only four possible meeting frequencies (namely 6, 12, 18, and 24 time steps) were considered, and controlled for the resource regeneration rate r and carrying capacity K (Table 3). Note that the interpretation of the model remains similar if the meeting frequency is introduced as a numerical variable. Table 3 shows censored regression estimations on CPRs’ life spans. The reference class for meeting frequency is six time steps.

The results clearly show a significant effect of meeting frequency, with less frequent meetings leading to shorter life spans for CPRs, that is, providing the opportunity for agents to change the institution more frequently increases the CPR’s longevity, which supports H4. Neither the carrying capacity nor the regeneration rate coefficients, however, are significant.

Table 3 The relation between the frequency of meetings and longevity of CPRs

Coefficients (location model):					
	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	9,88E+06	1,50E+06	6.581	4.67e-11	***
Frequency of meetings:12	-1,86E+06	3,69E+05	-5.053	4.34e-07	***

Frequency of meetings:18	-2,10E+06	3,68E+05	-5.704	1.17e-08	***
Frequency of meetings:24	-2,28E+06	3,67E+05	-6.205	5.45e-10	***
K	4,97E+01	4,25E+01	1.168	0.243	
r	-1,56E+06	4,32E+06	-0.361	0.718	

```
Coefficients (scale model with log link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  8.44860    0.03165     267   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Distribution: gaussian
Log-likelihood: -7557 on 7 Df
Number of iterations in BFGS optimization: 196
```

To summarize, we used an empirically tested model to explore some historical hypotheses on the development of CPRs' management institutions. By replicating the observed historical patterns, we aimed to identify parameters that help to explain their emergence. Our results were consistent with three hypotheses previously proposed in the literature on the subject: social shock results in the dissolution of CPRs, less focus on sanctioning has a positive effect on the CPRs' longevity and having frequent meetings among commoners has a positive effect on the CPRs' longevity. We also tested an additional explanation for the dissolution of the CPRs, based on the effect of environmental shocks on institutions, but found no support for it.

2.7 Summarizing Methodological steps for Testing Historical Hypotheses Using Agent-based Modelling

In this section we present a set of guidelines that can support the process of testing historical hypotheses as shown in Figure 7.

1- Hypotheses on historical patterns and trends
The first step in the process of studying historical patterns using agent-based modelling is to extract the patterns that are of interest in a particular historical context, such as the ones described in this article. These historical patterns are commonly accompanied by hypotheses that explain possible causalities. These hypotheses can be extracted from already published articles, but can also be formalized by statistically analysing historical datasets related to that specific context (here the CPRs). Here, we primarily used a historical dataset to extract the patterns, and used existing articles based on the same dataset to define the hypotheses.

2- An agent-based model representing the historical setting
An agent-based model is built that represents the historical context and that can reproduce the historical trends and patterns. This model needs to be validated to make sure that it is sufficiently representative of the context. Here, the dataset that was used to validate the model was completely independent of the dataset that showed the historical trends that were to be studied.

3- Parameter configuration of the model
The experiments are set up in such a way as to be able to reproduce the historical pattern. Therefore, the experimentation process is a repetitive task that aims to configure the parameters in the model so that the model produces specific outcomes.

4- Finding causal links between model parameters and historical patterns

By reproducing patterns that resemble patterns observed in history, we compare model parameters that were the cause of the emerging pattern to variables in the hypothesis to confirm or reject the hypothesis.

With this practice, we simply used ABM as a complementary tool to support theory development in historical studies.

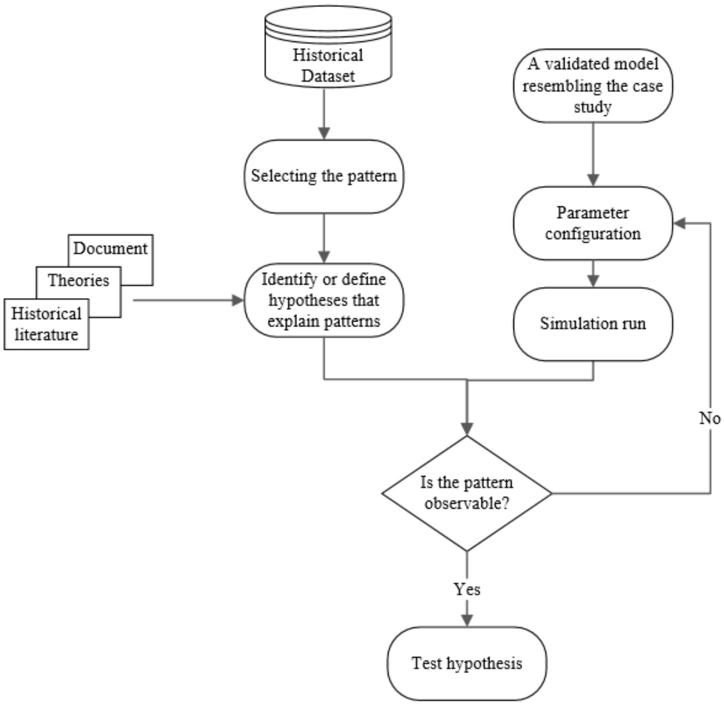

Figure 7. Testing historical hypotheses using ABM

2.8 Discussion and Conclusion

In this research, we used agent-based modelling as a complementary tool to support theory development in historical studies. By building models that produce historical patterns, we aimed to identify parameters that explain patterns and that are present in hypothesized causalities in historical studies. This practice allowed us to confirm existing hypotheses found in the literature.

For the particular case of institutions in CPR management, we used an existing and already validated agent-based model and identified patterns in a historical dataset that were important in explaining institutional dynamics for this management.

Three out of the four hypotheses that were extracted from published articles on the same historical dataset were corroborated:

1- Our model corroborated the fact that institutions that are endogenously built to manage CPRs faced rapid changes at the beginning, as agents were trying to find an acceptable institution that satisfied their needs, essentially based on trial and error. After that, the CPRs faced a period of institutional stability, as the agents were satisfied with the situation. However, social interruptions that lead to agents' loss lead to rapid institutional change, as the agents tried to adapt to the new situation with higher consumption (resembling personal demand with added taxation). They were not successful in their endeavours and the CPR died out as it was not able to meet the commoners' demand.

2- The model showed that sanctioning had a negative impact on the longevity of CPRs. Institutions without sanctioning mechanisms seemed to have been more effective in the long run, leading to longer CPR lifetime.

3- The model corroborated the fact that involving agents in institutional development in more frequent meetings contributed to the longevity of the CPRs. If commoners could change institutions more frequently, adjustments lead to more stable and longer lived CPRs.

4- The hypothesis that was rejected concerned the influence of environmental shock as the emerging pattern from the simulation was an "L" shape, suggesting that the agents were in fact able to recover from the shock and remained in a relatively stable institutional setting.

An important point to emphasize here is that the model used to the hypotheses was completely independent of the dataset used to generate those hypotheses. As such, we did not have any pre-specified relationships in the model that would bias our results. We do not claim here that testing historical hypotheses should be done by using an independent model that does not use associated data, but that this independence could increase the reliability of this type of research. The strategy of having independent datasets for training and testing models is also the gold standard in machine learning literature.

Moreover, rather than trying to focus on input data that represent reality, we considered the output of the model to replicate the investigated pattern. This helped us calibrate the model to represent the desired emerging patterns, rather than being fully data-driven. We were interested in qualitative representations of reality in the form of patterns and trends (Grimm et al., 2005), rather than quantitative accounts of reality. This supports the claim that abstract models that are not necessarily data-driven in nature, can generate important insights which otherwise may have been invisible.

This modelling practice, however, also has some limitations. First, the model that we used as the basis to test the hypotheses was quite abstract and missed certain important concepts in the CPR settings s. For example, agents were homogenous (apart from choosing different strategies) and therefore a power structure in which some agents had more rights than others was missing. We did not change the model to be able to test its existing validity. However, future extensions of the model could bring more in-depth insights. Second, the agents do not have any learning behaviour, which implies that even if we made new generations of agents, as they would be very similar to existing ones, and did not learn from experience, we would most probably observe the same behaviour. More intelligence and learning behaviour might therefore lead to other insightful explanations about the type of historical patterns we observed in our experiments. Third, the dataset has an implicit bias, as it included only CPRs that survived for over 200 years and had changed their regulations at least three times over this 200-year period. Short-lived CPRs, long-lived CPRs that used the same regulation over their entire life span, and other CPRs not meeting these criteria were therefore excluded and may have shown different results. Finally, related to model parameterization, given that the model was very abstract, there were minimal empirical basis for many of the parameters, requiring us to look into full parameter ranges. The current model was quite simple, therefore, looking at the whole parameter spectrum was feasible. Adding these details and complexities to the model however, would make parameter sweeping difficult, if not infeasible, calling for more linkage to real-world data.

2.9 Acknowledgements

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2.10 Appendix. The Model Description

This section describes the model in more detail using the ODD + D (Müller et al., 2013) standard for describing agent-based models.

MODEL OVERVIEW

PURPOSE

This model is an agent-based model of common-pool resources (CPRs) management to test hypotheses that were previously generated through a historical dataset. The ABM simulates the emergence of institutions for the management and use of CPRs. The goal of this work is to show how historical hypotheses can be tested with agent-based models. In other words, by comparing emerging patterns from historical datasets to emerging patterns from simulation models, one can explore the plausibility of the underlying mechanisms that have led to those patterns.

STATE VARIABLES AND SCALES

The model includes a number of appropriators and one shared resource. Appropriators select an institution at a specific time after the start of the simulation. Furthermore, we introduce two types of shocks in the model: social shock and environmental shock.

APPROPRIATORS

Variable	Description
Yield	Captures the amount of yield that the agents currently have. It decreases every tick based on consumption needs and increases based on appropriation activities.
Current action	the number of resource units the agents are consuming/appropriating at a point in time
Current condition	Under what condition the agents take action (e.g., every x ticks)
Cheated	A Boolean variable that shows whether the agent cheated in the previous tick
Cheating profitable	Is the outcome of the decision of the agent on whether it should cheat in this round or not. (Boolean)
Cheating propensity	The probability of cheating

RESOURCE

Variable	Description
Resource Growth (r)	In each round of the simulation, the amount of resource is increased by this value given a particular growth function.
Initial amount (K)	This is the amount of resource given at the beginning of the simulation

Resource type	The type of resource is fishery or irrigation in the model.

INSTITUTION

Variable	Description
Action	The action that has to be executed by every agent in the simulation. This is selected by the agents.
Condition	The condition under which the agents appropriate from the resource (execute action). This is selected by the agents.
Frequency of meetings	The number of ticks after which the institution is formed by the agents
Threshold for institutional change	The threshold needed to establish an institution.
Fine	The amount of penalty paid by agents in case they cheat, and in case their cheating is caught. This is selected by the agents.
Monitoring	The percentage of agents who will be monitored for cheating. This is selected by the agents.
Institutional_emergence_start	The trial and error phase of CPR before going to emerge the institutions.

SHOCKS

Variable	Description
Environmental shock interval	The interval that environmental shock happens.
Resource loss percentage	The percentage of resource that will be decreased in each environmental shock intervals.
Social shock time	When a social shock is introduced.
Taxation amount	The amount of penalty paid by agents in each ticks after social shock time.

PROCESS OVERVIEW AND SCHEDULING

The simulation model consists of two general processes which are depicted in Figure 2:

1 The initial appropriation process: during the initialization phase, the agents are created, the network is set up and agents are initialized with a random action and random condition pair as their individual strategy. The agents consume resource units based on their individual strategy. For example, an individual strategy might look like this: eat 5 units of resource every 2 ticks. In addition, agents consume a fixed amount of yield in each tick, representing their needs. The resource is renewed in each time step according to a logistic growth function. If agents are not satisfied with their energy level (i.e., their energy balance is negative), they change their strategy. This change of strategy can be completely random (representing innovative behaviour) or done by copying successful neighbours.

2 Appropriation based on institutional rules. At specific points in time if a majority of agents are unsatisfied, they come together to vote on an institutional rule, which is basically the most common individual strategy. Once in place, all agents have to follow the institutional rule, although under certain settings they can “cheat” and follow their individual strategy instead. While following the institution, the opinion of the agents about their individual strategy is continuously updated. If they cheat, monitoring and fine mechanisms will be applied. If a certain proportion of agents are unsatisfied with the current institution, the meet again to vote on a new institution. In addition to the threshold for satisfaction, another parameter determining the meeting frequency also influences how often the agents change the institution. The

simulation stops if there are no resource units left, or when the portion of agents with very low energy is higher than a certain threshold, or simply after a certain number of ticks. Environmental shock and social shock take place during this phase.

DESIGN CONCEPTS

THEORETICAL AND EMPERICAL BACKGROUND

The model is primarily based on the concepts proposed in IAD framework for management institutions in CPR system. It uses the ADICO grammar of institutions to build institutions which follow a pseudo-evolutionary process, i.e., mutation of institutions (innovation) and copying behaviour.

INDIVIDUAL DECISION-MAKING AND SENSING

The agents follow a basic decision-making process. They look at their yield level to make decision. The agents also decide whether they would comply with the institutional rule, or follow their own strategy. They do this by comparing the potential yield gain from each action and select the most profitable one, depending on the cheating propensity. This is also the only "prediction mechanism" in the model.

LEARNING

The agents do not have learning abilities. They only check their current yield level to decide whether they want to continue their existing strategy or select a new one.

INTERACTION AND COLLECTIVE ACTION

Each agent is placed in a network (random). The agents may copy the strategy of the successful neighbor in terms of energy level. Furthermore, the agents come together and collectively vote on the institution by proposing their own strategy. The most common strategy is selected as the new institution.

HETROGENITY

Agents are heterogeneous with respect to their behavioural strategies and homogeneous with respect to all other parameters.

DETAILS

IMPLEMENTATION DETAILS

The details of the implementation are explained in Section 4.2 of the paper.

INITIALIZATION

The model starts by all agents having 0 amount of energy. This amount will decrease based on a given constant value (energy consumption) and will increase (or decrease) based on the strategy that the agent is choosing then following.

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3 How Wealth Inequality Influences Cooperation in Common-pool Resource Management: an Agent-based Model to Compare Theoretical Hypotheses[1]

Abstract

Cooperation among common-pool resource users is fundamental to sustainable governance of the resource. Heterogeneity among members can affect their level of cooperation and involvement in collective action. This research focuses on one specific type of heterogeneity: wealth inequality. Wealth inequality has led to a debate about its influence on collective management of common-pool resources. While theoretical investigations propose that disparities in wealth can potentially enhance collaborative endeavors, specific empirical inquiries have emphasized the adverse consequences of such disparities on collective actions, with certain studies indicating a non-linear correlation. In this paper, we use an agent-based model to investigate how wealth inequality shapes individual and collective behaviour regarding participation in collective action. Initially, we investigate the relationship between wealth inequality and cooperation, and subsequently, we examine how this relationship can influence 1) institutional characteristics, 2) population characteristics, and 3) resource characteristics.

Our results confirm that inequality and cooperation have an inverse relationship: inequality decreases cooperation. The model illustrates that, at low inequality, common-pool resources perform better in terms of average wealth and availability of the resource. In similar unequal situations, when cooperation is higher, the average wealth and amount of resource are higher. Moreover, when cooperation is high, there are fewer agents who cheat or do not vote, and the first institution emerges later in time. In similar cooperative situations, cheaters and non-voters are less when inequality is less.

[1] This chapter is based on a journal article currently under review.
Aleebrahimdehkordi, M., Kreulen, K., Herder, P., and Ghorbani, A. How wealth inequality influences cooperation in common-pool resource management: an agent-based model to compare theoretical hypotheses.
The first author conceptualised and performed the research.

Keywords: institutional modelling, wealth inequality, cooperation, common-pool resources, institutional evolution

3.1 Introduction

Common-pool resources (CPR) are valuable resources like fisheries, forests, and pasture lands that are shared between multiple appropriators. Excessive utilization of common-pool resources can result in resource depletion, a situation commonly referred to as the "tragedy of the commons," as outlined by Hardin (1968). In order to avert this, resource users establish collective action institutions, which are frameworks comprised of regulations and enforcement mechanisms. These institutions facilitate the cooperative governance and sustainable utilization of said resources (Ostrom, 1990).

Research suggests that cooperation among CPRs' users can facilitate sustainable collective governance of resources (Bollig et al., 2014). Cooperative individuals participate in decision-making processes to manage the CPR (e.g., voting to establish new institutions) and/or by obeying (not cheating) the already established institutions (Killingback et al., 2010; Fehr & Leibbrandt, 2011). A contribution can be made by participating in decision-making processes to preserve the CPR (e.g., voting to establish new institutions) or by obeying (not cheating) the already established institutions.

The level of heterogeneity highly influences the level of cooperation among members of CPR in that population, both positively and negatively (van Klingeren, 2020; Markussen et al., 2021). Within the context of common-pool resources literature, this heterogeneity, which is also referred to as inequality, is characterized by a range of distinctions in terms of wealth, authority, social status, preferences, or income among individuals sharing common resources (Adhikari, 2005; Gaspart et al., 2007).

Although several studies explore the effect of inequality on cooperation, this is still an unresolved topic. While theoretical research suggests that inequality can positively influence cooperation (Baland & Platteau, 2007), certain empirical studies have emphasized the adverse consequences of inequality on cooperation (Adhikari, 2005; Cardenas, 2007). Considering the divergence in the literature on the relationship between wealth inequality and CPR governance, exploring this relationship further will shed light on how to sustain CPRs effectively.

To study the effect of heterogeneity on cooperation in CPRs, we narrow down the scope and focus on a specific form of economic heterogeneity, namely wealth inequality. Wealth is defined here as the amount of resource in possession of an individual agent. This work explores the role of wealth inequality in cooperation by using agent-based modelling and simulation (ABMS). This simulation approach allows us to study CPR management by varying agent, resource, and institutional parameters under different conditions over time (Andersson et al., 2011; van Klingeren, 2022). The modelling effort in this research complements the empirical research in the context of CPRs which has mainly taken the form of field studies and lab experiments (e.g., Bollig et al., 2014). Although such empirical methods are insightful for studying the status quo, modelling can assist in studying the dynamics of CPR management processes in the long run (e.g., cooperation among commoners) (Bandini et al., 2009).

With ABMS, we investigate how wealth inequality shapes individual cooperative behaviour in managing CPRs. We extend a previously validated model that deals with the creation of institutions used for controlling and utilizing CPRs (Ghorbani et al., 2017) to study the role of wealth inequality on population and resource status and institutional dynamics.

This paper is organised as follows: Section 2 discusses the background and identifies the knowledge gaps. Section 3 presents the agent-based model and its specifications. Section 4 presents the results. Finally, Section 5 provides conclusions.

3.2 Related Research

The relationship between inequality and cooperation has been extensively studied in the collective action and CPR literature. Some researchers have highlighted the negative effect of wealth inequality on collective action (e.g., Ledyard, 1993; Cherry et al., 2005; Adhikari, 2005; Levati et al., 2007; Cardenas, 2007; Markussen et al., 2021). For example, Cardenas (2007) uses lab experiments to show how wealth inequality negatively impacts collective action when extracting from a natural resource. Markussen et al. (2021) also confirm this negative impact of inequality on cooperation by driving field experiment in 56 communes in rural Vietnam.

On the contrary, theoretical research suggests that inequality can also positively influence collective action (Baland & Platteau, 2007; van Klingeren, 2020). Olson (1965) explains that in such situations, the rich bear the cost burden of cooperation for the poor.

In favour of the positive influence of inequality on cooperation, unequal situations might trigger wealthy appropriators to cooperate more with others. Shanmugaratnam (1996) explains this positive influence through differences in interests among appropriators with different wealth levels. In support of this difference in interests, Baland et al. (2018) refer to the leading role of the wealthy local elite in organising collective action. Baland and Platteau (1998) emphasise that cooperation would not necessarily decrease in unequal situations because wealthier appropriators are more likely to engage in voluntarily public activities. Even though the less wealthy appropriators may have insufficient motivation to participate in collective actions, cooperative commoners in unequal situations can be wealthy ones who compensate for the less wealthy (Baland & Platteau, 2007).

A limited number of articles indicate a non-monotonous relationship between wealth inequality and cooperation. Molinas(1998) shows that cooperation is not monotonously correlated to the level of inequality by using an econometric analysis of 104 peasant cooperative institutions in Paraguay. Molinas finds this relationship between inequality and cooperation as an inverted U-shape form. Dayton-Johnson & Bardhan (2002) show that the relationship between wealth inequality and cooperation is in the form of a U-shape. At very low and very high levels of inequality, high levels of cooperation can be seen.

In summary, the literature conveys different views on the impact of wealth inequality on cooperation in CPR management. Some researchers claim wealth inequality's negative effect on cooperation, others suggest a positive impact, and a minority indicate a non-monotonous relation.

In this paper, we use a validated ABM to explore the impact of wealth inequality on cooperation in CPR management settings.

3.3 An Agent-based Model of the Dynamics of Institutions in Common-pool Resource

3.3.1 Model Overview

We extend a previously validated model that deals with the creation of institutions used for controlling and utilizing existing CPRs where institutions emerge from interactions among appropriators (Ghorbani et al., 2017). In the original model, which was implemented in Netlogo, agents collectively consume a resource using their individual strategies or the institutions that have emerged during the simulation. In the beginning, there is no institution, and agents follow their strategies to gain income from the resource. Agents can change their individual strategies if they are not satisfied with their level of income. As time progresses, the agents collectively vote to choose an institution, essentially favoring the strategy endorsed by the majority. From that point in time, all agents must obey the selected institution, but they also have the opportunity for non-compliance (cheat). If they cheat, depending on the monitoring intensity (the percentage of agents who will be monitored), they may pay a fine (the sanction for non-compliance). The amount of fine and monitoring intensity are also part of the institution that the agents collectively agree on. The voting procedure repeats when several agents (above a threshold parameter set in the model) are dissatisfied with the current institution (i.e., their income is negative).

3.3.2 Theoretical Background

Before explaining the details, we define the model's theoretical underpinning. We use the Institutional Grammar (aka IG) (Crawford & Ostrom, 1995) to define institutions and individual agent strategies. As per the IG, A stands for Attributes, denoting the subjects to whom a strategy or rule is applicable; D represents Deontic, determining the manner in which an action is carried out (prohibition, obligation, and permission); I signifies Aims, representing the actions to which Deontic applies; C indicates Conditions, specifying when, where, and how a strategy or rule is applicable; and O denotes Or Else, indicating specific punishments when an agent violates the institutional rule (Crawford & Ostrom, 1995).

As mentioned, this research builds on the assumption that cooperative behaviour contributes to sustaining CPRs (Killingback et al., 2010; Fehr & Leibbrandt, 2011). In this model, cooperation is characterized by two distinct behaviours: 1) engaging in voting processes to establish institutional rules (Opp, 1986; Bernard et al., 2013; Dannenberg & Gallier, 2020) and 2) not cheating (Rasch et al., 2016) (i.e., complying with the collectively chosen institutional rule). A cooperative agent is thus defined, in this paper, as an agent that shows both behaviours.

Following (Nishi et al., 2015), associations with cooperation can be established concerning the observable wealth disparity within a localized context. Within a social network of connected agents, cooperation tends to diminish when individuals perceive a substantial wealth gap between themselves and their neighbors. To put it differently, the likelihood of cheating rises, and the likelihood of involvement in voting decreases. It's important to emphasize that this impact is specifically tied to the local level of inequality, specifically among neighboring agents (Nishi et al., 2015), and remains unaffected by global inequality.

3.3.3 Conceptualization

This section describes the model implemented for this research in Python using the Mesa library. The parts that extend the original model (Ghorbani & Bravo, 2016) are marked in the text.

The architecture of the model is presented in Figure 1. This model consists of three main components: agents, institutions, and a resource. The open access model and a comprehensive description, ODD + D based on (Müller et al., 2013), are available on CoMSES:

https://www.comses.net/codebase-release/5cf4f78a-de41-49ec-b3c1-b692ebaa6026/

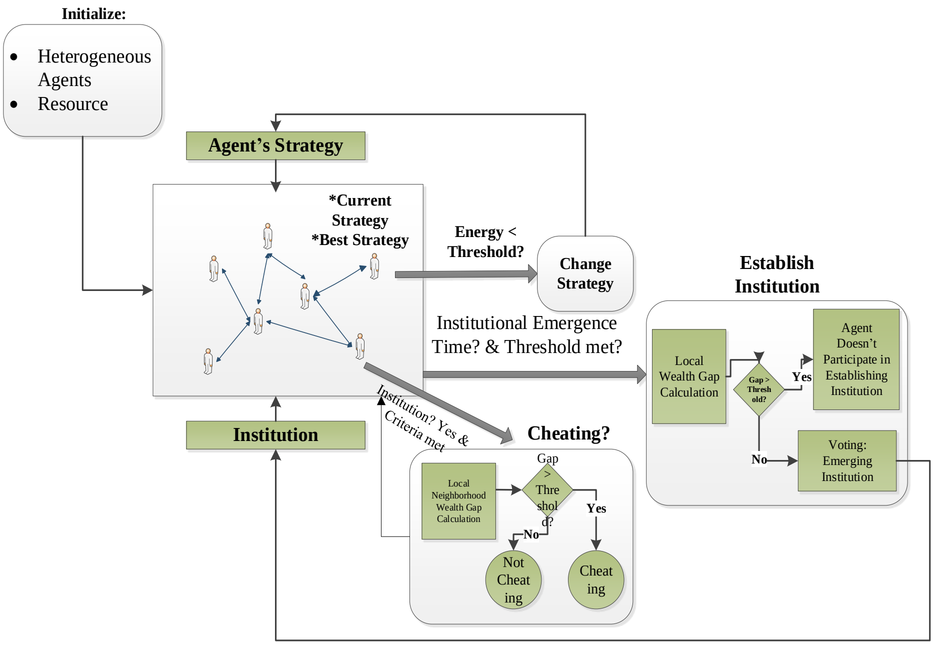

Figure 1. The model architecture

Agents. Each agent records its current strategy, the best past strategy location, neighbours, and wealth level. These individual strategies are coded using the IG (A, I, C components). The initial wealth of each agent is a random number in the range of 1000 – 2000.

- Individual strategy: Every conceivable pairing of action (aim in IG syntax) and condition forms a strategy. Agents maintain only one strategy at any given time. An action denotes the quantity of resources the agent will consume, while a condition specifies when or under what circumstances the agent will acquire that amount of resources (i.e., added to the agent's wealth). Initially, each agent is randomly assigned an individual strategy (a random combination of action and a condition). For example, an individual strategy might be: to take four units from the resource every three timesteps (referred to as ticks).

- Best strategy: Agents consistently retain (i.e., remember) the strategy that results in a higher consumption of resources. This parameter undergoes updates throughout the simulation, reflecting a straightforward learning behaviour[1] rooted in experience, influenced by new institutions or strategies (**extended part of the model**).
- Strategy change occurs when the agent's wealth falls below a predefined threshold (a parameter in the model). The change can proceed through three distinct mechanisms: 1) copying the strategy of the most successful neighbour with the maximum wealth, 2) randomly selecting another strategy (resembling an inclination for innovation), or 3) choosing the best strategy the agent has experienced thus far through learning (**extended part of the model**).
- Each agent has a conservative parameter (**extended part of the model**) and innovation tendency parameter. The first enhances the likelihood of employing the best strategy in the subsequent round, while the latter elevates the chances of devising an entirely novel strategy.

  When the innovation tendency is low (lower than a threshold parameter), the agent copies the strategy of a neighbour who currently has the highest amount of wealth. If the innovation tendency is high and the conservative value is true, the agent uses its best past strategy as the current strategy. If the agent inclined toward innovation doesn't adhere to conservatism, it randomly chooses a fresh pairing of action and condition, constituting a new strategy (Algorithm 1) (**extended part of the model**).

Algorithm 1: Changing strategy

```
If the agent is innovative then
        If the agent's conservative is True then
                Set current strategy as the best strategy
        Else
                Set current strategy as random strategy
If the agent is not innovative then
        Copy the strategy of best neighbour (neighbour with the maximum
wealth)
```

Institutional rules. Also coded following the IG.

At each institutional emergence time (the number of ticks after which the agents form the institution), if a portion of agents (above a threshold) are unsatisfied with their wealth levels, they come together and vote on an institution. The selected institution is the most popular individual strategy in the voting process. The agents must comply with the selected institution

[1] The agents have simple learning abilities. They have a memory to store the best strategy, which has leaded them to the maximum wealth. If the mood of changing strategy is ‘learning’, they check the wealth that they can gain based on a new wealth in comparison with the wealth associated with the best strategy. After that, they choose to go for the new strategy or not.

but may also cheat and follow their own strategies. An example institution can be: gain 5 units (action), every two timesteps (condition), if not, pay 2 (or else) with 2% probability (monitoring possibility). An individual strategy would be similar but without the or else.

- Cheating: Each agent compares the amount of wealth that it would gain by following its individual strategy with the amount of wealth gained by complying with the institution. If following the institution proves less financially rewarding, and the agent detects a gap (whether positive or negative) between its wealth and the average wealth of its neighbours following (Nishi et al., 2015), it may (based on a probability for both these cases) cheat (**extended part of the model**). This implies that the agent may opt not to conform to the established institution and instead act in accordance with its existing strategy. See Algorithm 2 below. This procedure is also influenced by the "social influence" parameter and the agent's "individual cheating propension" (two parameters in the model).

• **Algorithm 2:** Cheating procedure
• Inequality = abs (agent_wealth - avg_wealth_neighbors) / avg_wealth_neighbors + agent_wealth
• **If** (random (0, 1) < (individual-cheating-propension * (1 - social-influence) +
• (count link-neighbors with [cheated = true]/count link-neighbors) * social-influence)) **then**
• **If** random (0, 1) < inequality **then**
• The agent will cheat!

- Voting: similar to the procedure for cheating (algorithm 2), Agents experiencing a divergence (positive or negative) in their wealth compared to the average wealth of their neighbours are less inclined to participate in voting (**extended part of the model**).

For assessing the level of cooperation, we monitor the percentage of agents who have engaged in voting and followed the established institution.

In this study, the Gini coefficient (Mattison et al., 2016) is employed to assess the distribution of wealth inequality among agents. Ranging from 0 to 1, the Gini coefficient assigns higher values to indicate increased levels of wealth inequality.

3.4 Parameter Setup and Experiments

We first explore the relationship between wealth inequality and cooperation and, consequently, the impact of this relationship on CPR management. For that, we track three system characteristics under different cooperation levels and Gini: 1) Institutions, 2) Population, and 3) Resource.

3.4.1 Institutional Characteristics under Different Cooperation Levels and Gini

This part aims to observe the effect of the relationship between cooperation and inequality on institutional characteristics (number of institutional changes during the lifetime of CPR, emergence time of institution, and institutional stability). Table 1 shows the institutional characteristics and their definitions.

Table 1 Institutional characteristics

Parameter	Description
Number of institutional change	The number of institutional changes during simulation.
Emergence time of the first institution	The number of ticks, before the first institution emerges.
Institutional stability	The average number of ticks before institutions change divided by the number of institutional changes.

3.4.2 Population Characteristics under Different Cooperation Levels and Gini

This part explores the effect of the relationship between cooperation and inequality on population characteristics. Table 2 shows population characteristics regarding the number of cheaters, non-voters, and agents' average wealth.

Table 2 Population characteristics

Parameter	Description
Average agents wealth	The average amount of agents' wealth by the end of simulation, divided the number of agents.
Number of cheaters	The number of agents that cheated (did not follow the established institution) during a simulation.
Number of non-voters	The number of agents that did not vote in establishing institutions during the simulation.

3.4.3 Resource Characteristics under Different Cooperation Levels and Gini

This part focuses on the effect of the relationship between cooperation and inequality on the characteristic of the resource, which is the amount of resource at the end of simulation runs.

We ran 400 independent simulations, each run containing 2000 ticks. The number of runs and ticks are selected after parameter sweeps that led to the convergence and stabilisation of model outputs. The parameter setup of the model is shown in Table 3:

Table 3 Shared parameter setups

Parameter	Value(s)	Description
Actions	consume [2, 4, 6, 8, 10, 12, 14, 16, 18], [-5]	The list of possible amounts of appropriation from the resource
Conditions	True (every tick), ticks mod 250 = 0, ticks mod 2 = 0, ticks mod 3 = 0,	The list of possible conditions for the agents

Parameter	Value(s)	Description
	wealth <= 0, ticks mod 20 = 0	to take action (e.g., every x ticks).
Initial wealth (of each agent)	1000 - 2000 (uniform random integer)	Captures the amount of wealth that each agent starts with. It decreases every tick based on consumption needs and increases based on appropriation activities.
Voting Profitable (of each agent)	boolean (default value: true)	The result of the agent's decision regarding whether it should participate in voting during this round or not
Cheating profitable (of each agent)	boolean (default value: False)	The result of the agent's decision regarding whether it should engage in cheating during this round or not.
Institutional emergence time	200 (fixed)	the number of ticks (time intervals) after which the institution is established by the agents.
Individual cheating propensity	0.1 - 0.35 (uniform random float)	The probability of cheating for each agent.
Carrying capacity (K)	12000 – 20000 (uniform random integer)	amount of resource at the beginning of the simulation.
Growth rate (r)	0.1 – 0.2 (uniform random float)	In every simulation round, the resource amount is incremented by this value based on a specific growth function.
Number of agents	100 (fixed)	The number of agents.
Wealth consumption	5 (fixed)	The amount of wealth consumption per tick.
Innovation tendency (of each agent)	0 – 1 (uniform random float)	Enhances the likelihood of formulating an entirely novel strategy
Threshold for institutional change	0.4 (fixed)	The ratio of agents who are unsatisfied with the current institution.

Parameter	Value(s)	Description
Conservative	True or False	Elevates the likelihood of employing the optimal strategy in the upcoming round.
Type of network	Random network (fixed)	

3.5 Results

In our model, cooperation is assessed through voting and cheating, specifically by determining the proportion of agents participating in voting and adhering to the established institution, divided by the total number of agents. Such cooperative actions are contingent on the presence of an institution. Hence, we focus on the 311 out of 400 runs wherein institutions emerge, as not all runs result in the establishment of institutions.

Additionally, 14 simulation runs out of 311 are recognised as outliers. These are simulation runs that are associated with Gini < 0.2 or 0.5 < Gini. In real life, Gini index < 0.2 corresponds with perfect equality, and above 0.5 corresponds with severe inequality[1]. These Gini values are extremely rare. The number of countries with Gini index less than 0.2 or above 0.5 are very low[2]. Therefore, these outliers are removed before analysing outputs. Finally, there are 297 runs out of 400 independent runs.

In this section, first, we show the relationship between wealth inequality and cooperation. After that, we present the effect of cooperation and inequality relationship on 1) institutional characteristics, 2) population characteristics, and 3) resource characteristic.

3.5.1 The Relationship between Cooperation Levels and Inequality

Figure 2, shows cooperation versus Gini, as measured at the end of the run, for all the simulation runs considering outliers.

[1] https://www.unicef.cn/en/figure-27-national-gini-index-20032017
[2] https://data.oecd.org/inequality/income-inequality.htm

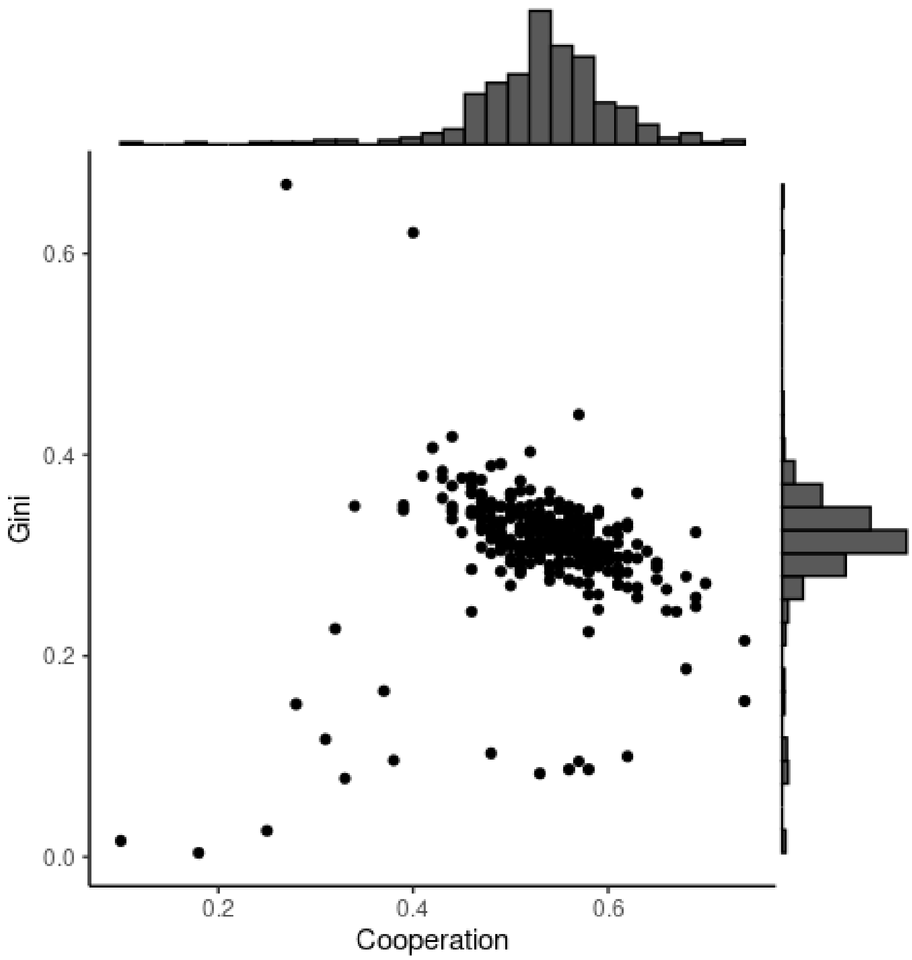

Figure 2. Cooperation versus Gini for all the simulation runs

To explore the impact of cooperation/inequality on the characteristics of institution, population, and resource (Table 1 and Table 2), we first removed outliers, then categorised the results into four classes as shown in Figure 3 by performing median split on Gini values and cooperation. The statistical description of the four classes are shown in Appendix A.

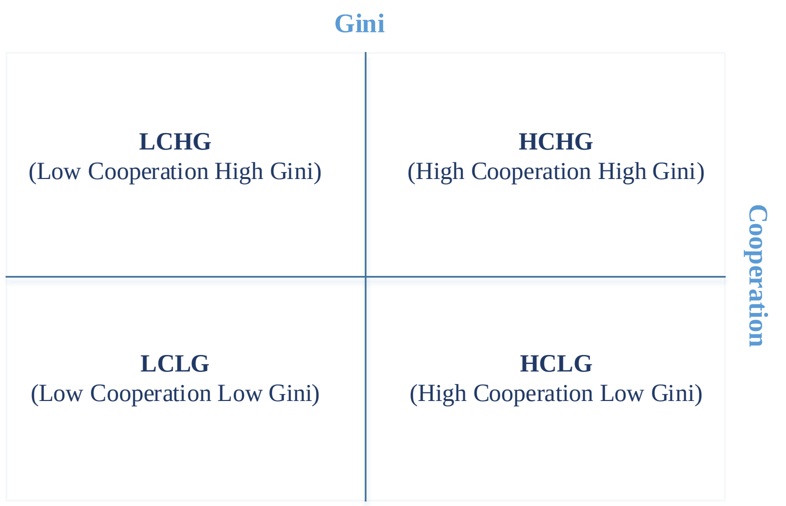

Figure 3. Description of the four classes of simulation runs (number of runs for HCHG=56, HCLG=102, LCHG=95, LCLG=44 simulation runs)

Figure 4 shows cooperation versus Gini for the simulation runs without outliers. The median of Gini is plotted as y-intercept and the median of cooperation as x-intercept (see red dotted lines).

As shown by the regression line in Figure 4, the model shows a negative relationship between wealth inequality and cooperation, implying that inequality could have an influence on decreasing cooperation. As we move to higher Gini, inequality reduces cooperation.

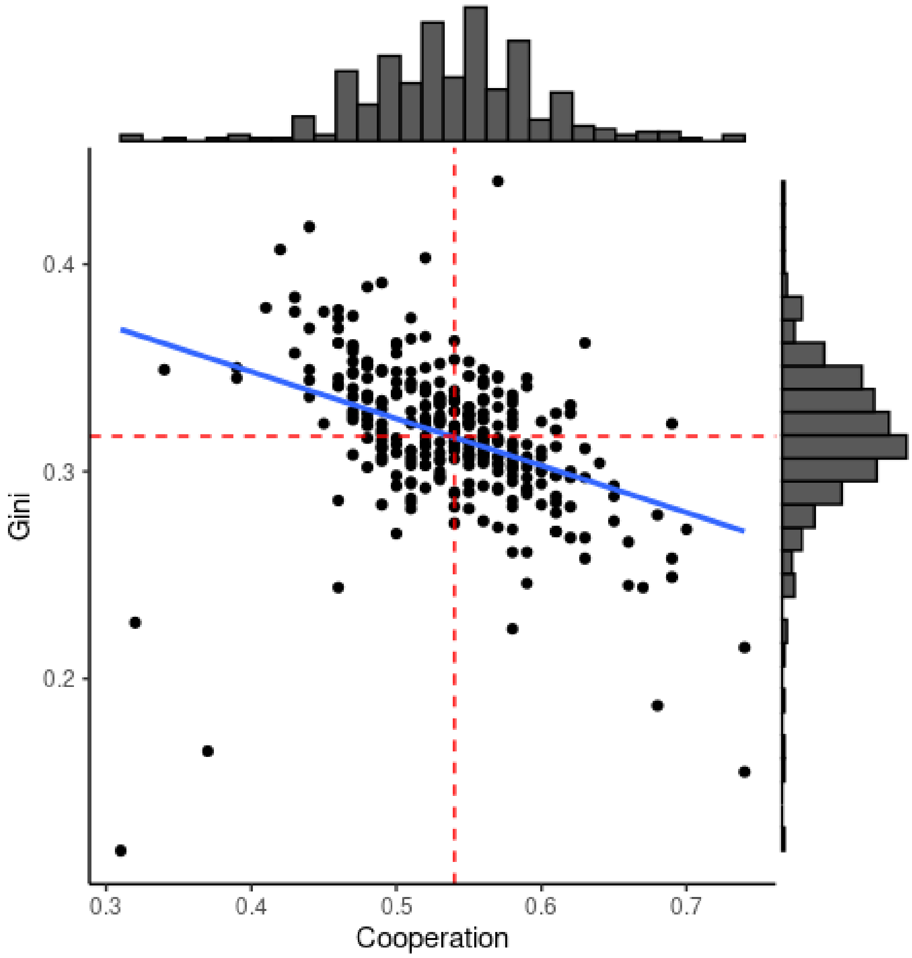

Figure 4. Cooperation versus Gini after removing outliers (a significant linear regression line and four classes are added)

3.5.2 Institutional Characteristics under Different Cooperation Levels and Gini

Analysing the medians of the number of institutional change, emergence time of the first institution, and institutional stability during the lifetime of the CPR did not show any significant differences across the four classes.

It is worth mentioning that it is unexpected to have the same medians for the number of institutional change. Since when inequality is high, there is a portion of agents who are relatively poor and therefore we supposed to see much more institutional change on average for those classes (which is not seen in the result).

However, the averages of emergence time of the first institution for the four classes (Appendix A) show differences. HCHG has the highest average. After that HCLG has the second highest average. These observations suggest that later emergence of the first institution, regardless the level of inequality, causes high cooperation at the end.

In the model, cooperation is defined based on not cheating and voting. When cooperation is high, cheating is low, and voting is high. When the first institution emerges late in the simulation, cooperation is higher. This could be because there are less opportunities for cheating and not voting, therefore, the value for cooperation tends to be higher.

3.5.3 Population States under Different Cooperation Level and Gini

Figure 5 shows the average agents' wealth of each class. The class HCLG (followed by LCLG), which has low Gini, has the highest average wealth of agents.

Given the low global inequality, there is lower chance to see a local gap between agents. When cheating is infrequent, it implies that a significant portion of population, on average, are happy with their level of wealth and therefore, follow the institution.

Therefore, we can conclude that low inequality whether cooperation is high or low, generally leads to better CPR management in terms of average wealth of appropriators. At the same time, it is worth highlighting that there are a significant number of runs (56 runs) with high inequality and high cooperation values, implying that high inequality does not necessarily translate to low cooperation, as the agents can still be in a situation where the local inequality is considered low by them and therefore, they still have the tendency to cooperate.

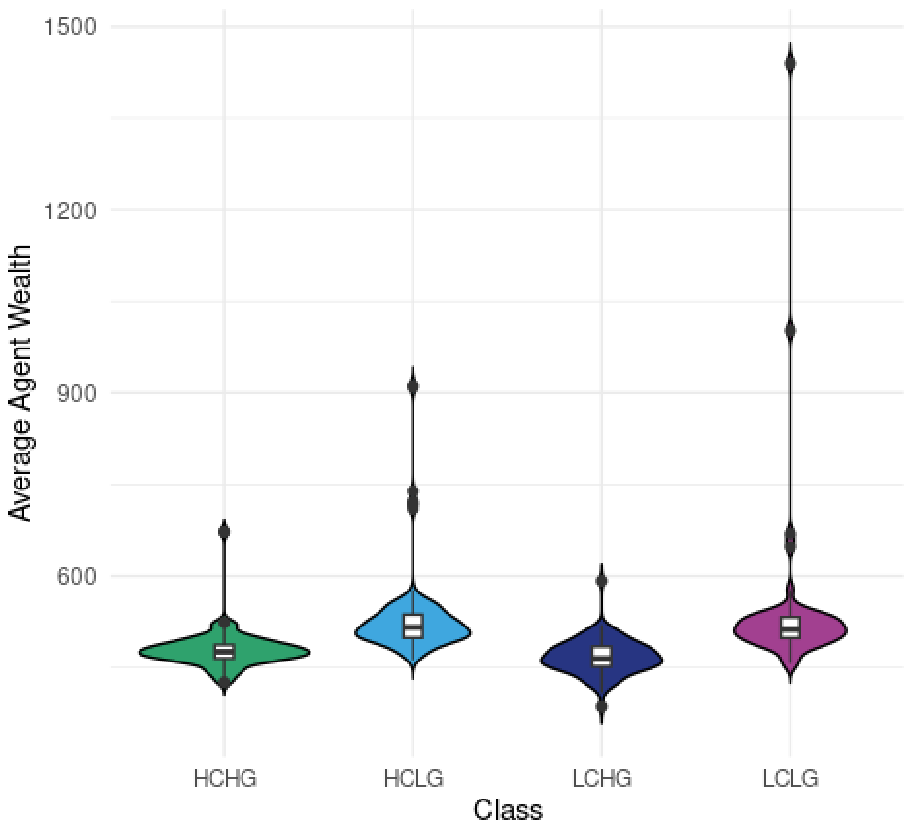

Figure 5. The average agents' wealth of each class

Following the argument above, inequality doesn't seem to play a significant role in the number of cheaters during simulation runs (Figure 6). As Figure 6 shows, in high cooperation situations, the number of cheaters is low, simply because, cooperation in the simulation is calculated based on the total number of cheaters. Therefore, putting aside the high Gini, in low collaboration situation, which is quite trivial given the model construction, whether the Gini is low or high (pink and light blue) does not significantly influence how many cheaters are present in the model. This outcome is quite counterintuitive as the common perception is that in communities with high inequality, the number of cheaters is also higher.

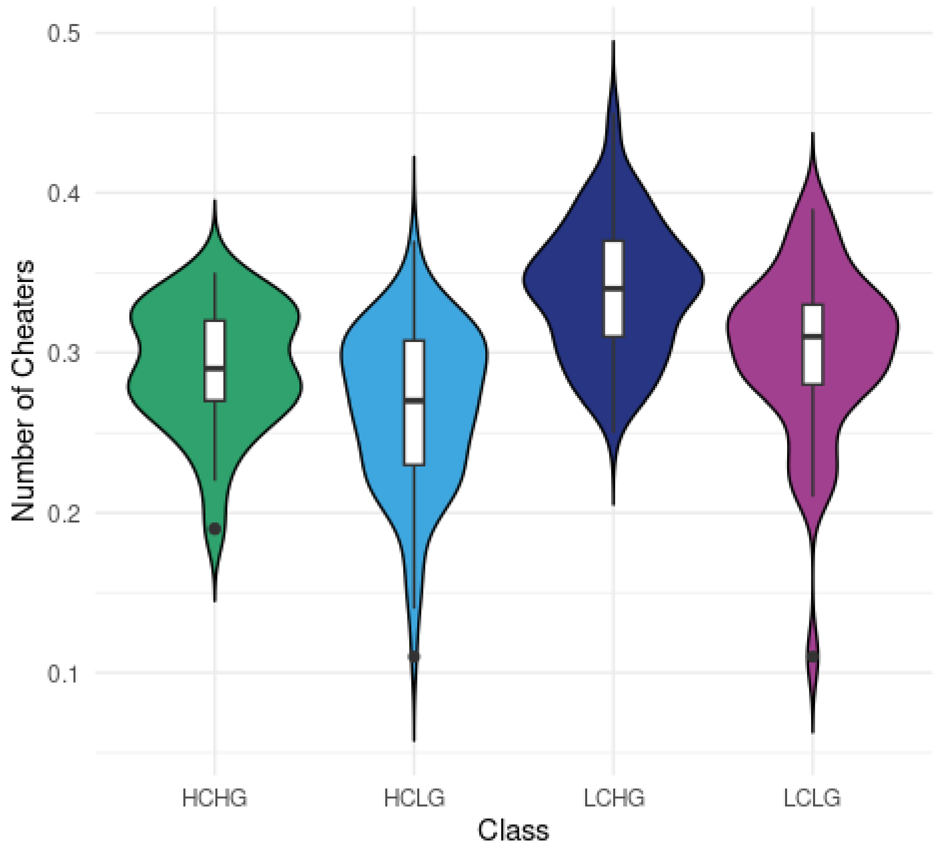

Figure 6. The number of cheaters for each class

Similarly, Figure 7 shows the number of non-voters relates to each class. Although participation in voting is not related to the level of inequality in the community, we observe a stronger relationship between non-participation and higher cooperation as compared to the cheater counts. In other words, participation in voting is more decisive in increasing cooperation than cheating behaviour. This holds for both high and low levels of Gini in the agent population.

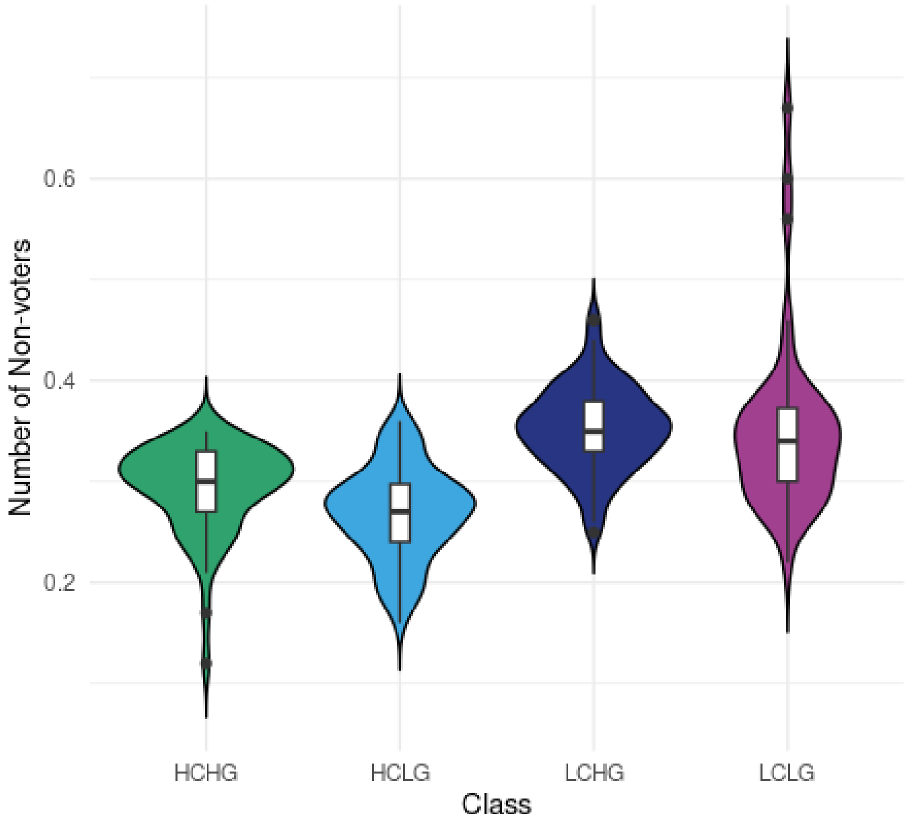

Figure 7. The number of non-voters for each class

3.5.4 Resource Characteristic under Different Cooperation Level and Gini

The amount of resource at the end of simulations for the four classes did not show any significant differences.

Although the medians are same across all classes, the averages are different (Appendix A). For HCLG and LCLG classes, which have low Gini, the amount of (average) end resource is higher. Therefore, we can conclude that low inequality, whether cooperation is high or low, generally leads to better CPR management regarding amount of resource left at the end of simulation.

3.6 Conclusion

The existing literature presents varying perspectives on the impact of wealth inequality on cooperation in CPR management. Although a negative correlation between wealth inequality and cooperation appears intuitive, certain studies propose the opposite (a positive correlation) or a non-monotonic relationship (positive in some parts and negative in other parts). This research seeks to examine the connection between wealth inequality and cooperation in CPR settings through simulations.

We explored the relationship between cooperation and inequality. Furthermore, we studied how this relationship influences the status of the CPR in terms of 1) institutional characteristics (number of institutional changes, emergence time of the first institution, and institutional stability), 2) population characteristics (average number of cheaters, average number of non-voters, average agents' wealth), and 3) resource characteristic (average amount of end resource).

The model confirmed an inverse relationship between inequality and cooperation. Higher levels of inequality harm cooperation. Looking at all diagrams, we can conclude, that low inequality and high cooperation level can be observed in most successful CPR management situations, where the resource and appropriators are generally in good conditions. However, in situations where the resource or the appropriators are in less acceptable conditions, no conclusions can be drawn about the state of cooperation or inequality.

Finally, previous research, highlight the importance of institutions for successful management of CPR. Taking that as a starting assumption, our results suggest that later emergence of the first institution, regardless the level of inequality, causes high cooperation at the end. We could not observe any significant relation between the number of institutional change and institutional stability and inequality/cooperation. One reason could be that the parameter settings in our model limited the number of institutional change. The average number of institutional change is between 7 to 8 for almost all classes. These numbers are model artifacts. The conceptualization allows agents to come together at specific moment during simulation (Institutional emergence time) to decide on whether they need to stablish a new institution or not. Therefore, the value of this parameter and also the number of total ticks, limit the number of institutional changes in a certain range. In the future works, we consider varying the institutional change more so that the effect of institutions could be explore better.

The study also faced some limitations. First, we simplified some agents' specifications. In future work, it is suggested to consider different types of heterogeneity (cast, power, or preferences) to increase the generalisation of the result from wealth inequality to heterogeneity in general and to define more sophisticated behaviour and rules. Also, it is recommended to extend the definition of cooperation by considering different types of cooperation and further analyse which types have what impact on the relationship between inequality and cooperation.

3.7 Appendix A. Statistical Description of the Four Classes

Statistical Description of the Classes

Characteristics of		**Institutions**			**Population**			**Resource**
Class	**Median/Mean**	**Number of institutional change**	**Institutional stability**	**Emergence time of the first institution**	**Agents' wealth on average**	**Number of cheaters**	**Number of non-voters**	**Amount of resource**
HCHG	median	8.0	200.0	399.0	473.0	29.0	31.0	1.0
	mean	7.8	200.0	445.7	471.5	28.6	29.6	0.9
HCLG	median	8.0	200.0	399.0	513.0	27.0	27.0	1.0
	mean	7.8	200.3	430.8	529.0	26.6	26.7	773.0
LCHG	median	8.0	200.0	399.0	464.0	34.0	35.5	1.0
	mean	8.1	200.0	370.1	466.4	33.7	35.5	298.6
LCLG	median	8.0	200.0	399.0	507.5	31.0	32.0	1.0
	mean	8.1	200.4	376.1	529.3	30.8	33.3	681.5

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4 Using Machine Learning for Agent Specifications in Agent-based Modelling and Simulation: A Critical Review and Guidelines[1]

Abstract

Agent-based modelling and simulation (ABMS), whether simple toy models or complex data-driven ones, is regularly applied in various domains to study the system-level patterns arising from individual behaviour and interactions. However, ABMS still faces diverse challenges such as modelling more representative agents or improving computational efficiency. Research shows that machine learning (ML) techniques, when used in ABMS can address such challenges. Yet, the ABMS literature is still marginally leveraging the benefits of ML. One reason is the vastness of the ML domain, which makes it difficult to choose the appropriate ML technique to overcome a specific modelling challenge. This paper aims to bring ML more within reach of the ABMS community. We first conduct a structured literature review to investigate how the ABMS process uses ML techniques. We focus specifically on articles where ML is applied for the structural specifications of models such as agent decision-making and behaviour, rather than just for analysing output data. Given that modelling challenges are mainly linked to the purpose a model aims to serve (e.g., behavioural accuracy is required for predictive models), we frame our analysis within different modelling purposes. Our results show that Reinforcement Learning algorithms may increase the accuracy of behavioural modelling. Moreover, Decision Trees, and Bayesian Networks are common techniques for data pre-processing of agent behaviour. Based on the literature review results, we propose guidelines for purposefully integrating ML in ABMS. We conclude that ML techniques are specifically fit for currently underrepresented modelling purposes of social learning and illustration; they can be used in a transparent and interpretable manner.

Keywords*:* machine learning, agent-based modelling, modelling purpose, structured literature review, guidelines

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4.1 Introduction

Five decades after Schelling's (1971) model of segregation, the embryonic decades of agent-based modelling and simulation (ABMS) have passed, and its role has changed into a more mature method with worldwide and domain diverse applications. As the application of ABMS in different fields of study has increased, the demand for efficient and intelligent tools that enable the development of more advanced models is evident and also highlighted in the literature (An, 2012; Kavak et al., 2018; Macal & North, 2010; Rand & Rust, 2011). In addition, agent-based models (ABMs) also face challenges related to insufficient or incomplete data (Heppenstall et al., 2011), dealing with uncertainty (Galán et al., 2009; Sun & Müller, 2013), modelling human irrational behaviour (Sankaranarayanan et al., 2017) and tuning parameters (Zhang et al., 2016). Another, more conceptual, challenge with ABMS is that these models are rule-based (Kocabas & Dragicevic, 2013) meaning that the modeller programs predefined rules that the agents behave upon. However, if agents are to learn from their past experiences, they may need to adapt those hard-coded rules (Lorscheid, 2014) and parameters (Remondino & Correndo, 2006) during simulation runs.

In order to address many of these challenges, it is beneficial to increase the degree of intelligence and learning in ABMS, which has also been encouraged and highlighted in the literature (An, 2012; Kavak et al., 2018; Macal & North, 2010; Rand & Rust, 2011). Machine Learning (ML) techniques can provide great potential to bring higher degrees of intelligence and learning into the models. ML is a subfield of Artificial Intelligence that aims to enable computers to learn based on input data without explicitly programming all requirements (Samuel, 1959). ML allows for developing more precise and reality-based models and provides better means for handling data (Bonabeau, 2002).

In ABMS literature, ML techniques are already used to address various challenges. For example, to represent or enhance decision making, modellers use Bayesian Networks as a learning tool for highly uncertain conditions (Alexandridis & Pijanowski, 2007; Lei et al., 2005; Sun & Müller, 2013), Neural Networks for building realistic simulations and providing specific behavioural features for each agent (Laite et al., 2016) and Decision Trees to construct rules that agents will act based upon (Chu et al., 2009). The literature provides a wide range of case-specific approaches that either aim to bring learning in the model or to process output data.

Yet, the ABMS literature is still marginally using ML techniques; we identify two reasons. First, ML is a broad field with numerous techniques, making it difficult to choose the most appropriate ML technique to support a specific modelling challenge, e.g., improving behavioural representativeness and accuracy. Second, depending on what purpose the model is aiming to serve, e.g., prediction or explanation (Edmonds et al., 2019), the usefulness of ML techniques may vary. Determining the modelling purpose is crucial for determining “how one builds, checks, validates and interprets a model” (Edmonds et al., 2019, p.1). Hence, the ABMS purpose also influences the choice of the ML technique that is selected to overcome certain ABMS challenges. Therefore, a literature review that provides an overview of techniques useful to address various challenges in ABMS based on modelling purposes can greatly benefit this flourishing modelling community.

There are already a handful of literature reviews on using ML in ABMS. W. Zhang et al. (2021) review literature on ML for the agents' decision-making, distinguishing between micro-agent-level situational awareness learning, micro-agent-level behaviour intervention, macro-ABMS-level emulator, and sequential decision-making. Dahlke et al. (2020) provide a general literature review on using ML for the structural specifications and outputs of ABMS. Their findings constitute an insightful summary of the common advantages and disadvantages of using ML in ABMS. However, it remains unclear which ML techniques can support different ABMS purposes and respective challenges and how. A review of ML and data-driven methods in energy-market models is given by Prasanna et al. (2019). Pereda et al. (2017) provide a brief introduction to the use of ML in the analysis of ABMS outputs. Despite their insightful contributions, none of these reviews considers the specific challenges in ABMS nor the modelling purposes while analysing the use of ML in ABMS.

This paper aims to bring ML more within reach of the ABMS community by proposing guidelines to use the most appropriate ML technique that addresses a specific modelling challenge given a modelling purpose. We provide a structured literature review on the application of ML in ABMS with a specific focus on model purpose according to Edmonds et al. (2019). The identified purposes will be linked with ABMS challenges that ML can address, e.g., increasing computational efficiency. Hence, our main research questions (RQs) are also formulated on exploring these two relationships: “Which ABMS challenges are most relevant for which modelling purpose?”, and “Which ML techniques can support which ABMS challenges?”. Answering these RQs has these added values: First, it gives a state-of-the-art overview of the use of ML in ABMS. Second, guidelines for purposefully supporting ABMS with ML can be derived. Lastly, research gaps in the use of ML in ABMS can be identified.

Given the broad range of ML techniques – from statistical regression to deep learning (Jordan & Mitchell, 2015) – we narrow down the scope in several ways. First, we divide the overall ABMS process into two parts: structural specification, and output analysis. Techniques used for the analysis of simulation output are usually common data analysis and data mining approaches[1] (Libbrecht & Noble, 2015). This step is quite independent of the main purpose of modelling or the actual simulation. Furthermore, there is a grey area in data science research about ML techniques (i.e., is regression a ML technique or statistics?) and leading to a very high number of articles, where the contribution of ML is not necessarily explicit for ABMS purposes but for data analysis in general. Since our goal is to show how ABMS can benefit from ML to address various modelling challenges, we will focus on ML techniques that are integrated into the model for structural specifications: into the decision making of agents, agent logic, or agent interaction rather (and not for the analysis of output data). Finally, to further narrow down the scope of our paper, we will not be looking into agent-oriented software systems that are mainly for control purposes and are installed in real-world applications, e.g., agents in smart grids or traffic systems, usually referred to as multi-agent systems (MAS) (Macal, 2016). Because these systems have different objectives such as real-time response or security, the application of ML can be different - see Prasanna et al. (2019) for an overview. Hence, we only focus on agent-based simulation models.

This paper is organized as follows: The section ‘Theoretical Background’ sets the scene by providing the theoretical foundations on purposeful modelling and a summary of the foundations of ML in ABMS. The section ‘Methodology’ presents the research methodology. The section ‘Results’ presents the results. The section ‘Discussion and Guidelines’ includes the

[1] It is worth mentioning here that the domain of ML is different from Data Mining (DM), which is the process of finding data patterns from large datasets by using intelligent methods (Han et al., 2011). The main difference here is *learning*: ML techniques learn based on data while DM techniques find hidden patterns without using learning ability. However, there are some common techniques that can be used with or without learning, meaning that some techniques e.g., clustering can be categorized in DM as well as in ML techniques depending on how users apply them.

discussion as well as the guidelines. Finally, the section 'Conclusion' summarizes the article, describes the limitations, and proposes future research possibilities.

4.2 Theoretical Background

This section provides the theoretical background both for understanding the modelling purposes and for the application of ML in ABMS.

4.2.1 Modelling purposes

ABMs can be created for multiple purposes. Edmonds et al. (2019) distinguish seven modelling purposes[1], summarized shortly in the following:

- **Prediction:** Prediction is defined as the ability to anticipate ***specified aspects*** of ***currently unknown*** data with a ***valid level of precision*** in a ***reliable*** manner through a computational model. Often, the capacity of a model to make predictions is considered the most robust indicator of a model's "truth". For example, Lee et al. (2018) use an ABMS to predict the bitcoin price trend by simulating the rational agents' behaviour in the market.
- **Explanation**: Explanation is defined as the creation of a ***possible causal chain*** from an event to its ***consequences*** based on the structure of a simulation model. Particularly with complex social phenomena, there is a special interest in understanding why something happens. This understanding is essential for managing complex systems. As an example, Xanthopoulou et al. (2022) use an ABMS to explain the casual architectures of bullying.
- **Description:** Simulation models can be used to ***partially*** represent the ***important aspects*** of a particular system. This however does not mean that description aims at entirely replicating the system – but rather focusses on documenting what is important. For example, Pagani (2022) applies an ABMS to describe the importance factors in the process of relocations of tenants.
- **Theoretical exposition:** Theoretical exposition means a systematic mapping and establishment of consequences of mechanisms. It includes formulating and ***subsequently*** evaluating or testing ***hypotheses*** on the ***general behaviour*** of a mechanism. For example, Ale Ebrahim Dehkordi et al., (2021) use an ABMS to support theory development and test hypotheses about the underlying reasons why some specific historical patterns emerged in hundreds of years.
- **Illustration:** Illustration focusses on ***clearly*** communicating an idea in often a ***simplified*** and ***exemplary*** manner. It is important that illustrations do not impose assertions but rather focus on highlighting complexities in systems. For example, Delay and Piou (2019) illustrate the impact of resource scarcity on group cooperation by using an ABMS.
- **Analogy:** We speak of an analogy when ***processes*** in a simulation are used as a ***tool*** to ***informally think about something***. It often includes using ideas or concepts from other domains and hence can be useful in reflecting about something with a different perspective. The computational game proposed by Axelrod (1984) is one example of Analogy type of ABMS, which shows a new way of thinking about the process of cooperation.
- **Social learning:** Social learning "encapsulates a ***shared understanding*** (or set of understandings) of a ***group of people***" (p.16). For social learning, the participatory factor is of overriding importance. The model helps people, often from different domains and

[1] Although other modelling purposes can exist, these seven appear most relevant for social simulations (Hauke et al., 2017; Squazzoni et al., 2014).

with different world views, capture a unified understanding. For example, Dumrongrojwatthana et al. (2011) use an ABMS to manage the conflicts between herders and foresters on land-use in northern Thailand. This social learning model helps them to come up with a mutual understanding on the land-use dynamics.

According to Edmonds et al. (2019, p.1) the modelling purpose determines “how one builds, checks, validates and interprets a model”. Hence, if an existing model is used for a different purpose, the modelling processes needs to be reiterated for the new purpose (Edmonds et al., 2019). This means that the modelling purpose also influences the choice of the ML technique, which is selected to overcome the modelling challenges.

4.2.2 Machine Learning in Agent-based Modelling and Simulation

This sub-section summarizes the various ML categories and techniques and provides an overview of the reasons for applying ML in ABMS.

Categorization of ML techniques

ML techniques refer to algorithms that can find patterns and predict outcomes by learning from input data and without programming all requirements explicitly (Murphy, 2012; Samuel, 1959). Many different techniques and algorithms are labelled as ML. Yet, all ML algorithms have three common components (Domingos, 2012): representation, optimization, and evaluation. The *representation* of the ML algorithm must be in a formal way that can be interpreted by a computer. The *optimization* aims to find the minimum or maximum of a goal function under given constraints. In fact, each ML technique can be assumed as an optimization problem in the sense that it learns to optimize solutions for a specific goal function. Finally, the *evaluation* component determines whether an ML algorithm performs according to expectations. In general, ML techniques can be divided into three main learning categories (Alpaydin, 2009):

- **Supervised learning (SL)**: In SL, the output variables are known (labelled) and the algorithm learns to map inputs to outputs (Cunningham et al., 2008). This mapping can then be applied to unknown input data to predict the desired output (Cunningham et al., 2008). For example, spam detection is a SL problem that a set of labelled examples (spam or regular emails) is provided for the model. The algorithms learn to find the pattern to distinguish between these two categories and predict if a new email is spam or not. SL includes classification and regression problems – see Alpaydin (2009) .
- **Unsupervised learning (UL)**: In contrast, there are no output variables to learn from in UL algorithms (Mohri et al., 2012). Instead, the algorithm learns to identify the distribution, or the structure of input variables. For example, customer segmentation is a UL problem, which finds the clusters of customers based on common characteristics. UL algorithms include clustering, and association problems - see Dutta et al. (2018) and Hastie et al. (2009).
- **Reinforcement learning (RL)**: In comparison to the other categories, RL agents[1] receive information by interacting with the dynamic environment and learn through trial-and-error by receiving rewards for good behaviour (Mohri et al., 2012). The goal of the RL

[1] The term “agent” is both used in RL and ABMS. To avoid confusion, we always refer to agents in RL as RL agents.

agent is to maximize its rewards (Kaelbling et al., 1996). RL is similar to training a dog - the dog learns what to do or not to do through rewards.

In Table 1, the main characteristics of the three categories of ML techniques are highlighted.

Table 1. Overview of ML categories

ML category	Data	Objective	Learning
Supervised	Labelled	Prediction	By mapping inputs to desired outputs
Unsupervised	Unlabelled	Identification of structures or patterns	By identifying the distribution or the structure of input
Reinforcement	Interaction with environment	Optimization	By rewarding good behaviour

ML techniques in ABMS

In the following, we provide a brief explanation for the four most common[1] ML techniques in ABMS:

- **Bayesian Network (BN):** A BN is a probabilistic dependency graph including a set of interconnected nodes, where each node represents a variable, and the connecting links represent the causal relationships between these variables (Niedermayer, 2008). Each variable has its probability in the dependency graph. BNs aim to model conditional dependencies and causations in the form of directed graphs. Hence, BNs are useful for predicting the occurrence of an event considering all possible causes. BNs can be trained both in a supervised manner via expert knowledge, or in an unsupervised manner based on large datasets (Flores et al., 2011; Horný, 2014). Overall, BN is a good white-box method to deal with small and incomplete datasets, uncertainty, and different sources of knowledge (Jensen, 1996; Uusitalo, 2007). However, converting the expert knowledge into probability distributions can be difficult (Uusitalo, 2007).
- **Neural Network (NN):** NNs are artificial networks, which attempt to simulate the biological nerve cell network. They include many interconnected processing elements working in parallel to solve a certain problem, which can be both supervised and unsupervised. Moreover, as NNs are nonparametric algorithms (Fogel et al., 1990), which do not need a bounded set of parameters (Russell & Norvig, 2016), they can be used for a large diversity of problems. Although NNs are strong in adaptation, learning, and approximation, the convergence speed is low. Also, since it is a black box, the interpretation can be a challenge (Shapiro, 2002). Additionally, data gathering, and parameterization can be difficult.
- **Decision Tree (DT):** DTs are predictive algorithms in the form of trees, which have branches that represent observations and leaves that outline conclusions. There are two ways of applying DT: classification and regression (Olkin, 2002). For the classification DT (discrete values), leaves are class labels and branches are the links between class labels. In contrary, in a regression DT (continuous values) the leaves can have ranges for

[1] Each category of ML includes several techniques. And some techniques can be differently used in more than one category. These four techniques are the most common ML techniques used for the structural specifications of agents, identified from the 71 articles from the structured literature review conducted in the next chapter, see Figure 5.

the regression. DTs are mostly used in a supervised approach. The advantage of using DTs is the clear knowledge representation, easing interpretation even by non-experts (Jadhav & Channe, 2016). Moreover, DTs can map non-linear relationships quite well and can handle missing values (Wu et al., 2008). The disadvantages of these algorithms are the long training time (Jadhav & Channe, 2016), overfitting, and no support of real-time learning, meaning that the tree needs to be rebuilt for new data (Brijain et al., 2014).

- **Reinforcement Learning (RL):** RL builds on reinforcement agents that learn by interacting with the environment and receiving rewards for correct answers. This implies that the correct answer or labelled data is not required for the training phase (Mohri et al., 2012). The reinforcement agents determine their own performance according to the received reward as a feedback from the environment (Sutton & Barto, 2018). One of the most popular RL algorithms is Q-learning. Q-learning enables reinforcement agents to act optimally in Markovian domains by experiencing the consequences of actions, without requiring them to build maps of the domains. At each specific state, the reinforcement agent tries an action and evaluates its consequences in terms of the immediate reward or penalty it receives from the environment and estimates the value of the state that is taken. By trying all actions in all states repeatedly, the reinforcement agent learns the best overall solutions (Watkins & Dayan, 1992). As RL is basically a search algorithm, the time for finding a good solution increases in relation to the size of the data (Marsland, 2011).

Addressing challenges in ABMS using ML

To explain how modellers can benefit from these ML techniques, we divide the overall ABMS process into two main parts: (1) structural specifications, and (2) model output analysis. The structural specifications can be further represented as a cycle: agents observing the world, agents updating their internal model, and agents taking action (Rand, 2006). For each of the two main parts we identify key ABMS challenges from literature, which can be addressed with the help of ML as depicted in Figure 1.

- **Structural specifications:**
    - In ABMS, we are dealing with non-linear multi-parametric models where noise is an intrinsic part of input data. According to Heppenstall et al. (2011), ML techniques can be used to minimize the impact of these noises, which include missing or insufficient data. When data is sufficiently available for modelling purposes, ML techniques can be applied on raw data for pre-processing and calibration – see Zhang et al. (2016) and Lamperti et al. (2018). Alternatively, ML techniques can be applied to find meaningful patterns or trends based on real-world data (e.g., extracting a DT from real-world data). Finally, in cases where real-world data is not used in the model, ML techniques can be used to generate synthetic data (Ratner et al., 2016). All in all, ML can be helpful to ***improve the data pre-processing*** for the ABMS input.
    - With regards to the internal specifications of the model such as defining agent behaviour, decision making, and interaction, we determine multiple ABMS challenges which can be addressed by ML: Dealing with uncertainty (Galán et al., 2009; Sun & Müller, 2013), modelling human irrational behaviour (Sankaranarayanan et al., 2017), as well as rule definition and adaption (Lorscheid, 2014). Macal (2016, p.152) refers to this as the “behavioural modelling challenge” and hence, we summarize these challenges in one ABMS challenge: ***improving the accuracy of behavioural modelling***.

  - Another considerable hurdle during the model executing stems from the increasing scale of ABMS and the resulting computational challenges such as long simulation time (Macal, 2016). ML can be helpful in ***improving the computational efficiency*** of ABMSs– for instance via surrogate models (van der Hoog, 2019). A surrogate ML model can be seen as a computational approximation or emulator of an ABMS, which learns the relationship between ABMS in- and output to achieve reliable results in a more efficient and timely manner (van der Hoog, 2019).
  - Moreover, ML can ***improve the ease of implementation*** of ABMSs, e.g., easier model-adjustment to new geographic locations (Drchal et al., 2019).
  - Lastly, Macal (2016) mentions a lack of transparency of ABMS, which can lead to low credibility of results. Some ML techniques can help overcome this hurdle by making the structural specifications more transparent – see Sun & Müller (2013). We call this ABMS challenge ***increasing model understanding***.
- **Model output:** With the increasing complexity of large-scale ABMS, it becomes more and more difficult to extract meaningful information from the simulation output (Macal, 2016). ML techniques can be used to analyse the output of the simulation and to extract patterns. Additionally, these intelligent techniques can be applied for validating ABMSs (Parry et al., 2013) and checking the robustness of results (Filatova et al., 2013). Overall, ML can ***increase the understanding of model outputs***.

These reasons for using ML are not mutually exclusive, as two modelling challenges might reinforce each other, nor are they collectively exhaustive, as other ABMS challenges and hence ML reasons might exist.

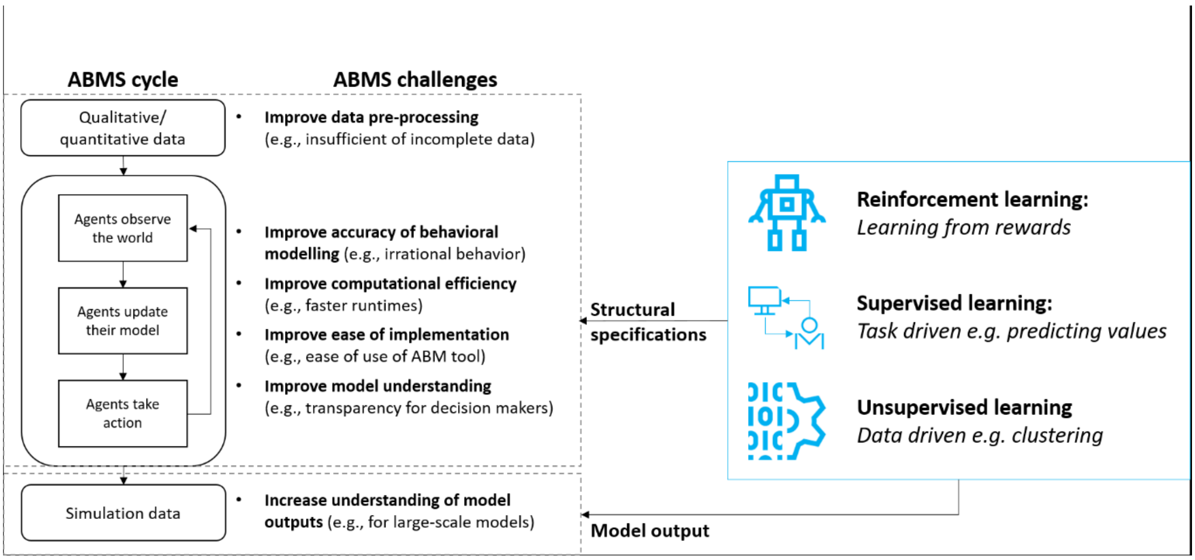

Figure 1. ML in the ABMS process – ABMS cycle adapted from Rand (2006)

As it appears in the literature, intelligent techniques are extensively used for the analysis of simulation outputs (Remondino & Correndo, 2006). These techniques, however, are mostly for advanced data analysis and data mining, which are not necessarily specific to ABMS. Another issue related to output usage of ML techniques in ABMS is that it is a grey area between routine statistics, data mining and machine learning, making it difficult if not impossible to distinguish ML techniques from other techniques such as regression techniques. Given that our aim in this research is to bring ML more within reach of the ABMS community by adding more "intelligence" into simulations, we leave out the output phases of ABMS and only focus on how the actual model [i.e., agents and interactions] can benefit from these techniques.

To summarize, an ABMS is designed for a specific purpose such as social learning. These models can face a variety of challenges that ML can address e.g., improving the accuracy of behavioural models. Thus, there is a 1 to N relationship between the ABMS purpose and the ABMS challenge. To address these challenges, modellers can choose from different ML techniques such as NN. As the ML techniques can support multiple ABMS challenges, there is a N to M relationship between ABMS challenge and ML technique. The relationship between these three features is summarized in Figure 2.

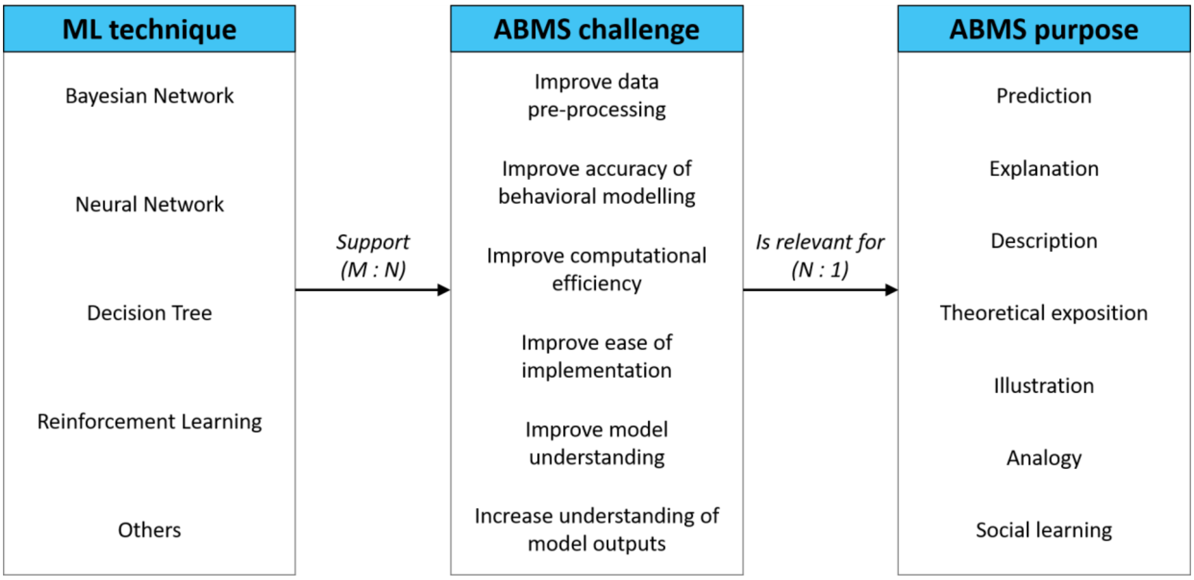

Figure 2. Relationship between ML technique, ABMS challenge, and ABMS purpose

4.3 Methodology

We conduct a structured literature review (SLR) according to the guidelines of Kable et al. (2012). The purpose of this SLR is to identify papers in which ML is applied for the structural specifications of agents. Hence, the research string – see Figure 3– combines three different categories of keywords: ABM, ML, and structural specification. Although there are papers which use the term of ABMS and MAS synonymously (Macal 2016), we exclude MAS from the research string as this would drastically increase the research results. To identify the application of ML in ABMS, we include the ML categories (see Section 'Theoretical Background') in the search string. Lastly, to identify the use of ML for the structural specifications of agents, we search for "decision making", "agent logic", and "agent specification". Additionally, common abbreviations such as "ABM" are included.

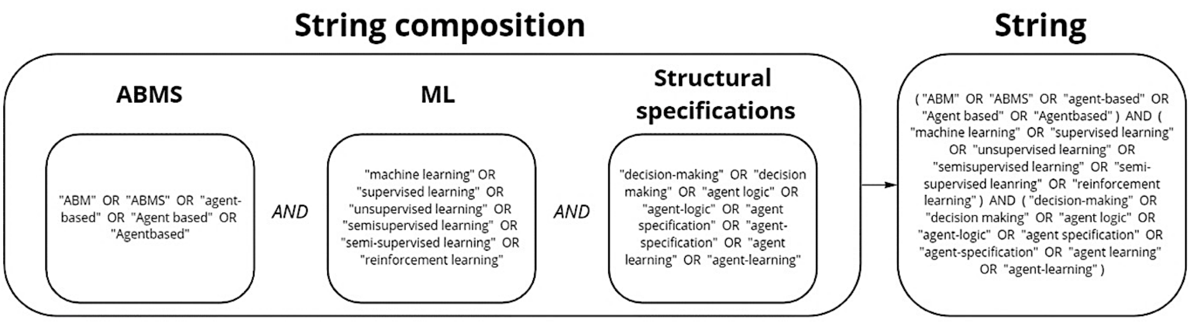

Figure 3. Search String Composition

To conduct the search, we use the bibliography search engine Scopus. We search for records within the titles, keywords, and abstract to have a better chance of identifying suitable articles. Furthermore, only English papers are searched for. Moreover, reviews are excluded, as we want to identify specific ABMS applications to be able to identify the modelling purpose. The full search string is shown in the appendix A.

The review was conducted on the 8th of December 2021 and resulted in 238 hits. A multi-stage screening is applied to the results. First, we exclude 68 records, as they do not discuss ML in ABMS, e.g., books containing separate articles on ML and ABMS. Second, 101 records are removed, as they do not apply ABMS, but MAS instead. The excluded articles focus mostly on traffic, production, financial, and energy control systems focussing on system control and optimization. Third, we remove 16 articles, as they do not focus on specific ABMS applications, which are required to determine the ABMS purpose. Next, three articles are excluded as they focus specifically on analysing output of ABMS using ML without targeting the agent behaviour. Lastly, we remove seven articles, as they are not accessible or in a different language despite applying the English filter. This results in 43 suitable articles, which we directly identified via the SLR. Using snowballing, 28 additional eligible records were identified[1], leading to 71 articles in total.

These 71 articles are analysed with regards to the modelling purpose, the applied ML techniques, and the ABMS challenge. Despite the fact it is fundamental for determining the usefulness for an ABMS, (as argued for by Edmonds et al., (2019)), the modelling purpose is often not explicitly mentioned in the papers. Hence, we classify the purposes based on the author's descriptions of the modelling process and results. When the authors refer to another paper for all the ABMS details, we assume no change in purpose and analyse the purpose based on the original paper. Similarly, we identify the ABMS challenge from the description of the modelling challenges.

Sometimes the description of the model is associated to more than one specific purpose and most often the purpose is not clearly stated in papers. To minimize bias, this analysis is conducted by a group of interdisciplinary researchers. Two researchers classify the purpose of the model used in each paper, the ML technique, and the ABMS challenge independently. In case of misalignment, the cases are discussed and resolved, sometimes with the help of a third researcher. This 4-eye review in combination with the interdisciplinary backgrounds reduces the potential effect of observer dependency on the classification results.

4.4 Results

The identified articles are summarized in Table 3 in appendix B together with the classification of the respective ML techniques, the ABMS challenges and the modelling purposes. The articles are distributed between the years 1999 - 2021, whereas more than half were published in the last five years as shown in Figure 4.

[1] These articles, which have been found in this round were not necessarily based on the Scopus. For these articles we focused on finding the articles' titles anywhere rather than concentrate on one specific database.

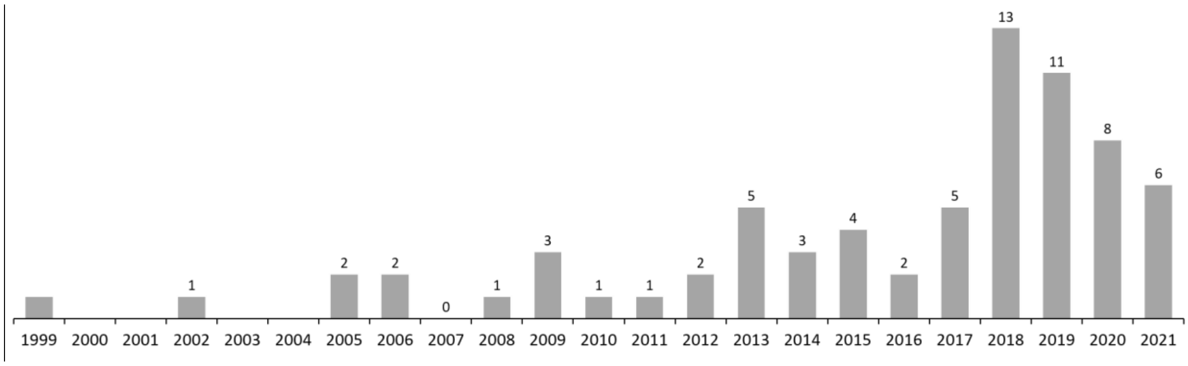

Figure 4. Distribution of included articles over the years

First, we analyse the distribution of modelling purposes, ABMS challenges, and ML techniques as depicted in Figure 5. The following observations can be made:

- **ABMS purpose:** In total, there are 73 ABMSs, as two papers include multiple models for which ML is applied. Two third of the ABMSs have prediction, explanation, and description as a purpose. By contrast, illustration, social learning, and analogy are less common, with only five applications each.
- **ABMS challenge:** Improving the accuracy of behavioural modelling is by far the most common ABMS challenge with 65 applications. Moreover, improving data pre-processing is a relatively relevant challenge with 17 applications, followed by computational efficiency with 11 applications. Improving model understanding (6), ease of implementation (5), and understanding of model output (4) are least common. Again, it is important to highlight that we only look at applications of ML for the structural specifications of agents.
- **ML techniques:** Four ML techniques stand out: RL with 38 applications, followed at a greater distance by NNs with 12, DTs with 10 and BNs with 9 applications. The remaining ML techniques are genetic programming, support vector machines, self-organizing maps, and k-nearest neighbour and other algorithms, which in total are applied 10 times.

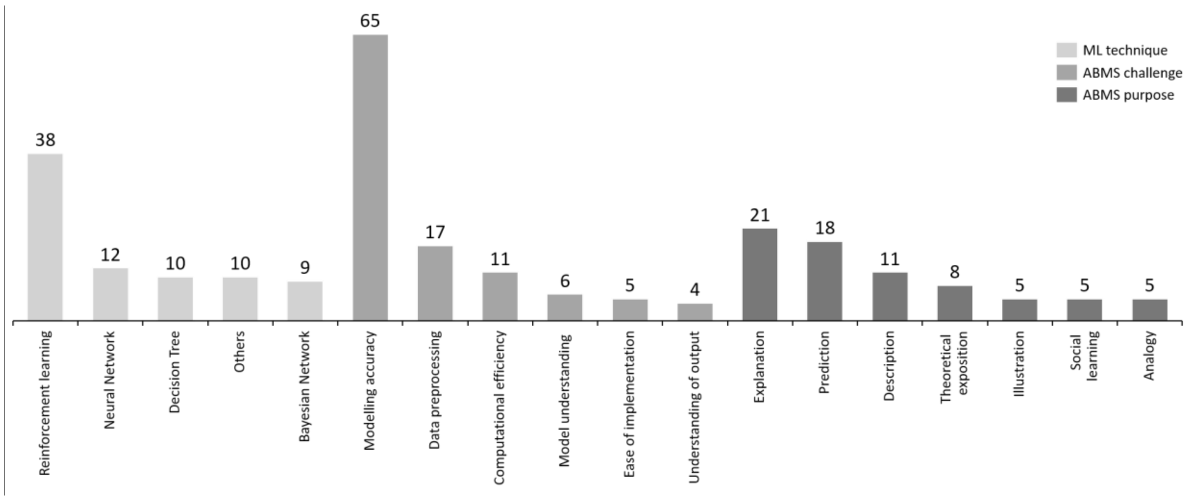

Figure 5. Number of applications of ML techniques, AMBS challenges, and modelling purposes

The results are further analysed regarding the relationship between ABMS purpose, ABMS challenge, and ML technique as shown in Figure 6 (and in Figure 7 in appendix D). To answer the first RQ, it is important to understand which ML techniques are applied for which ABMS challenge. Our results show that increasing the accuracy of behavioural modelling plays a significant role for all modelling purposes (50% to 80%). However, we cannot identify scientifically significant differences between the modelling purposes. This is partially driven by the fact that the number of observations for certain purposes are too low to derive conclusions e.g., for illustration.

To answer the second RQ, which considers the use of ML techniques for supporting ABMS challenge, the following two observations can be made. First, improving the accuracy of behaviour modelling has a relatively high proportion for all ML techniques (> 45%), especially RL (84%). RL is applied in 37 cases to improve the modelling accuracy of agent behaviour. Second, DTs and BNs with 6 applications each appear common ML techniques to improve the accuracy of data pre-processing for agent-behaviour. These two observations will be detailed in the following using examples from the SLR.

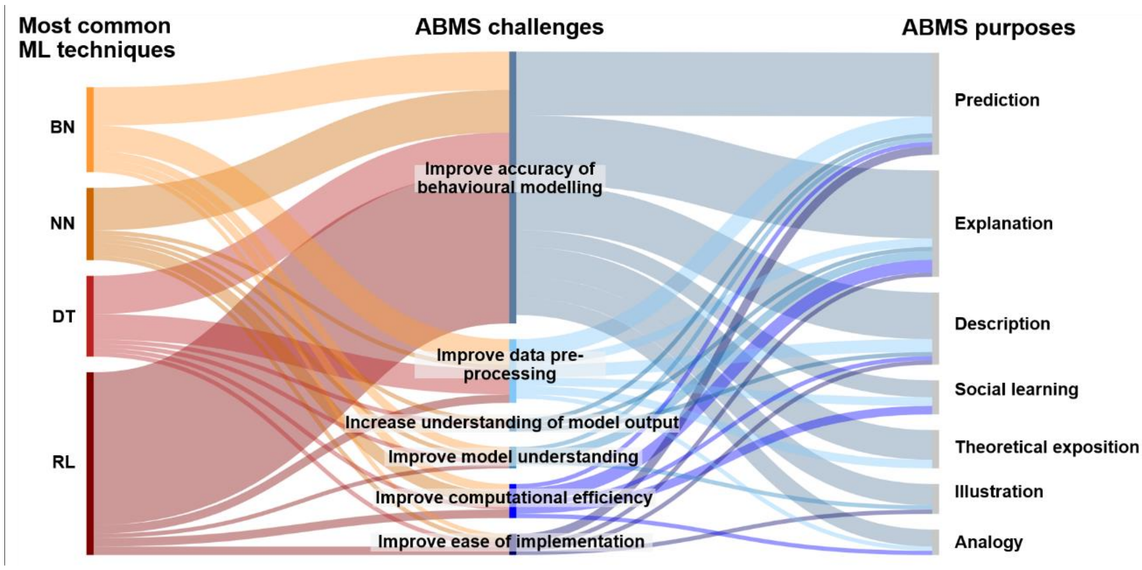

Figure 6. Relationship between applications of ML techniques, ABMS challenge, and ABMS purpose

4.4.1 Application of Reinforcement Learning to Improve the Accuracy of Behavioural Modelling

Our results show that to improve the accuracy of behavioural modelling in ABMS, RL is applied in more than 50% of ABMSs[1]. Therefore, we can assume RL as a relevant technique for improving the accuracy of behavioural modelling. It is applied in a large variety of domains. For instance, Li et al. (2019) apply an extended RL model, which takes into account both personal but also other agent's learning for the agent's decision-making in a residential land growth ABMS in Nanjing, China. According to Li et al. (2019, p.10) the extended RL model "contributed to the improvement of the model's simulation power and modelling agent's adaptive decision-making process to a certain extent." Gaines & Pakath (2013) compare two RL systems – a classical and an extended learning classifier – for the decision-making in the Iterated Prisoner's Dilemma. Bone & Dragićević (2010) use RL in an ABMS for multi-stakeholder forest management. Here, RL helps incorporating optimization procedures in ABMS, which enables forest companies to interact with the environment and with each other while learning how to maximize their profits.

[1] Based on Figure 7, RL is applied in 37 ABMSs to improve accuracy of behavioural modelling. While the summation of using other techniques to improve accuracy of behavioural modelling in total is 34.

In particular, Q-learning appears to be a popular RL technique in our domain. For example, Chen et al. (2020) use deep recurrent Q-learning to research complex economic systems. Instead of relying on ad-hoc rules for decision-making, this ML technique allows agent interactions with the environment for improving their strategies over time. Using such adaptive decision-making strategies enables the representation of internal feedback and emergence.

To understand the "popularity" of RL for improving behavioural modelling accuracy, we analyse the author's arguments for applying this ML technique. We identify four main reasons. First, RL appears a suitable technique for the optimization of decision rules that govern the agent behaviour (Froelich et al., 2006; Junges & Klügl, 2012). Second, RL can help in modelling adaptive agent behaviour (Gazzola et al., 2016; Li et al., 2019; Ramchandani et al., 2017). Third, RL can be used to model human decision-making more realistically (Al-Khayarin & Halabi, 2021; Hassanpour et al., 2021; Li et al., 2020; Pang et al., 2018). For instance, Al-Khayarin & Halabi (2021) apply RL to emulate the behaviour of people in the real-world in the context social distance measures. Lastly, by using RL, agents are able to learn from interacting with each other (Bone & Dragićević, 2010; Li et al., 2019) and with the environment (Jamshidnezhad, 2015).

4.4.2 Application of Decision Trees and Bayesian Networks to Improve Data Pre-processing for the Agent Behaviour

DTs and BNs appear favoured techniques of the ABMS community to support data pre-processing for agent-behaviour. Hence, it is of interest to see how and why these ML techniques are applied.

Decision Trees

Our results show a large span of DT applications for data pre-processing. For instance, Gaube et al. (2009) apply DTs from survey data and statistics for agent decision-making in the domain of land use change. Sengupta et al. (2018) apply DT to extract rules that govern the movement of monkey groups in Uganda based on GPS movement data. Sánchez-Maroño et al. (2017) derive behavioural rules for an ABMS, which models the low-carbon transition in Europe using a DT learned from questionnaire data. In the ABMS of Rosés et al. (2021, p. 6), agents "decide whether to commit a crime or not by means of a decision tree" based on a large variety of quantitative data (e.g., crime, street, taxi, weather, or land-use data).

We identify three main reasons from the authors' arguments for applying the DT for data pre-processing: First, DT appears a useful tool for extracting rules from data which then can be implemented in the simulation model for the decision-making (Rosés et al., 2021; Sengupta et al., 2018). Next, DTs can be applied on questionnaires or survey results hence providing an empirical foundation for the agent behaviour (Gaube et al., 2009; Sánchez-Maroño et al., 2017). Lastly, Sánchez-Maroño et al. (2017) highlight the DT's transparent structure and results which can be interpreted and critiqued by non-technical experts.

Bayesian Networks

Our results also highlight a variety of BN applications for the data pre-processing for agent-behaviour. For instance, Abdulkareem et al. (2018) use BNs for a cholera spreading model in Ghana to extract and model the behavioural patterns in an uncertain context. They show that intelligent agents using BN perceive risk in a more realistic way. Pooyandeh & Marceau (2014) use BNs amongst others to deal with incomplete information in their ABMS for simulating the negotiation procedure between agents in land development in Canada. The results show that the agreement can be achieved in fewer simulation runs because of the more human-like and intelligent algorithm. Sun & Müller (2013) use BN in agents' payment decision-making process for ecosystem services in land-use changes. The BN structure is derived from qualitative empirical data, expert knowledge, and quantitative survey data. This structure is then embedded in the agents to enable them to make land-use decisions under uncertainty. Kocabas & Dragicevic (2013) apply BN to derive behavioural rules from census data for simulating the negotiations for the evaluation of land development scenarios. This enables agents to learn based on their historical actions instead of using pre-defined rules.

To understand why the BN is common for improving data pre-processing to model agent behaviour, we analyse the authors' arguments for applying this technique and identify four main reasons: First, Abdulkareem et al. (2019), Kocabas & Dragicevic (2013), Sun & Müller (2013), Tian et al. (2020) highlight the ability of BN to deal with both qualitative data such as expert knowledge and quantitative data e.g., from surveys, which facilitates better decision-making (Heckerman & Wellman 1995; Uusitalo 2007). Second, Kocabas & Dragicevic (2013), and Pooyandeh & Marceau, (2014) emphasise BNs ability to handle incomplete or small data sets. Third, BNs are cable of dealing with uncertainty in decision-making (Abdulkareem et al., 2018; Sun & Müller, 2013). Lastly, BNs are capable to model causal relations (Sun & Müller, 2013), which better captures the decision-making of the agents (Ma et al., 2007).

4.5 Discussion and Guidelines

In this section, we discuss the results and derive guidelines for the application of ML in ABMS. While the first subsection "Discussion of results" focuses on how ML is currently used in ABMS, the second subsection "Guidelines for purposefully supporting ABMS with ML" is forward-looking and shows how ML can be used in ABMS.

4.5.1 Discussion of Results

In the following based on Figure 6 and Figure 7 in appendix D, we discuss the identified patterns of the ABMS purposes, ABMS challenge, and ML techniques.

ABMS purposes

For each purpose, based on the associated ABMS with, we investigate if the purpose is (un)common between the other purposes or not. We can distinguish two reasons why certain modelling purposes are common or uncommon[1] for ABMS applications that use ML: (a) the modelling purpose is in general (un)common for ABMS, and (b) ML is an (un)favourable tool for the ABMS community to support this purpose. Using this logic, we analyse the results to determine why certain purposes might be particularly (un)common.

- **Explanation:** We conclude that explanation is used in more than a quarter of the papers that use ML in ABMS and hence is a relatively common purpose in this cluster. At the same time, Macal (2016, p.146) argues that ABMS provides a "framework for explicitly specifying causal mechanisms." Hence, explanation in general appears a common purpose in ABMS, which can explain the high number in our ABMS/ML cluster.

- **Prediction:** We identify prediction as another common purpose in articles that use ML in their models. However, according to Edmonds et al. (2019, p.5): "Prediction (as we define it) is very hard for any complex social system. For this reason, it is rarely attempted". Hence, based on Edmonds et al. (2019, p.5), we conclude that it is not a common purpose for ABMS in general. ML is seen by the ABMS community as a suitable tool to increase

[1] There are also 8 ABMS for Theoretical exposition. The reason why we did not mention this purpose was that we aimed to mention the purposes with the highest number of ABMS associated with and simultaneously the purposes with the lowest number of ABMS.

the reliable anticipation of data, which is one of the key pillars of a prediction model (Edmonds et al., 2019). This is supported by our results showing that *increasing modelling accuracy* is the most relevant ABMS challenge that can be addressed by ML. It means that although prediction is a common purpose based on our analysis, the more than half of the cases (16 out of 27) there are related to *improving the accuracy of behavioural modelling.*

- **Description:** Description is the third most common purpose in articles that use ML in ABMS research. On the one hand, this can be explained by the fact that ABMS provides a good basis for descriptive purposes as actors can be directly described via agents and as it allows the representation of dynamics and interactions in a system (Edmonds et al., 2019). On the other hand, Edmonds et al. (2019, p.8) highlight that the "simulation has to relate in an explicit and well-documented way to a set of evidence, experiences and data." Our results support this argument by showing that DT or BN are suitable tools to build descriptive models based on a variety of data sources.

- **Illustration:** We only identified a few cases of ABMS with illustrative purposes. We think that ML might not be the right tool to support illustrative purposes. For illustrations, the model clarity is of overriding importance (Edmonds et al., 2019). Rudin (2019, p.206) points out problems with so-called "black box" ML models, which are mainly models that are "too complicated for any human to comprehend". Hence, adding such an untransparent algorithm can negatively impact the model clarity. This might explain why illustrations are so rarely observed.

- **Social learning:** We only observe five ABMSs with a social learning purpose in our cluster. It appears that ML is not seen as a highly suitable tool to support social learning ABMS. On the one hand, the development of social learning models (for environmental management) can be very time-consuming (Barreteau et al., 2003). Adding ML to the model development process might thus exceed the available timeframes. On the other hand, the lack in transparency of some black box models might counteract a shared understanding.

- **Analogy:** Analogies are also rarely observed. On the one hand, we think that analogies are not common for ABMS in general, as not every idea might be applicable in a bottom-up manner. The ABMS community might view ML as too complicated and resource-intensive to support an informal way of thinking about an idea.

ABMS Challenges

Here we reflect on the main challenges for the structural specifications of agents, which the ABMS community perceives can be overcome with the help of ML. We will discuss in the following why certain ABMS challenge are more common than others.

- **Accuracy of behavioural modelling:** According to Van Dam et al. (2012, p. 60) the "overall system (or model) behaviour is an emergent property of the interactions between all of the agents behaviours and the environment." As the agent behaviour drives the system behaviour, we argue that increasing the accuracy of the agent behaviour directly influences the accuracy of the system behaviour. We, therefore, conclude that increasing the accuracy of behavioural modelling plays a crucial role in ABMS. This can explain why this ABMS challenge is mentioned so frequently.

- **Data pre-processing:** As argued before, we specifically look at ML techniques, which process real-world data to model agent-behaviour. Sometimes, the ML technique is applied to find some meaningful patterns or trend based on real-world data, which help to build agents' behaviour. Hence, using ML for data pre-processing might indirectly help improving the accuracy of the agents' behavioural modelling. Moreover, An et al. (2021, p.9) mention data limitation as "one of the most fundamental reasons" why the progress of Artificial Intelligence in ABMS is slower than expected. This can explain why improving data pre-processing is the second most common ABMS challenge.

- **Computational efficiency:** Only a fraction of authors (11) use ML to improve the computational efficiency. Often, increasing computational efficiency appears a secondary challenge next to improving the accuracy of behavioural modelling. In the remaining cases, ML is often used to create surrogate or meta-models which learn the relationship between ABMS in- and output to achieve reliable results in a more efficient manner, see Vahdati et al. (2019), ten Broeke et al. (2021), or Yousefi et al. (2018). As outlined by van der Hoog (2019, p.1260) surrogate ML models have the potential to drastically reduce "the complexity and computational load of simulating agent-based models".

- **Model understanding:** Similar to computational efficiency, improving the model understanding is often regarded as a secondary ABMS challenge. Moreover, the use of black box ML techniques might hinder model understanding. Technological advances have led a majority of scientists to the belief that "the most accurate models for any given data science problem must be inherently uninterpretable and complicated." (Rudin & Radin, 2019, p.2). Hence, ML might not be seen by the ABMS community as a tool to improve model understanding, as this may otherwise negatively impact their main ABMS challenge, the ML accuracy. This can explain why model understanding is an uncommon ABMS challenge. To compensate for this lack in transparency, often a "second (post hoc) model is created to explain the first black box model" (Rudin, 2019, p.206). For instance, Cummings & Crooks (2020) use explainable AI for RL in their ABMS. These explanation models are usually not reliable and can easily be manipulated (Lakkaraju & Bastani, 2020; Lipton, 2018; Rudin, 2019). According to Rudin (2019), the trade-off between accuracy and transparency is a myth, as oftentimes there is no significant performance difference between complex black box models and transparent counterparts. Therefore, the conclusion would be to use transparent ML techniques instead (Rudin, 2019).

- **Ease of implementation:** Improving the ease of implementation is always combined with other ABMS challenges such as improving the accuracy of behavioural modelling. Hence, we conclude that it is also a secondary challenge. Moreover, if the ABMS community thinks that high performing ML techniques are inherently complicated (Rudin & Radin, 2019), it appears counterintuitive to add such a complicated model to improve the ease of implementation. This can explain why this ABMS challenge is scare in our results.

- **Understanding of model output:** ML is only applied for understanding the model output for the creation of surrogate models. The main challenge of surrogate models is however the computational efficiency. This explains their rare appearance in our results.

ML Techniques

Our results show that four techniques particularly stand out in the ABMS literature: RL, NN, DT, and BN. RL is by far the most common technique. Looking at the main reasons why authors apply RL such as the optimization of decision rules, adaptive behaviour, or the ability of reinforcement agents to learn from the environment and from each other (see Section 'Results'), we see lots of similarities to the nature of ABMSs. Similar to ABMS, RL is also built upon agents that interact with the environment and adapt their behaviour based on the interactions. This not only means that the two techniques fit together conceptually, but also that RL can reinforce core concepts of ABMS, such as agent adaptiveness (Van Dam et al., 2012). This might further explain the popularity of RL for improving behavioural modelling.

A currently underrepresented ML technique in our results is Genetic Algorithm (GA). GA is an evolutionary algorithm (Bäck, 1996), which is used for optimization and searching problems (Mitchell, 1998). The algorithm is inspired by the process of natural selection (Kumar et al., 2010) by making slow changes until the best solution is reached. In this process, the fittest portion of a population is selected for reproducing the next generation in each round based on a fitness or goal function. Mutations in subsequent generations allow the algorithm to search the whole domain area to prevent solutions being trapped in local minimums. This biologically inspired learning can be useful for agent specifications. The behaviour or agents' specification in certain condition can be coded into bit strings as chromosomes of GA (Weidlich & Veit, 2008). The most successful ones are consequently transferred to the next generation. Hence, the behaviours which are associated with more benefits that lead to maximize the agents' goal function will be preserved and passed to the next generation by a mutation process. Consequently, the set of agents' behaviour which leads to more fitness can be extracted. For instance, Lorscheid & Troitzsch (2009, p. 7) apply a GA which "extends the behaviour rules with new rules by adding mutated copies of existing event-action trees." Therefore, we recommend researchers to take into consideration GAs as potential ML techniques for the application in ABMS.

4.5.2 Guidelines for Purposefully Supporting Agent-based Modelling and Simulation with Machine Leaning

In previous part, we have focused on what articles suggest on using ML in ABMS. In this part, we recommend ML techniques that might be used for each specific purpose of the ABMS. When selecting a ML technique, it needs to be aligned with the purpose of the ABMS. This is also important when integrating ML into an existing model. We put the focus on highlighting selection criteria, which should have a high priority when choosing ML to support a certain purpose. The criteria are determined in a bottom-up manner based on the fundamental goals of each purpose. Table 2 shows the prioritized selection criteria for choosing ML technique, which are associated with each modelling purposes; in addition to the candidate ML technique.

- **Explanation:** Explanatory ABMS help in creating a causal chain from event to consequences. To support identifying these causal relations, we argue that the ML technique should be transparent. For instance, our results show that BNs appear suitable for explanations, as they provide a transparent way of modelling causal relations. DTs are also a transparent ML technique that can support this purpose.
- **Prediction**: If the modelling purpose is prediction, we recommend using ML techniques, which support reliable anticipation of data. Hence, we suggest techniques with a high accuracy. For instance, our results show that RL can achieve a high accuracy for behavioural modelling.
- **Description:** When a descriptive model is to be supported using ML, we suggest using ML techniques which are capable of establishing a "direct and immediate connection with observation, data or experience" (Edmonds et al., 2019, p.8). This includes the ability of the ML technique to derive information from data. Our results show that DTs and BNs are suitable techniques to support data pre-processing.
- **Theoretical exposition:** According to Edmonds et al. (2019, p.11) "a near complete understanding of the simulation behaviour is desired" for models focused on theoretical exposition. Therefore, for supporting this purpose, we recommend using transparent ML techniques so that modellers can track the step-by-step process and the output (e.g., DTs or BNs).
- **Illustration**: If the ABMS purpose is illustration, adding a black box ML technique such as NNs (Mas et al., 2004) might counteract with the model clarity. Hence, we suggest using transparent ML techniques instead e.g., DTs or BNs (Singh et al., 2016).
- **Social learning:** For social learning two points need to be considered. On the one hand, the modelling and executing time of the ML technique should not drastically worsen the already time-intensive participatory process. On the other hand, transparent techniques

should be used to enable a shared understanding by non-technical experts. Therefore, DTs or BNs seem to be the most suitable techniques.

- **Analogy**: If analogies are to be supported with ML, the ML technique should be easy to implement to be able to experiment with the simulation model without substantial implementation efforts. Hence, ML techniques with good availability of tools and mature libraries such as BNs or NNs are recommended.

The prioritized selection criteria (Table 2) can give readers an idea of which characteristics play a relevant role for their desired modelling purpose so that they can best align the ABMS purpose with the ML technique. However, setting priorities on certain selection criteria doesn't mean that other factors should not be considered. Furthermore, we would like to emphasise that ML is by no means always the best solution to overcome modelling challenges in ABMS. When selecting ML for agent specification, the pros and cons should be thoroughly considered. In addition, we would like to underline that the performance of a technique regarding a criterion can be considered a snapshot in time and can change in the future. For instance, technological improvements of surrogate models could make NNs more transparent and thus make them more suitable for explanatory purposes.

Table 2. Guidelines for selecting ML techniques to support agent specifications

Purpose	**Prioritized selection criteria for ML technique**					**Possible ML techniques**
	Accuracy	Transparency	Ability to process data	Time-intensity	Tool availability	
Explanation		✓				BNs and DTs
Prediction	✓					RL
Description			✓			DTs and BNs
Theoretical exposition		✓				DTs and BNs
Illustration		✓				DTs and BNs
Social learning		✓		✓		DTs and BNs
Analogy					✓	BNs or NNs

4.6 Conclusion

Research shows that by bringing more intelligence into models, ML can address various ABMS challenges and thus significantly improve modelling practices. This literature review used ABMS modelling purposes to analyse the applicability of ML techniques in this modelling domain as the purpose influences the entire modelling process and hence also the selection of the ML technique to overcome the ABMS challenges. As the sheer vastness of the ML domain makes it difficult to choose the right ML technique for an ABMS purposes, we explore the following research questions: *"Which ABMS challenge are relevant for which modelling purpose and which ML techniques are applied to support which ABMS challenge?"*

To answer these research questions, we focused our structured literature review on the use of ML for agent specifications. We analyse the existing body of literature regarding the purpose of the ABMS, the ABMS challenges, and the applied ML techniques. Our results show that explanation, description, and prediction are common modelling purposes in the literature that uses ML in comparison to illustration, social learning, and analogy purposes. Both the commonality of these purposes in ABMS in general, and the suitability of ML to support these purposes can explain this pattern. Improving the accuracy of behavioural modelling is the most relevant ABMS challenge for all modelling purposes followed by improving data pre-processing for agent behaviour. Increasing the computational efficiency, model understanding, ease of implementation, and understanding of model output are secondary ABMS challenges. We identified four main ML techniques in the ABMS literature that are used to address the mentioned improvements: RF, BN, DT, and NNs. RF appears a suitable technique to improve the accuracy of behavioural modelling, partially because it is conceptually similar to ABMS. Moreover, DTs and BNs show favourable characteristics for modelling agent behaviour using real-world data and are hence commonly applied to support this ABMS challenge.

To make ML more accessible to the ABMS community, we derive guidelines from these results. We highlight for each ABMS purpose which criteria should be prioritized when selecting an ML technique. This can help ABMS researchers better match the ML technique to the purpose of their ABMS. Moreover, we emphasize that ML techniques can be both accurate and transparent and underline the use of transparent ML techniques for the currently underrepresented ABMS purposes of social learning and illustration.

This work has several limitations. First, we focus on the core part of ABMS, the structural specifications of the agents, and do not include the papers on using ML in output of ABMS. Second, the search string only contains ABMS-related keywords. Hence, we neglect papers that apply ABMS but refer to it as MAS. Third, only one database, Scopus, is used to identify articles. Fourth, we classify ABMSs based on authors' descriptions because authors often do not specify the modelling purpose. Although we perform double-checking, this approach is still observer dependent, which might affect the classification results. Finally, given the diversity of ML techniques, we narrowed our focus on the techniques that have been already applied in the ABMS field to learn from best practices. However, the next step would be to expand our vision to see what other techniques can be useful for this field and how that can be used.

Based on these limitations, future iterations are recommended, for example by extending the research to other databases such as Web of Science and by including MAS and ML techniques in the search string. This would allow for better article identification and hence improve the statistical significance of the results. Moreover, we recommend author's to explicitly highlight the modelling purpose, as stated in the ODD protocol, as this would allow readers to better understand the model (Grimm et al., 2020). Lastly, despite us focusing only on structural specifications of the agent it would be interesting to see how ML is used for the output of ABMS. Hence, we recommend a literature review on the use of ML for the ABMS output as a next step.

4.7 Appendices

4.7.1 Appendix A: Full Research String

TITLE-ABS-KEY (("ABM" OR "ABMS" OR "agent-based" OR "Agent based" OR "Agentbased") AND ("machine learning" OR "supervised learning" OR "unsupervised learning" OR "semisupervised learning" OR "semi-supervised learning" OR "reinforcement learning") AND ("decision-making" OR "decision making" OR "agent logic" OR "agent-logic" OR "agent specification" OR "agent-specification" OR "agent learning" OR "agent-learning")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (EXCLUDE (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English"))

4.7.2 Appendix B: Literature Review

Table 3: Literature review results[1]

Author	ABMS purpose	ML technique					ABMS challenge					
		BN	NN	DT	RL	Other	Data pre-prepro.	Modelling accur.	Comp. efficiency	Ease of impl.	Model underst.	Output underst.
(Abdulkareem et al., 2018)	Theoretical exposition	✓					✓	✓				
(Abdulkareem et al., 2019)	Theoretical exposition	✓					✓	✓				
(Abdulkareem et al., 2020)	Explanation	✓						✓				
(Aguilar et al., 2019)	Analogy				✓			✓				
(Al-Khayarin & Halabi, 2021)	Prediction				✓			✓				
(Baghcheband et al., 2019)	Illustration				✓			✓				
(Batata et al., 2018)	Prediction		✓	✓		✓		✓				
(Bennett & Tang, 2006)	Explanation		✓			✓		✓				
(Bone & Dragićević, 2009)	Explanation				✓			✓				
(Bone & Dragićević, 2010)	Description				✓			✓				
(Cenek & Franklin, 2017)	Explanation			✓				✓				
(Chen et al., 2020)	Theoretical exposition				✓			✓				
(Cruz Cortés & Ghosh, 2020)	Explanation				✓			✓				
(Cummings & Crooks, 2020)	Illustration				✓			✓			✓	
(Drchal et al., 2019)	Prediction			✓			✓	✓		✓		
(Fano & Slanzi, 2019)	Illustration				✓			✓				
(Froelich et al., 2006)	Description				✓			✓				
(Gaines & Pakath, 2013)	Analogy				✓			✓				
(Gaube et al., 2009)	Social learning			✓			✓	✓				
(Gazzola et al., 2016)	Description				✓			✓				
(Hassanpour et al., 2021)	Prediction				✓			✓				
(Heinrich & Gräbner, 2015)	Explanation				✓			✓	✓			
(J. Lee et al., 2018)	Description				✓			✓				
(Jäger, 2019)	Analogy		✓				✓	✓				
(Jamshidnezhad, 2015)	Theoretical exposition				✓			✓				
(Junges & Klügl, 2012)	Illustration				✓			✓		✓		

[1] Each row represent an ABMS. As both Osoba et al. (2020) and ten Broeke et al. (2021) describe multiple ABMS applications within their papers, there are multiple rows of the same authors in the table.

(K. Lee et al., 2018)	Prediction				✓			✓				
(Kocabas & Dragicevic, 2013)	Prediction	✓					✓	✓		✓	✓	
(Laskowski, 2011)	Prediction					✓					✓	
(Lei et al., 2005)	Description	✓						✓				
(Li et al., 2019)	Explanation				✓			✓				
(Li et al., 2020)	Prediction				✓			✓				
(Ling et al., 2016)	Prediction				✓			✓				
(Lorscheid & Troitzsch, 2009)	Explanation				✓	✓		✓				
(Mei et al., 2014)	Prediction					✓	✓	✓				
(Moriyama et al., 2019)	Analogy				✓				✓			
(Nawa et al., 2002)	Theoretical exposition				✓			✓				
(Nawaz & Hadzikadic, 2018)	Prediction			✓		✓	✓	✓				
(Norman et al., 2018)	Social learning				✓			✓				
(Osoba et al., 2020)	Analogy				✓			✓				
(Osoba et al., 2020)	Prediction				✓			✓				
(Ozik et al., 2021)	Explanation					✓	✓					
(Padilla et al., 2014)	Theoretical exposition		✓					✓				
(Pageaud et al., 2017)	Prediction				✓			✓				
(Pang et al., 2018)	Explanation				✓			✓				
(Pooyandeh & Marceau, 2014)	Social learning	✓					✓	✓	✓			
(Pope & Gimblett, 2015)	Explanation	✓						✓				
(Vahdati et al., 2019)	Explanation			✓					✓			✓
(Ramchandani et al., 2017)	Description				✓			✓				
(Remondino, 2008)	Social learning				✓			✓				
(Resta, 2015)	Theoretical exposition					✓		✓				
(Rosés et al., 2021)	Prediction			✓			✓	✓				
(Sánchez-Maroño et al., 2017)	Description			✓			✓	✓			✓	
(Sankaranarayanan et al., 2017)	Explanation		✓					✓		✓	✓	
(Schuster, 2012)	Theoretical exposition				✓			✓				
(Schwab & Maness, 2013)	Description				✓		✓	✓		✓		
(Sengupta et al., 2018)	Description			✓			✓	✓				
(Shukla et al., 2013)	Prediction		✓	✓				✓				
(Songhori & Garcia-Diaz, 2018)	Illustration				✓			✓				
(Sun & Müller, 2013)	Explanation	✓					✓	✓			✓	
(Takadama et al., 1999)	Explanation				✓			✓				
(ten Broeke et al., 2021)	Explanation					✓			✓			✓
(ten Broeke et al., 2021)	Explanation					✓			✓			✓
(Tian et al., 2020)	Explanation	✓					✓	✓	✓			
(Tkachuk et al., 2018)	Prediction		✓					✓				
(Valluri & Croson, 2005)	Explanation				✓		✓	✓	✓			
(Wolf et al., 2015)	Explanation		✓					✓				

(Zhang et al., 2018)	Social learning		✓						✓			
(Yao et al., 2020)	Description		✓					✓	✓			
(Yousefi et al., 2018)	Prediction		✓						✓			✓
(Zangooei & Habibi, 2017)	Prediction				✓			✓				
(Zhao et al., 2019)	Description		✓					✓				
(Zubiria Perez et al., 2021)	Explanation				✓			✓				

4.7.3 Appendix C: Literature Review References

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Appendix D: Analysis Results

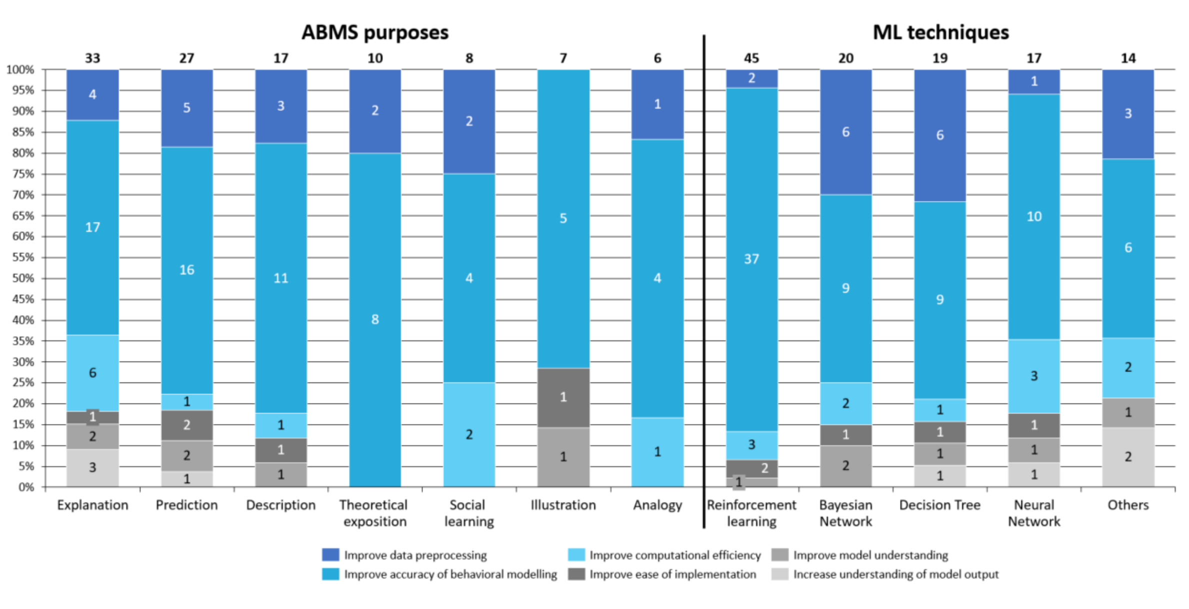

Figure 7. Proportional and absolute distribution of applications of ABMS challenges over ABMS purposes and ML techniques

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5 Examining the Interplay between National Strategies and Value Change in the Battle against COVID-19: an Agent-Based Modelling Inquiry[1]

Abstract

Social disruptions caused by the COVID-19 pandemic challenged existing institutional arrangements that govern the society. During that time, nation-states had to prevent the collapse of society and rapidly establish new institutions and adapt existing ones to address public health, job security, and freedom-of-movement concerns. At the same time, institutional developments are explicitly or implicitly related to the cultural and moral values relevant to societal well-being. Values hold a significant role in governing society during crises, guiding states' institutional response to unforeseen challenges. However, values themselves are not static: research has shown that values may change rapidly during crises. This paper studies the relationship between value change and institutional change in times of crisis using agent-based modelling and machine learning techniques. In our model, we represent countries as agents who define institutional strategies to control disease spread and subsequently protect the well-being of their citizens. Institutional change and value change are modelled as two independent processes. Yet, the model confirms the seemingly trivial inverse correlation between them: when the value of openness-to-change increases in a society, the institutional strategies also become less strict. Conversely, when conservatism increases, the strategies become stricter on average. However, there is no direct causal relationship between the two changes: being open to change does not necessarily make a government select more relaxed rules, but this correlation is rather an emergent consequence of being more flexible in changing rules, whether the new ones are stricter or more relaxed.

Keywords: institutional modelling, institutional evolution, values, value change, crisis

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5.1 Introduction

The disruptions caused by the COVID-19 global pandemic significantly challenged societal structures (ESCAP, UPU, and WHO, 2020). The nations' responses to the COVID-19 pandemic depended on their status of healthcare systems, economies, public services, and their ability to provide social safety. From the perspective of welfare economics and the capability approach (Sen, 1993), this crisis deprived societal well-being by threatening citizens 'essential needs like having good health, having a decent job, and having the freedom-of-movement to pursue a good life (Anand et al., 2020). The urge to secure the well-being of citizens invoked nation-states to deal with numerous dilemmatic situations where vital decisions had to be made. Governing the global pandemic, while at the same time being ill-informed about the risks involved, resulted in heterogeneous institutional responses and challenges (Hull, 2020). Conditioned in an uncertain pandemic situation (Lempert et. al., 2003), nation-states opted for different pathways in containing and resolving this global health crisis.

Institutions, i.e., systems of rules and enforcement mechanisms that govern human behaviour and interaction (Ostrom, 1990), are dynamic and are constantly adapted. For example, there are records for establishing new institutions on a daily basis during COVID-19 for some nation-states (ACAPS COVID-19 Government Measures Dataset, 2020). Although the institutions themselves were quite similar between countries, the frequency of changes and the number of institutions were different between countries. At the same time, research has shown that the nation states' values also changed during crisis (Bojanowska et al., 2021; Bonetto et al., 2021). In general, it is a common sense that values play a significant role as they guide the state's institutional response to unforeseen challenges. The way institutions are organized explicitly or implicitly commits to underlying cultural and moral values. These values provide guidance and justifications for the decision-makers who shape societal institutions. By referring to social psychologist Schwartz (2003, p. 261), we conceptualise values as “deeply rooted, abstract motivations that guide, justify or explain attitudes, norms, opinions and actions”, and an analysis of which “can provide predictive and explanatory power” and “reflect [a] major social change in societies and across nations”.

Values and institutions have both been evidenced to change during a crisis such as the COVID pandemic. At the same time, common sense tells us that values play a significant role in defining institutional arrangements. So, is value change what has driven institutional change in the crisis? And if so, to what extent did it play this role?

The objective of this research is to study, whether there is a causal relationship between value change and institutional change. In other words, whether the changes in the values of the society, lead to changes in how the pandemic is governed.

Answering this question can bring insights into better understanding how societies function and how we can improve the functioning of institutions to address societal problems and promote greater social and economic well-being. This, in turn, can help us make better informed and adaptive policies that align with societal values and promote institutional effectiveness.

To inquiry into this question, we take an agent-based modelling (ABM) approach to explore the dynamics of change in institutions and in values over time. The ABM outcomes can provide us a dynamic view of the interplay between individual behaviour and social structures (Bianchi & Squazzoni, 2015). To be able to study the relationship between value change, and institutional change, these two processes have to be modelled independently of each other. In other words, values should not directly be an influencing factor in choosing strategies. Therefore, we use independent data for each of these processes in the same context to study such relationship. For modelling value change we use Schwartz Value Survey (Schwartz, 2003) to conceptualise and parameterize country values. For modelling institutional change, we use real-world data from ACAPS[1] dataset on the COVID-19 government measures and EU COVID-19 datasets[2] and machine learning (ML) techniques to inform our country agents' decisions about changing institutions. In other words, rather than basing the decision on the value of agents, they are informed by how countries in reality decide on interventions based on factors such as number of infections.

Recently ABM has been applied to study values and their dynamicity. For example, Mercuur et al. (2019) studied the role of values on agents' behaviour. ABM has also used extensively for modelling different dimensions of the pandemic. For example, Dignum (2021) developed the ASSOCC model for the COVID crisis which also incorporated values and culture and explore the relation with the management of the pandemic.

This article is organized as follows: Section 2 presents the related conceptual and theoretical background; Section 3 describes the model; Section 4 shows the implementation of the model; Section 5 presents the results; and Section 6 presents discussion and conclusion.

5.2 Conceptual and Theoretical Background

5.2.1 Institutions and Institutional Change during a Pandemic

Institutions

The set of rules, whether formal or informal, that influence interactions, and decision making in society are called institutions (North, 1991; Hodgson, 2006).

To model institutions, we use the ADICO grammar of institutions (IG) which pro-vides five concrete concepts for defining institutional statements (Crawford & Ostrom, 1995). In the ADICO grammar, A denotes Attributes: specifies subject, to whom a strategy or rule applies; D refers to Deontic: determines how an action is done (prohibition, obligation, and permission); I represents Aims: identifies the actions toward which Deontic applies; C indicates Conditions: under which condi-tions or, when, where, and how a strategy or rule applies; and O denotes Or Else: determines specific punishments to be applied when an agent acts in violation of the institutional rules. For example, in an institution: 'All people have to keep 1.5 meter distance in any public area whether indoor or outdoor', A is 'all people', D is 'have to', I is 'keep 1.5 meter distance', C is 'in any public area', and we do not have any sanctions (O).

According to Ostrom, a shared strategy is a social concept of behavioural patterns, which many individuals observe. A shared strategy contains AIC elements. There-fore, it is neither associated with any deontic modality nor having a reward or punishment (Crawford & Ostrom, 1995).

We look at institutions at a country level, meaning that we do not focus on whether the people within a country follow the rules or not. Rather we look at these country-level rules as "strategies" that countries take in combatting the pandemic (e.g., introducing social distancing). In this definition, "a country government" is the attribute of the institutional statement, who

[1] https://data.humdata.org/dataset/acaps-covid19-government-measures-dataset
[2] https://data.europa.eu/euodp/en/data/dataset/covid-19coronavirusdata/resource/55e8f966-d5c8-438e-85bc-c7a5a26f4863

implements certain policies under specific conditions (e.g., R-rate being above 1). Most of these institutional strategies are similar across countries as there is also a lot of "copying behaviour" that makes some strategies more common than others. Therefore, the rule-setting behaviour among countries can be viewed as shared strategies globally.

Institutional change during a pandemic

Although actors may recognise and potentially comply with institutions, they may also shape and change them within a social system (North, 1993). Individuals or organisations can change their decisions based on new learning and skills (internal triggers) or environmental factors (external triggers), which could lead to institutional change (North, 1993).

In this study, we explore institutional emergence as the result of an external shock (i.e., changes at the beginning of COVID-19 pandemic) (Powell, 1991; Rao et al., 2003). Additionally, we consider institutional adjustments and changes in previous institutions causing by new learning and skills, especially after the starting point of the crises.

5.2.2 Values and Value Change during a Pandemic

Defining values

Values play an important role in comprehending individual and social behaviours and their alignment with social institutions. A study of values allows to capture underlying societal mechanisms to equip the decision-making capacities of different regulatory bodies (e.g., policy-makers). However, the conceptual environment around values is somewhat ambiguous as various academic disciplines provide different definitions of values. In philosophy, values often pertain to what is considered as good (ontology), or what we believe (epistemology) or what we express (semantics) as being good (Hirose & Olson, 2015). Anthropologists consider values as ideas about worthiness or as a conception relating to a code or standard (Belshaw, 1959). In the realm of social sciences, a more empirically grounded approach is taken to study values, with scholars commonly referring to values as attitudes, preferences, and interests (Rokeach, 1973).

One of the most influential empirical studies on values was conducted by the social psychologist Shalom Schwartz in 1992. Inspired by Rokeach's work (1973), Schwartz conducted an extensive value survey across countries. He subsequently developed the intercultural theory of basic human values, which conceptualises values as beliefs forming an interrelated hierarchical system. This system guides individuals and/or groups to desirable goals (Schwartz et al., 1999). Schwartz's value theory proposes a value typology including 56 values that are universal across cultures. Schwartz (1992) found that values can be arranged into ten value clusters that characterise individual variations in value priorities: conformity, tradition, universalism, benevolence, power, achievement, hedonism, stimulation, self-direction, and security. Figure 1 shows these ten value clusters:

- Power: This value emphasises the pursuit of social status, prestige, and dominance over others.
- Achievement: This value emphasises the pursuit of personal success, competence, and mastery of skills.
- Hedonism: This value emphasises the pursuit of pleasure, enjoyment, and sensory gratification.

- Stimulation: This value emphasises the pursuit of novelty, excitement, and challenge.
- Self-direction: This value emphasises the pursuit of autonomy, creativity, and personal freedom.
- Universalism: This value emphasises the pursuit of social justice, equality, and concern for the welfare of all people.
- Benevolence: This value emphasises the pursuit of caring, empathy, and concern for the welfare of others.
- Tradition: This value emphasises the pursuit of respect for cultural and religious traditions, social order, and family values.
- Conformity: This value emphasises the pursuit of obedience to authority, social norms, and group loyalty.
- Security: This value emphasises the pursuit of safety, stability, and protection from harm.

The ten value clusters can be categorised into two main groups: individualistic values and social values. The first four value clusters - conformity, benevolence, universalism, tradition - represent social values, emphasising consideration for others. The remaining six clusters - power, hedonism, self-direction, security, achievement, and stimulation - reflect individualistic values.

Visualising the ten value clusters in a two-dimensional space helps to understand them better. The first dimension distinguishes self-enhancement values from self-transcendence values. Self-transcendence values prioritise the well-being of others, while self-enhancement values emphasise personal achievement and benefits. The second dimension distinguishes openness-to-change values from conservation values. It indicative of whether individuals are open to new things and ideas versus whether they have a preference for tradition and conformity. Openness-to-change dimension includes the values of self-direction and stimulation, and emphasises the pursuit of creativity, novelty, and personal growth. While the conservation dimension includes the values of tradition, conformity, and security, and emphasises the pursuit of preserving the status quo, stability, and social order.

Values within the same value cluster are prioritised similarly, reflecting their shared characteristics. On the other hand, values belonging to clusters that are wide apart from each other in the two-dimensional space are typically prioritised very differently, indicating their distinct nature. Values positioned closer together in this two-dimensional space are more compatible, suggesting that individuals who prioritise these values are likely to share common perspectives. Conversely, values positioned wide apart values are more likely to conflict, representing different viewpoints and priorities. This prioritisation typically guides decision-making in a particular situation; people are typically tempted to act upon the values they prioritise.

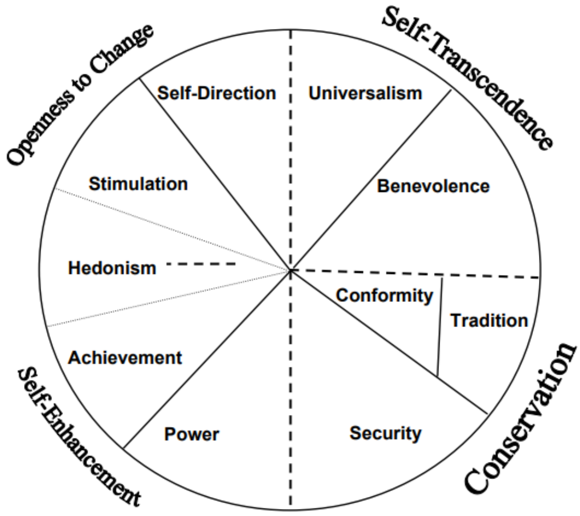


Figure 1. The ten clusters Schwartz value clusters (Davidov 2008)

How values can change during a crisis: COVID-19 pandamic

In the theory of basic human values, values are considered to be relatively stable (Schwartz, 1992). Their prioritisation typically forms during childhood (Cieciuch et al., 2015). While there's consensus among psychologists that value prioritisation stabilises around the age of adolescence (Cieciuch et al., 2015; Sagiv et al., 2017), significant life transitions (e.g., moving to another country) can be an exception (Sagiv et al., 2017). The global pandemic quite substantially triggered rapid changes in lifestyle and reconsiderations of what is deemd "normal" and socially acceptable behaviour. Compliance with movement restrictions and social distancing, job losses, and the urgent need to digitise essential activities like schooling were unprecedented challenges that prompted people to alter their behaviour.

An extensive study of value change in the context of pandemic utilised a topic modelling approach based on the large text corpora (Van De Poel et al., 2022). This study indicated that the most significant change in value prioritisation took place at the beginning of pandemic, whereas the long-term effects seem to be limited (Van De Poel et al., 2022).

Another insightful perspective on value change during the pandemic was offered by Steinert (2021) who links it to the amplifying effect of information technologies, in particular social media, on human emotions and values. Steinert (2021) indicates that sharing online one's negative emotions in relation to pandemic facilitates emotional climate that can contribute to societal value change. In particular, Steinert (2021) suggest that what he calls emotional contagion though social medial can induce to change in value prioritisation with a bigger emphasis on the conservation and security values. Furthermore, Steinert (2021) signifies an important link between personal values and political preferences. He suggests that: "When people perceive their values to be threatened, they prefer policies that protect these values and are more inclined to accept measures that limit their civic freedom"(Steinert, 2021).

Similar to Steinert's insights were concluded by a working group headed by psychologist Inglehart and Lampert (2021), who emphasise that although values related to survival gain more relevance, the lack social contact and freedom of mobility increased the importance of social solidarity, equity, community, and self-determination values (Lampert et.al., 2021). In contrast, basing on the insights form survey data, other studies, have indicated that values remained relatively stable and what we witnessed was "more an emotional than a rational response to institutional functioning" (Reeskens et al., 2021, p. 5163).

In the growing body of value change scholarship, several studies have followed Schwartz's conceptual tradition, highlighting the reprioritisation of both value sets 1) openness-to-change and 2) conservatism. These studies empirically examined the evolution of basic human values during the COVID-19 pandemic in France and Poland (Bojanowska et al., 2021; Bonetto et al., 2021). Similarly to Lampert et al. (2021), their findings revealed insightful patterns that conservatism values (i.e., security and conformity) were more valued during the outbreak than usual. In contrast, values relating to openness-to-change were less prioritised during the COVID-19 outbreak than in ordinary circumstances. These findings about changes in value prioritisation reflect a correlation between the threat imposed by the crises and conservatism. Similar insights were gained during research of the 2008 world financial crisis where researchers also drew a link between the decreasing role of openness-to-change and strengthening the role of conservatism (Sortheix et al., 2019).

From individual values to countries' values: A situated perspective on institutions

In this research, we extend the idea of a change in the level of individual value prioritisation to the collective level. In particular, we are interested in the level of value-informed goals that nation-states pursue in order to tackle the challenges of the pandemic. Although values are not fixed, and the prioritisation can change over time in response to social and historical contexts, they remain a powerful force that shapes individual and collective actions. On the one hand, studies revealed that crises can lead to changes in the prioritisation of deeply rooted motivations for decisions and actions. In our view, this claim can also be extended to including country's values. Crises disrupt the normal functioning of society and require individuals and societies to swiftly adapt their values and behaviours in order to respond effectively. For instance, in response to the COVID-19 pandemic, many countries implemented policies aimed at protecting public health and promoting social welfare. These value-informed goals of policies reflect the tendency that occurs on the individual level as they capture a shift towards values that prioritise the well-being of others over individual freedoms.

The pandemic created double-sided impacts on value change that were seemingly contradicting: On the one hand, many uncertainties led countries (i.e. their governments[1]) to prioritise conservatism more strongly. These challenges included concerns about health and safety, economic insecurity, and social disruption. In response to these challenges, countries became more risk-averse and resistant to change. On the other hand, the pandemic also created new opportunities and challenges that required individuals and governments to adapt and innovate, which promoted a greater openness-to-change. For instance, the pandemic accelerated the adoption of new technologies, such as remote working tools and telemedicine, and created a need for experimentation and innovation in areas such as public health and social welfare. In response to these challenges, countries became more open to trying new approaches.

One may however, question the generalizability of individual values to a country as a whole, and it's government in particular. Although Schwartz's (1999) exploration of human values started on the level of individuals, in the later work, a number of patterns were drawn from the cross-country study of values and value orientations (Schwartz, 2008). In particular, in chapter five of the book "Cultural value orientations: Nature and implications of national differences", Schwartz (2008) suggests that "the prevailing cultural value orientations in a country are likely

[1] In this article, we use the term “country” to refer to the government of a country.

to find expression in the major social policies of governments and practices of society." Building on this point, in our paper we assume that nation state value system represents an aggregated system of citizen's (individual) values. In assuming so, we intentionally take a simplistic view on how a state represents the aggregation of citizen's values and leave out other factors to exclusively focus on an exploration of a value-based approach. In other words, this research builds on the assumption that when people within a country score high on certain values (e.g., stimulation), then the country as a whole and its government also score high on that particular value.

To make the reasoning behind the assumed level of "agency," more explicit, let us briefly elaborate on the origin of this assumption. Our objective in this research is to focus on capturing the dynamics between value change and international policy responses to the spread of COVID-19. We deliberately opted to integrate a value perspective with an institutional economics perspective, as, in our view, the global pandemic is an interesting case of the emergence of institutions (i.e., shared strategies) due to unprecedented challenges that required rapid international policy response. In order to ground this perspective on institutions, we build our assumption on the work of Dolfsma and Verburg (2008). Following Dolfsma and Verburg (2008), we claim that North interpretation of institutions is based on the individual account of what they call the agent approach (individualist), as opposed to the structuralist approach (collectivist).

This dichotomy in understanding institutions traced back to an age-old debate between proponents of the agency approach, who argue that explanations of social facts always arise from individual preferences, expectations, behaviours, and motives, and proponents of the structural approach, who claim that institutions should always be studied within social systems in which they emerge and therefore should not be reduced to individual parts. In our research, we align with the agency approach because we contend that the urgency of the COVID-19 case left no space for the rise of structured regularities. Instead, it necessitates immediate state action (policy response) aimed at protecting citizens and oriented toward other states' (expected) actions.

5.3 An agent-based Model of Institutional and Value Change during COVID Crisis

In this section, we explain the assumptions that the model is based upon, the abstract model architecture and the modules. We then define, the dataset we used as input data.

5.3.1 Assumptions

We build our model based on a set of assumptions.

- We represent countries as agents where the properties of these agents are at country-level.
- We do not give specific names to countries to avoid the claim that we are predicting the behaviour of a country. We are only looking at the changes in value prioritisation and institutions that occur during the pandemic.
- Since we focus on the introduction and emergence of institutions, we only consider the 'Introduction/extension of measures' in the used dataset.

- Following the previous assumption, we model the establishment of institutions during COVID-19 rather than their discontinuation.
- The institutions are defined in relation to the well-being of citizens: being healthy, having a job and having freedom-of-movement.
- Each timestep in the simulation represents two weeks as this was on average the period in which countries assessed the performance of the current policy in place, to potentially introduce a new one[1].
- We model institutions as shared strategies as we are modelling country-level institutional dynamics. In other words, the institutions we define do not have a sanctioning (i.e., if a country does not implement the policy, the country is not sanctions by the UN) nor a deontic (countries do not have any obligation to implement these rules) from a global perspective but they may follow other countries' footsteps.

5.3.2 Using the Data in the Agent-based Model

The overall architecture of the simulation is shown in Figure 2, which will be explained in detail in this section. The initial amount for each of ABM parameter settings is a random number in a specific range; the specific range is derived by real-world data[1,2,3].

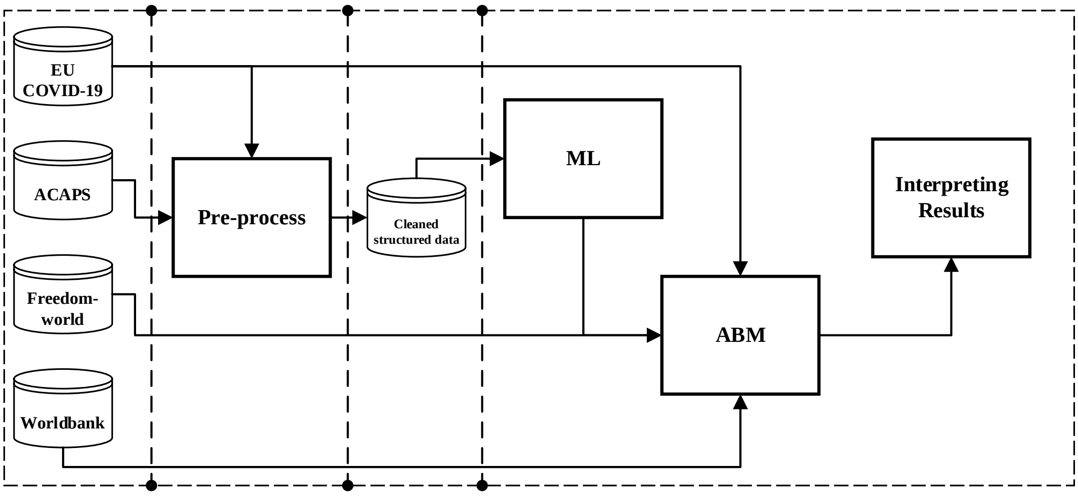


Figure 2. The architecture

Pre-processing

Pre-processing starts with selecting required fields from ACAPS dataset on the COVID-19 government measures and EU COVID-19 datasets. The cleaning procedure includes managing null values, missing data, and formatting records. ACAPS includes measurements, which have been implemented by countries in addition to the implemented data and country name. EU COVID-19 consists of number of infected cases reported per day per country. After that, we

[1] https://data.humdata.org/dataset/acaps-covid19-government-measures-dataset
[2] In the dataset that was used to train the ML, each of these interventions were further divided into different sub-interventions. An intervention would get the value of 1, if all these sub-interventions were implemented, and less otherwise.
[3] http://www.worldvaluessurvey.org

join tables on common fields. Moreover, we categorise ACAPS measurements (category + measures) into four standard interventions (NoLockdown, SocialDistancing, SoftLockdown, HardLockdown) following Kreulen et al. (2022):

- NoLockdown: only raising public awareness,
- SocialDistancing: informing about the virus and social distancing,
- SoftLockdown: staying home as much as possible,
- HardLockdown: closing non-essential locations.

It is worth mentioning that the four interventions are independent: they have accumulating impacts on the number of COVID cases and there may be more than one intervention at a time. Additionally, they have different impact weights, for example, Hard Lockdown has higher impact on reducing cases. In the dataset that was used to train the ML, the interventions were assigned to each one of these four higher level interventions. In other words, each of the four interventions above were further divided into different sub-interventions. Each intervention can have a weight in the range of [0, 1]. An intervention would get the value of 1, if all these sub-interventions were implemented. Based on the data, we have 8 sub-interventions for NoLockdown, 6 Social Distancing, 5 SoftLockdown, and 10 HardLockdown. Therefore, we assign the following weights for each specific intervention according to it's number of sub-interventions (more information can be found in Appendix A):
['No Lockdown', 'Social Distancing', 'Soft Lockdown', 'Hard Lockdown'], value = [0.125, 0.17, 0.2, 0.1]

Most of the COVID rules and cases are updated bi-weekly. Therefore, we set the granularity of the data to two weeks, i.e., we aggregate data for each two weeks in one record. This new granularity starts from the day that the first country implemented an intervention. Therefore, there may be several interventions in each two weeks. We use the summation of the weights of interventions in each two weeks and average of 'Cumulative_number_for_14_days_of_COVID_19_cases_per_100000' for the records to avoid duplication in calculating the cases.

Finally, to improve the accuracy, we round data by applying the below procedure:

- If the weight of an intervention (i.e. sum of it's sub-interventions) is greater than 0.6: we assign 'high' (1)
- If the weight is greater or equal to 0.4 and less or equal to 0.6: we assign 'middle' (0.5)
- If the weight is less than 0.4: we assign 'low' (0)

Using ML to train agents in the model

ML techniques refer to algorithms that have the ability to find patterns and predict outcomes by learning from input data and without programming all requirements explicitly (Samuel, 1959; Murphy, 2012). ML techniques can provide great potential to bring higher degrees of intelligence and learning into the models (Macal & North, 2010; Rand & Rust, 2011; An, 2012; Kavak et al., 2018; Dehkordi et al., 2023).

ML can bring the opportunity to cover the world knowledge (past experiences) in the model, build an informed picture of how countries react in specific situations, and decrease the degree of model abstractness.

In this research, we use Decision trees as the ML technique. Decision tree (DT) is a predictive algorithm, which is mostly used in a supervised approach, in the form of tree which has branches that represent observations and leaves that outline conclusions. There are two ways of applying DT: classification and regression (Olkin, 2002). A classification DT is a DT where discrete values are allowed. For this type of DT, leaves are class labels and branches are the links between class labels. In contrary, in a Regression DT continuous values are allowed, and the leaves can have the ranges for the regression.

The advantage of using DTs is that the knowledge represented by a DT is very clear. Therefore, the learned knowledge by a DT can be interpreted easily by even non-experts (Jadhav & Channe, 2016). Another advantage is that a DT is able to map non-linear relationships quite well. Additionally, it can handle missing values (Wu et al., 2008). The disadvantages are: it has long training time (Jadhav & Channe, 2016), it easily overfits and it does not support online learning; meaning that with new data, the tree needs to be rebuilt (Brijain et al., 2014). DT have been widely used in ABM. We used multivariant regression DT to predict the weights of four interventions at each time learned by cleaned structured data. The input parameters for our trained DT are:

['week_bin', 'REGION', 'Cumulative_number_for_14_days_of_COVID_19_cases_per_100,000']

And the Output parameters are:

['No Lockdown', 'Social Distancing', 'Soft Lockdown', 'Hard Lockdown'].

One output sample could be:

{'No_Lockdown': 0.0, 'Social_Distancing': 0.0, 'Soft_Lockdown': 0.5, 'Hard_Lockdown': 0.0}

We split the cleaned structured data into training and validation sets by the split ratio 80:20. That is 80% of the data goes into the training set and 20% to test set. After the DT has learned based on the training set, the DT is validated on test set.

First, we calculated the Mean Absolute Percentage Error (MAPE), which is a commonly used metric for evaluating the performance of regression models. MAPE, Equation 1, is a percentage metric that measures the average absolute percentage difference between the predicted and actual values across all instances in the dataset. It is expressed as a percentage and represents the average magnitude of the error relative to the actual values.

MAPE = (SAE / sum (actuals)) * 100% (1)

Where SAE is the sum of the absolute differences between the predicted and actual values, and sum (actuals) is the sum of the actual values across all instances. The MAPE on test set for our DT is 14%.

While MAPE is a useful metric for evaluating the overall performance of the model, it does not provide a per-target variable measure of performance. As we used multivariate regression DT, we have four outputs. Therefore, we calculated the accuracy of each intervention. Accuracy measures the overall correctness of the model's predictions by comparing the number of correctly predicted instances to the total number of instances for that specific intervention. The accuracy of our DT on test set for each output (intervention) with accepting 0.1 error is:

- Number of correct predictions with accuracy of 0.1 for NoLockdown: 0.72
- Number of correct predictions with accuracy of 0.1 for SocialDistancing: 0.73
- Number of correct predictions with accuracy of 0.1 for SoftLockdown: 0.69
- Number of correct predictions with accuracy of 0.1 for HardLockdown: 0.81

5.3.3 ABM Conceptualisation

The flowchart of the model is shown in Figure 3. In the initialisation phase, the agents are created, the network is set up and agents are initialised with random attributes for their value systems, region, following country, tolerable threshold for infected cases, tolerable threshold for unemployment, tolerable threshold for freedom, and well-being parameters related to health, freedom, and unemployment (we define and conceptualise well-being later). At each tick (two weeks), each agent checks its well-being. A country satisfaction is measured by comparing the current status of well-being variables of the agent with the related tolerable thresholds. If one or more than one element do not meet the tolerable thresholds, the agent is not satisfied with the situation. In this way, agents who are more sensitive to freedom or unemployment, will be dissatisfied faster based on their unemployment and freedom elements.

If the agent is satisfied with its well-being, nothing will happen. Otherwise, the agent follows the two independent processes of change: value change and institutional change. If the agent is dissatisfied with the current well-being, the agent changes the strategy. We conceptualise 4 types of strategy change (ML, Copy, Mutation, and Case-based). The type of strategy change, which each agent might chose is a probability that is determined based on the parameter settings of the scenarios of simulation. After each change, the parameters will be updated. And the overall values and the shared strategy will be calculated. The entire process is iterative. The simulation stops after a certain number of ticks.

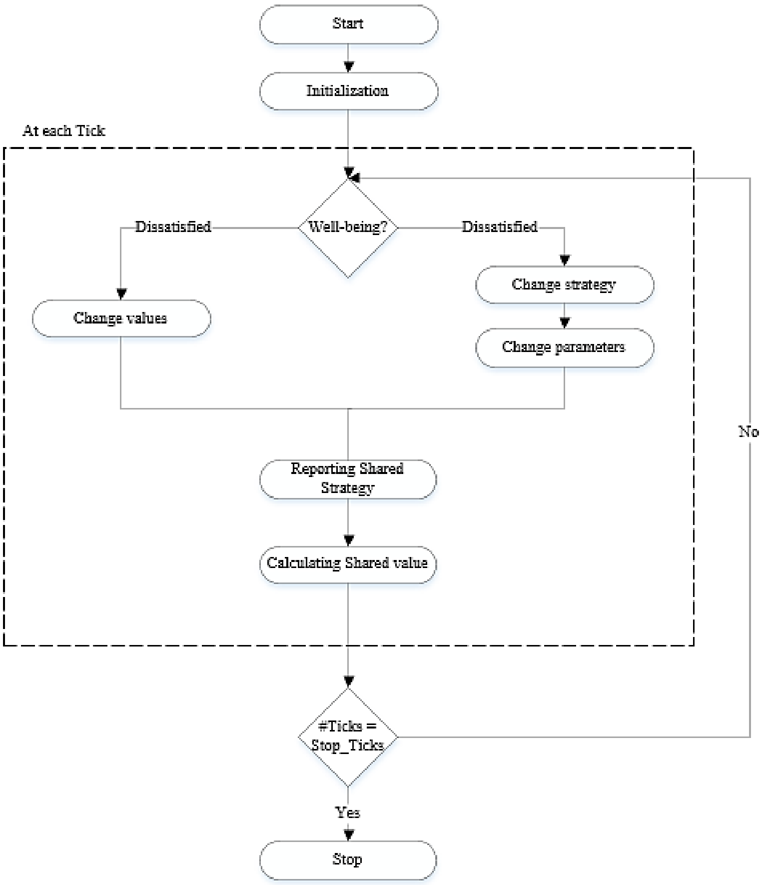


Figure 3. Flowchart of the model

The model includes the following components.

- **Agents**. The country agents have certain attributes: region, country-to-follow, tolerable threshold for infected cases, tolerable threshold for unemployment, tolerable threshold for freedom, well-being (with its two states: satisfaction and dissatisfaction), a value system, frequency of value change, change degree and country change threshold, and country strategies to deal with the pandemic.

  Well-being is defined in terms of granting essential "doing and being" like an opportunity to be healthy, employed, and mobile by providing equal access to the healthcare services, job market and unrestricted mobility (Sen, 1993; Anand et al., 2020). It is the government's role to set institutions that would support citizens' well-being. Therefore, we conceptualised well-being as a function including three elements: health, which is number of infected cases for 14 days ago per 100,000 population; unemployment rate; and freedom rate (civil liberties). The initial amount for each of these parameters is a random number in the specific range; derived by real-world data[1][2][3].

  A country satisfaction (on its well-being) is measured by comparing the current status of well-being variables (number of cases, unemployment rate, and freedom rate) of that

[1] https://data.humdata.org/dataset/acaps-covid19-government-measures-dataset
[2] https://freedomhouse.org/report/freedom-world
[3] https://databank.worldbank.org/

agent with the related tolerable thresholds which are cases_threshold, unemployment_threshold, freedom_threshold (the ranges of the variables are derived by real-world data[i, iv, v] and the tolerable thresholds are determined based on the initial variables + a random number or initial variables – a random number, see Table 1).

If one or more variables do not meet the tolerable thresholds, the agent is not satisfied with the situation. In this way, agents who are more sensitive to freedom or unemployment, will be dissatisfied faster. Yet, the type of institution that is selected as a result of this dissatisfaction is not in anyway, related to the values of the agents.
For the country's value system we use two sets of Schwartz values: Openness-to-change and Conservatism.
1) Openness-to-Change (OSS) covers the two values: Self-Direction, Stimulation;
2) Conservatism (CST) covers the two values: Security, and Tradition.

We introduced two variables with a range [0, 1] to represent these two value sets for each agent, such that OSS + CST = 1 following the existing literature (Bojanowska et al., 2021; Bonetto et al., 2021).

Country strategies. We defined four interventions, following Ghorbani et al. (2020): NoLockdown, SocialDistancing, SoftLockdown, HardLockdown.

A country strategy is a collection of the four interventions, Country Strategy = {'NoLockdown': *value*, 'SocialDistancing': *value*, 'SoftLockdown': *value*, 'HardLockdown': *value*}. Each intervention is a float variable in the range of [0, 1][vi] (more details will be explained in section 3.3.1). This implies that at any point in time, a country can have more than one of these interventions, which form the overall strategy of that country. Each agent records its current strategy (the combination of above-mentioned interventions) which is coded using the ADICO grammar, along with its three well-being variables.

We measure the "strictness" of a country strategy, which is the weighted summation of all four interventions of a country strategy based on Equation 2. The weights are selected in such a way that weights of stricter interventions are higher (the weight of HardLockdown is higher than SoftLockdown and so on). The weights for each intervention are derived manually by us. Since for all scenarios we use the same weights, they are comparable.

$$W_{CS_t} = CS_t[NoLockdown] * 1 + CS_t[SocialDistancing] * 10 + CS_t[SoftLockdown] * 100 + CS_t[HardKockdown] * 1000 \quad (2)$$

- **Strategy change.** Over time with increasing numbers of infected cases, increase in unemployment rate, or decrease in freedom rate, if agents are not satisfied with their current situation, they change their strategy. Satisfaction is measured by comparing the current status of well-being variables with the related tolerable thresholds for each agent, which is a parameter in the model. Changing strategy means changing the values of the four interventions.

  Countries can copy the strategies of other countries during the pandemic. An example of countries copying other countries' strategies during the pandemic is the widespread (adoption) of mask mandates. This strategy was first implemented in Asian countries such as South Korea and Taiwan and was later copied by many other countries around the world as a way to slow the spread of the virus (Hun et al., 2020). However, our current assumption is that every country has a unique value system, economic, and social factors, and what works in one country may not work in another, so each country's strategy change is tailored to its specific circumstances. Therefore, the strategy changes are not coded to always result in an increase or decrease of the well-being parameters. Countries have different mechanisms to change their strategies, if it is needed, that might result in a stronger or weaker strategy.

We model strategy change in four different ways:

1) <u>ML</u>, the strategy changing process makes use of extensive data that trains our agents in choosing the most realistic strategy based on what actually happened during the pandemic. A Regression Decision Tree is trained using real-world data on the conditions (e.g., number of infected cases) that lead to specific combination of interventions.

2) <u>Copying</u> the strategy of an agent (country) that this particular agent is following (i.e. the initial values are similar to the country's initial values). This strategy change mimics the way that countries copying each other's strategies, as mentioned above.

3) <u>Mutation</u>, randomly changing one of the intervention values to 1 to form a new strategy,

4) <u>Case-based</u> with a degree of evaporation, which means agents change their strategies (interventions 'weights) according to the rise in cases: more cases, stricter interventions.

Additionally, to replicate the strategy lifting that can happen in reality over time, each intervention may evaporate with a degree. The procedure is based on Algorithm 1:

Algorithm 1: Case-based changing strategy

```
If country_cases < country_cases_threshold then
        Nothing
If country_cases_threshold  <= country_cases < 1.5 * country_cases_threshold then
         NoLockdown = 1
If 1.5 * country_cases_threshold  <= country_cases < 2 * country_cases_threshold then
         SocialDistancing = 1
If 2 * country_cases_threshold  <= country_cases < 2.5 * country_cases_threshold then
         SoftLockdown = 1
If 2.5 * country_cases_threshold  <= country_cases then
        HardLockdown = 1
```

It is worth to mention that in reality, it might happen that one strategy is a combination of several countries 'strategies. Although, we did not define a strategy change in a way that produces a joint strategy (i.e., combining the strategies of several countries) as a result of one step of change, it may occur gradually over several strategy changes.

Updating parameters. Based on the new chosen country strategy, the three well-being parameters of each agent will be updated. The effects of new strategy on well-being parameters are inspired from (Nussbaumer-Streit et al., 2020), who studied the effect of different strategies on essential well-being elements (explained in Appendix B). Under this assumption, the effect of HardLockdown intervention in decreasing cases, increasing unemployment, and decreasing freedom, is greater than other softer interventions.

- **Value change.** Changes in the values prioritisation occur when the agent is not satisfied with the current well-being status. In this situation, value change occurs by decreasing or increasing the previous value based on its initial state (Bonetto et al., 2021). If the initial OSS is high (>= 0.5), the new OSS will decrease: OSS – change_degree. If the initial OSS is low (< 0.5), the new OSS will increase: OSS + change_degree. Consequently, CST will be updated to 1 – OSS. However, not all countries seek to change their values at each tick. They might change or not, based on their well-being status and parameters related to value change as describe below.

The change_degree is different for each country at each changing time. This determines how much one value can change for each country. This is a random variable between 0 and changing threshold (country_change_threshold) for that specific country. Additionally, value change for each country has a threshold: country_change_threshold. This threshold determines, for each country, how much the initial values can change. This threshold is different for each country based on their initial values. The summation of all change_degrees during the simulation for each country cannot exceed this threshold. The more openness agents have higher threshold and vice-versa.

Additionally, each agent has a frequency of value change. The 'frequency_of_value_change 'determines how many ticks the agent should wait before changing the values. This parameter is based on the initial values of the agent. The frequency of change is low for the countries with the low initial OSS (the country rarely changes its values). If the initial OSS is high, the country is more open to change, therefore frequency_of_value_change is higher. In other words, if the agent is not satisfied with its well-being, it is not always going to change the values. The agent waits until its frequency of change allows it to change. For example, if the frequency of change is 2 for an agent, it should wait two ticks, until while the agent is dissatisfied, and then change the values.

When values change, the unemployment_threshold and freedom_threshold also will be updated accordingly. If the initial OSS is high, the unemployment_threshold will decrease and the freedom_threshold increases by one unit. If the initial OSS is low, the unemployment_threshold will increase and the freedom_threshold decrease by one unit (see Table 1).

As pandemic changes things rapidly, the memory of the previous social order is still fresh and will pull back when possible. Therefore, we assume a roll back mechanism as one option for designing our scenarios. When values changes of a country reach a specific threshold (different for each country, country_threshold), there is a probability that the country's values roll back to the initial values or the status quo.

- **Shared strategy.** Later on in time, the average of all country strategies shows the average weights of interventions across all countries and here we refer to it as the shared strategy.

  For example suppose we have three countries with: Country1 Strategy = {'NoLockdown': 0, 'SocialDistancing': 0, 'SoftLockdown': 1/2, 'HardLockdown': 0}, Country2 Strategy = {'NoLockdown': 0, 'SocialDistancing': 0, 'SoftLockdown': 1/2, 'HardLockdown': 1}, and Country3 Strategy = {'NoLockdown': 0, 'SocialDistancing': 1, 'SoftLockdown': 0, 'HardLockdown': 0};

  the shared strategy will be {'NoLockdown': 0, 'SocialDistancing': 1/3, 'SoftLockdown': 1/3, 'HardLockdown': 1/3}.

  We measured the "strictness" of a shared strategy, which is the weighted summation of all four interventions of a shared strategy based on what is mentioned in 'Country strategies 'part, Equation 3.

$$W_{SS_t} = SS_t[NoLockdown] * 1 + SS_t[SocialDistancing] * 10 + SS_t[SoftLockdown] * 100 + SS_t[HardKockdown] * 1000 \quad (3)$$

- **Accumulated value**. Accumulation of values is a variable that is calculated in the model, showing the sum of all OSS values for all countries. We keep track of this to explore the relationship between overall value of countries and shared strategy at each time.

Dissatisfaction about well-being serves as a starting point for both updating processes of values and country strategies. However, the actual update functions of these two are completely independent of each other. In that way, we ensured that any relationships between shared strategies and accumulated values could only be the outcome of the model and would not be coded into the model.

5.4 Model Implementation and Sensitivity Analysis

5.4.1 Implementation Details

The model was implemented in Python using Mesa (ABM part) and Sklearn (ML part) libraries. The class diagram of the model is shown in Appendix C. The codes of this study are openly available on CoMSES:
https://www.comses.net/codebase-release/29022830-747d-401b-80fb-177e45b94559/

We use random initial parameter setup (to explore the whole domain space) in specific ranges. The specific ranges for our parameters are derived by real world data (Sattenspiel et al., 2019) (as mentioned in Section 3.2). The model parameters are shown in Table 1. Note that each element of well-being, also has a tolerable threshold.

Moreover, we defined three groups of countries: countries with very high initial OSS, countries with very high initial CST, and countries in between.

Table. 1. ABM Input Parameters and Variables (see Appendix D)

Name	Base value	Threshold parameter	Parameter /Variable	Description
Number of agents	100	-	P	Number of agents
cases_for_14_days_per100000	random integer [0, 2]	Cases_threshold = random integer [30, 60]	P-P	The number of infected cases per 100,000 in 14 days. The threshold of tolerating cases.
unemployment	random integer [0, 30]	unemployment _threshold =	P-V	The initial unemployment

		unemployment + random integer [0, 10]		rate. The tolerable threshold for unemployment.
freedom	random integer [40, 90]	Freedom_threshold = freedom - random integer [0, 30]	P-V	The initial freedom rate. The tolerable threshold for freedom.
OSS	random uniform [0, 1]	-	V	The probability of generating an agent with high (greater or equal to 0.5) or low (less than 0.5) USS has been fed by a model parameter
CST	random uniform [0, 1]	-	V	1 - OSS
r	0.2 (initial value) In each tick: r (new) = cases_this_tick / cases_previous_tick	-	P	Reproduction rate.
frequency_of_value_change	if the initial OSS >= 0.8: frequency_of_value_change=1 if 0.5 <= initial OSS < 0.8: frequency_of_value_change=2 if 0.5 < initial CST < 0.8: frequency_of_value_change=4 if the initial CST >= 0.8: frequency_of_value_change=8	-	P	How many ticks the agent wait to change the values.
decrease_freedom	random uniform [0.03, 0.09]	-	P	

increase_unemployment	random uniform [0.03, 0.05]	-	P	
increase_cases	if r < 1: cases_14_100000 * random.randint(0, 5) or random.randint(0, 100) if r >= 1: cases_14_100000 * r	-	V	
initial_strategy	{'NoLockdown': 0, 'SocialDistancing': 0, 'SoftLockdown': 0, 'HardLockdown': 0}	-	V	The initial country strategy.
change_degree	if the initial OSS >= 0.5: min (initial OSS, initial CST) if the initial CST > 0.5: min (initial OSS, initial CST)/2	-	P	How much the initial values can be changed?
need_to_change_strategy	0	-	P	A flag to show whether it needs to change strategy or not. It feeds based on the output of well-being function.
region	Probability based on real distribution of countries in regions from ACAPS dataset (REGION_Africa,REGION_Americas,REGION_Asia,REGION_Europe,REGION_Middle east,REGION_Pacific: 0.3, 0.2, 0.1, 0.2, 0.1, 0.1)	-	P	The region of the agent.
countrycountry-to-follow	An Agent (with similar initial OSS/CST values)	-	P	The similar agent in terms of initial values.

5.4.2 Sensitivity analysis

We use sensitivity analysis on the model level variables to explore input/output domain space in order to identify parameters for which small variations most affect the model's output (Lee et al., 2015).
The parameters, on which we did OFAT (one-factor-at-a-time) sensitivity analysis (Ten Broeke et al., 2016), are shown in Table 2. 'OSS Degree' determines the probability of generating

countries with high (OSS greater or equal to 0.5) or low initial OSS (less than 0.5). We assumed three values for this parameter to cover low, medium, and high initial OSS. 'ML Degree' is the probability of using past experiences (trained ML) in selecting strategies among countries. It shows, which portion of the world use 'ML' when they need to change their strategies. Greater' ML Degree' shows a simulated world, where most countries use past experiences (trained using real-world data) to change their strategy. 'Innovation Degree' represents the probability of countries being more innovative in changing their strategies or just simply go to copy their strategy from another country. Lower value for 'Innovation Degree' probability means higher chance to go for copying.

Table. 2. Model level parameters

Value	Varied Range
OSS Degree	0.3, 0.6, 0.9
ML Degree	0, 0.3, 0.6, 0.9
Innovation Degree	0, 0.3, 0.6, 0.9

To find the sensitivity of the model, for each combination of model parameters, we run the model 100 times (in total 4800 independent simulation runs). The model outcomes for sensitivity analysis phase are shown in Appendix E.

Based on the result of sensitivity analysis, we reached to these parameter ranges: OSS Degree 0.3, 0.6, 0.9; ML Degree 0, 0.3, 0.6; Innovation Degree 0.3, 0.6, 0.9.

The goal of our experiments is to see the overall pattern between accumulated value and shared strategy over time. We designed four scenarios as shown in Table 3, where the mechanisms of strategy change, and whether there is roll back in the value change process easing for interventions, vary.

Table 3. Parameter setups

Scenario	Strategy Changing	Roll Back?	Strategy Evaporation?	OSS Degree	ML Degree	Innovation Degree
Scenario 1	Mutation, Copy, ML	No	No	0.3, 0.6, 0.9	0, 0.3, 0.6	0.3, 0.6, 0.9
Scenario 2	Mutation, Copy, ML	Yes	No	0.3, 0.6, 0.9	0, 0.3, 0.6	0.3, 0.6, 0.9
Scenario 3	Case-based, Copy, ML	No	Yes	0.3, 0.6, 0.9	0, 0.3, 0.6	0.3, 0.6, 0.9
Scenario 4	Case-based, Copy, ML	Yes	Yes	0.3, 0.6, 0.9	0, 0.3, 0.6	0.3, 0.6, 0.9

5.5 Results

We executed 10800 independent simulation runs (4 scenarios, each combination of model parameters 300 runs: 4*3*3*3*100 = 10800).

The goal is to extract general patterns between accumulated value change and shared strategy. Figure 4 shows the strictness of the shared strategy (in blue) and the accumulated value (in green) averaged over runs for all four scenarios. First, we look at the slope of diagrams, then discuss the general pattern between shared strategy and accumulated value, the correlations, the causes by analysing dissatisfaction (well-being parameters), interventions, and agents ' specifications by exploring the differences between the scenarios.

<u>Adaptation speed to the pandemic</u>: The results in Figure 4, indicate that at the beginning of the pandemic, there are big changes in strategies; meaning that countries change their strategies significantly to adapt to the pandemic as shown by the slope of the diagram (Figure 4) at the beginning. This is in line with the theory that suggests institutional change is more frequent as the start of a collective situation (Farjam et al., 2020). After the cross point between accumulated value and shared strategy, the slope for both diagrams slowly flattens. This can be the consequence of selecting more effective strategies as a result of learning behaviour driven by the data-trained decisions.

<u>General pattern</u>: A general inverse relationship between shared strategies and accumulated values is observable (Figure 4). When the summation of OSS values for all countries is high (on average), the strategies are less strict on average and vice versa. One reason for this pattern is that when the overall accumulated OSS is high, the agents change their values more often, to adapt to new situations and therefore, there is less dissatisfaction. On the other hands, when the overall accumulated CST is high, the agents rarely change their values. Consequently, they are suddenly faced with dissatisfaction caused by the pandemic (immediate changes in the number of infected cases, unemployment rate, or freedom rate which are not in the tolerable threshold ranges of the country).

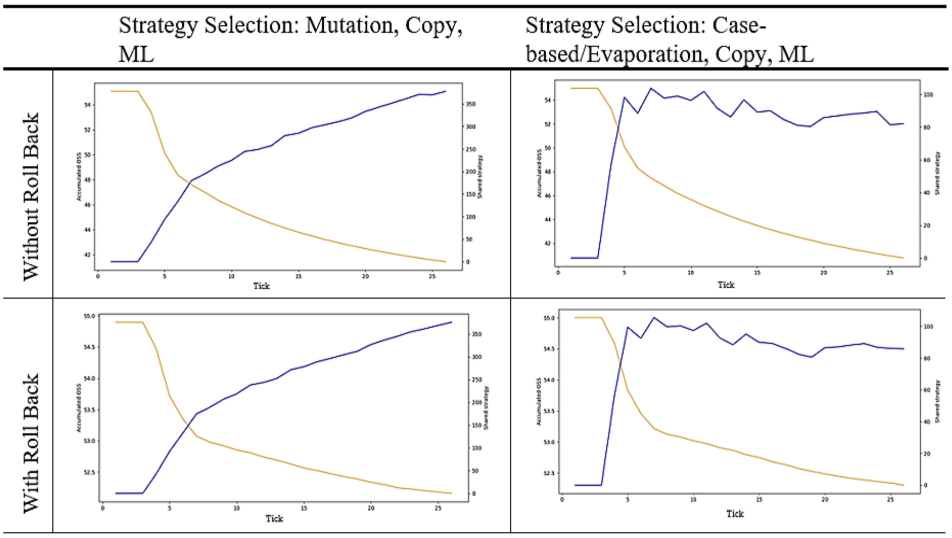


Figure 4. The general relationship between shared strategies and accumulated values. The strictness of the shared strategy (in blue) and the accumulated value (in orange) averaged over runs, per tick for the four scenarios

Figure 4 also shows the effect of having random selection of interventions (i.e. mutation) as opposed to being sensitive to number of infections (i.e. case-based). The strictness of interventions follows a smoother curve when mutation take place, while being have a case-based selection criteria has a much steeper path towards strictness. This is due to the fact that agents can choose stricter interventions only based on the rising of cases. This difference is also observed in the correlation analysis: it is stronger with the presence of mutation (the correlation between shared strategy and accumulated value (OSS) is -0.99), and lower with the presence of case-based/evaporation strategy selection (-0.72). Having rollback mechanisms for values (i.e. Scenarios 2 and 4 compared to Scenarios 1 and 3) does not however, create too much of a difference among the correlations.

Well-being: Figure 5 shows the countries' dissatisfaction values, for the four scenarios over time. The average number of countries who are not satisfied with each well-being elements are shown with different colours: dissatisfaction caused by the number of infected cases (in brown), increasing the unemployment rate (in light green), decreasing the freedom rate (in dark green). The dissatisfaction caused by cases shows (semi) stability after the first peak as a result of the interventions being implemented over time.

When there is a roll back mechanism (i.e. there is a probability that the country's values roll back to the initial values or the status quo, when values changes of a country reach a specific threshold), the satisfaction caused by unemployment and freedom rates is lower. Since in roll back mechanism, agents have the opportunity to tune their thresholds related to unemployment and freedom rates more often. Therefore, they adjust their tolerable thresholds over time and can better deal with the pandemic. Having a case-based selection/evaporation in place however, instead of mutation, does not influence the average satisfaction level of countries over time.

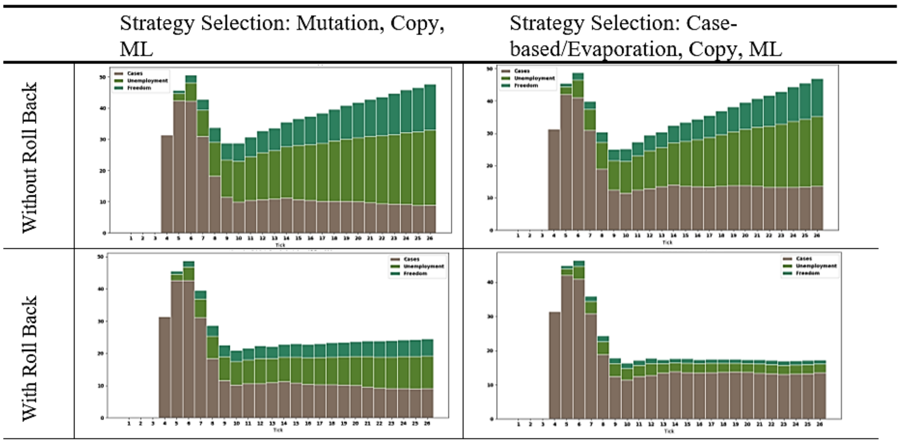


Figure 5. The well-being results. The average number of countries which they are dissatisfied due to the number of infected cases (in brown), increase in unemployment rate (in light green), de-crease in the freedom rate (in dark green)

Interventions: Figure 6 shows the histograms of each interventions 'weights over time for each scenarios. In Scenarios 1 and 2, agents choose stricter interventions. However, in Scenarios 3 and 4, they are choosing lighter ones.

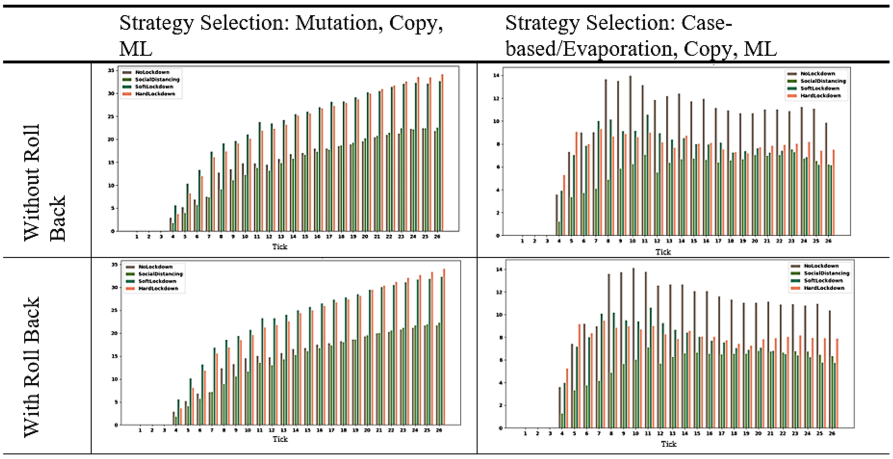


Figure 6. The histogram of each interventions' weights (the intensity) over time (Tick) for each scenario, NoLockdown (in brown), SocialDistancing (in light green), SoftLockdown (in dark green), and HardLockdown (in orange).

Agents' specifications: By exploring agents' specification in four scenarios, there is no differences between their parameters except for unemployment and freedom thresholds (Figure 7). As we discussed earlier, in situations with higher frequency of change, countries have more opportunity to adjust their unemployment and freedom tolerances when there is a roll back mechanism.

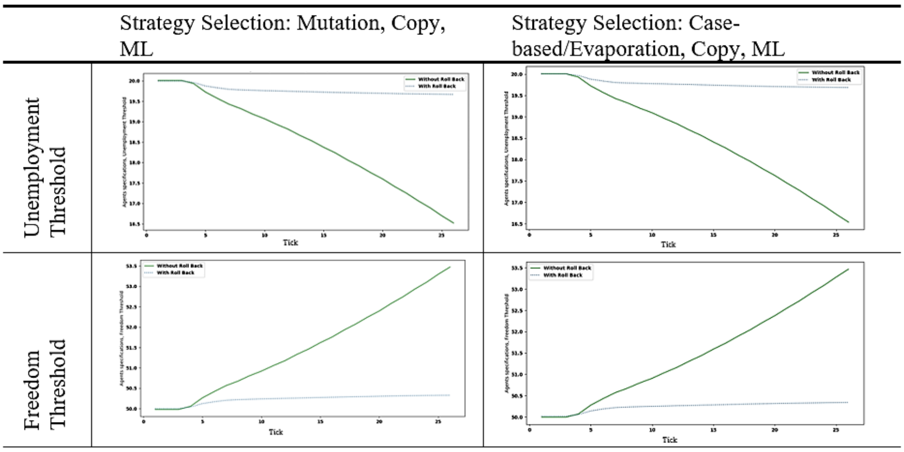


Figure 7. Averages of unemployment and freedom thresholds of countries when there is a roll back mechanism (in blue), and when these is not a roll back mechanism (in green).

5.6 Discussion and Conclusion

This paper aimed to study and test the relationship between value change and shared strategy change during a crisis. In this work, we brought together computational capacities of agent-based modelling and machine learning to explore the relationship between change of value prioritisation in agents and emergence of shared strategies among agents.

While implementing strategy change and value change as two independent processes, we observed that the relationship between overall strategy (the intensity) change and accumulated value change under the pressure of a crisis (COVID-19 in this case) in general is inverse. Given that the selection of strategies was not directly influenced by the values of agents, this is an insightful confirmation of what may seem a trivial relation between values and institutions. When the overall openness-to-change value (OSS) among agents is high on average, the shared strategies are less strict (on average) and vice versa. This is an interesting observation as the agents are programmed to change their values more often and are therefore, able to more quickly adapt to new pandemic circumstances. In other words, being open to change, does not immediately make a government select more relaxed rules, but this correlation is rather an indirect consequence of being more dynamics in changing rules.

To better explain the findings of this research, it is also worth looking more closely at the impact of conservatism. When the overall accumulated CST among agents is high, the agents rarely change their values (i.e. OSS, CST). Therefore, they are faced with higher dissatisfaction rates caused by the pandemic in at least one of the well-being dimensions. Their responses to combat this dissatisfaction thus also needs to be large requiring them to choose more strict interventions. In other words, being more conservative does not make agents choose stricter rules, but these strict rules are the indirect consequence of not being open to (value) change.

The key message or explanation we draw from this research is, being open to change, does not necessarily cause a government to select more relaxed rules, but this correlation is rather an indirect and emergent consequence of being more flexible in changing rules, whether the consequent ones are more relaxed or more strict.

. In this work, we aimed to incorporate data-driven decision making while also giving the possibility to explore a wider space of outcomes. This data-driven aspect of the work allowed us to model the process of institutional change and value change quite independently, as the selection of strategies was driven by actual decisions made by countries, rather than the result of value change in the model. Therefore, taking this data-driven decision making approach proved to be highly useful for our specific goal.

This modelling practice, however, also faced some limitations. First, the model that we used as the basis to test the relation was quite abstract both in terms of specifications of countries (agents) and the world in general. Therefore, we did not really aim to model and study the dynamics of the pandemic in anyway, and rather used this situation as a proof-of-concept and source of data for intervention change. As such, we are not drawing any conclusion about how a pandemic can be better managed nor whether the existing institutions and values had any positive or negative impact on the way the pandemic played out. Second, we exclusively focused on shifts in values, encompassing diverse directions, rather than the intensification of values in the same direction. Specifically, countries with initially high OSS scores would experience a decrease in OSS (becoming more conservative), while countries with low OSS (high CST) would see an increase in OSS (becoming more open) in case of dissatisfaction. This is a very simplistic representation of value change and therefore, served as an illustration of how value change, and its relation with other components of a social system can be modelled. In addition to more advanced value change processes, for future work, it is also worth implementing feedback loops to inform agents about the consequences of their strategy selection on their state of well-being.

5.7 Appendices

Appendix A: Pre-processing

Pre-processing

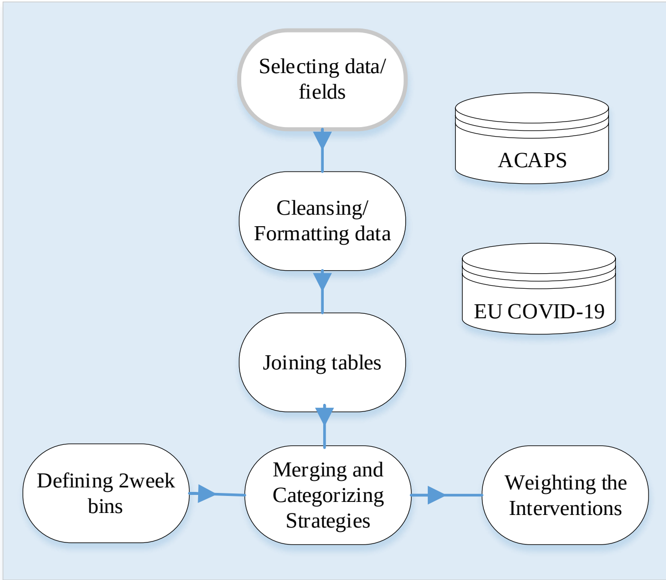


Figure 8. Pre-processing

ACAPS Used Fields

Table 4. ACAPS used fields

Field	Description
Country	Country of the record
Region	Region of the record
Log-Type	Introduction / extension of measures or Phase-out measure
Category	Sub-intervention category
Measure	Sub-intervention measure
Data-Implemented	The implementation date

ACAPS Sub-interventions

Table 5. ACAPS sub-interventions

Category	Measure	Merged	Intervention
Governance and socio-economic measures	Limit product imports/exports	Governance and socio-economic measures.Limit product imports/exports	NoLockdown
Governance and socio-economic measures	Economic measures	Governance and socio-economic measures.Economic measures	NoLockdown
Movement restrictions	Border checks	Movement restrictions.Border checks	NoLockdown
Movement restrictions	Visa restrictions	Movement restrictions.Visa restrictions	NoLockdown

Movement restrictions	Additional health/documents requirements upon arrival	Movement restrictions.Additional health/documents requirements upon arrival	NoLockdown
Public health measures	Health screenings in airports and border crossings	Public health measures.Health screenings in airports and border crossings	NoLockdown
Public health measures	Awareness campaigns	Public health measures.Awareness campaigns	NoLockdown
Public health measures	Strengthening the public health system	Public health measures.Strengthening the public health system	NoLockdown
Public health measures	Other public health measures enforced	Public health measures.Other public health measures enforced	SocialDistancing
Public health measures	General recommendations	Public health measures.General recommendations	SocialDistancing
Public health measures	Requirement to wear protective gear in public	Public health measures.Requirement to wear protective gear in public	SocialDistancing
Public health measures	Testing policy	Public health measures.Testing policy	SocialDistancing
Public health measures	Psychological assistance and medical social work	Public health measures.Psychological assistance and medical social work	SocialDistancing
Public health measures	Obligatory medical tests not related to COVID-19	Public health measures.Obligatory medical tests not related to COVID-19	SocialDistancing
Lockdown	Partial lockdown	Lockdown.Partial lockdown	SoftLockdown
Movement restrictions	International flights suspension	Movement restrictions.International flights suspension	SoftLockdown
Public health measures	Isolation and quarantine policies	Public health measures.Isolation and quarantine policies	SoftLockdown
Public health measures	Mass population testing	Public health measures.Mass population testing	SoftLockdown
Social distancing	Limit public gatherings	Social distancing.Limit public gatherings	SoftLockdown
Governance and socio-economic measures	Emergency administrative structures	Governance and socio-economic measures.Emergency administrative structures activated or established	HardLockdown

	activated or established		
Governance and socio-economic measures	State of emergency declared	Governance and socio-economic measures.State of emergency declared	HardLockdown
Lockdown	Full lockdown	Lockdown.Full lockdown	HardLockdown
Movement restrictions	Border closure	Movement restrictions.Border closure	HardLockdown
Movement restrictions	Surveillance and monitoring	Movement restrictions.Surveillance and monitoring	HardLockdown
Movement restrictions	Domestic travel restrictions	Movement restrictions.Domestic travel restrictions	HardLockdown
Movement restrictions	Curfews	Movement restrictions.Curfews	HardLockdown
Movement restrictions	Complete border closure	Movement restrictions.Complete border closure	HardLockdown
Social distancing	Schools closure	Social distancing.Schools closure	HardLockdown
Social distancing	Closure of businesses and public services	Social distancing.Closure of businesses and public services	HardLockdown

Appendix B: Updating Parameters

Unemployment and freedom rates will be updated according to Table 6. There are two parameters increase_unemployment and decrease_freedom, which shows the amount to be increased or decreased at each tick (these two parameters are described in Table 1). For updating unemployment and freedom rates, we use a weighted sum of increase_unemployment/ decrease_freedom * $Effect\_Intervention_i$, where $Effect\_Intervention_i$ is the effectiveness of applying intervention i based on Table 6.

Table 6. Updating

Variable	NoLockdown	SocialDistancing	SoftLockdown	HardLockdown
Unemployment	0.25	0.50	0.75	1
Freedom	0.25	0.35	0.65	0.90

Appendix C: Class Diagram

The class diagram of the model is shown in Figure 9. Pre-processing is necessary for both ML and Agent classes. One trained and validated ML model can be applied in one or many agents (in Agent class). In addition, one Model class consists of several agents instances from Agent class.

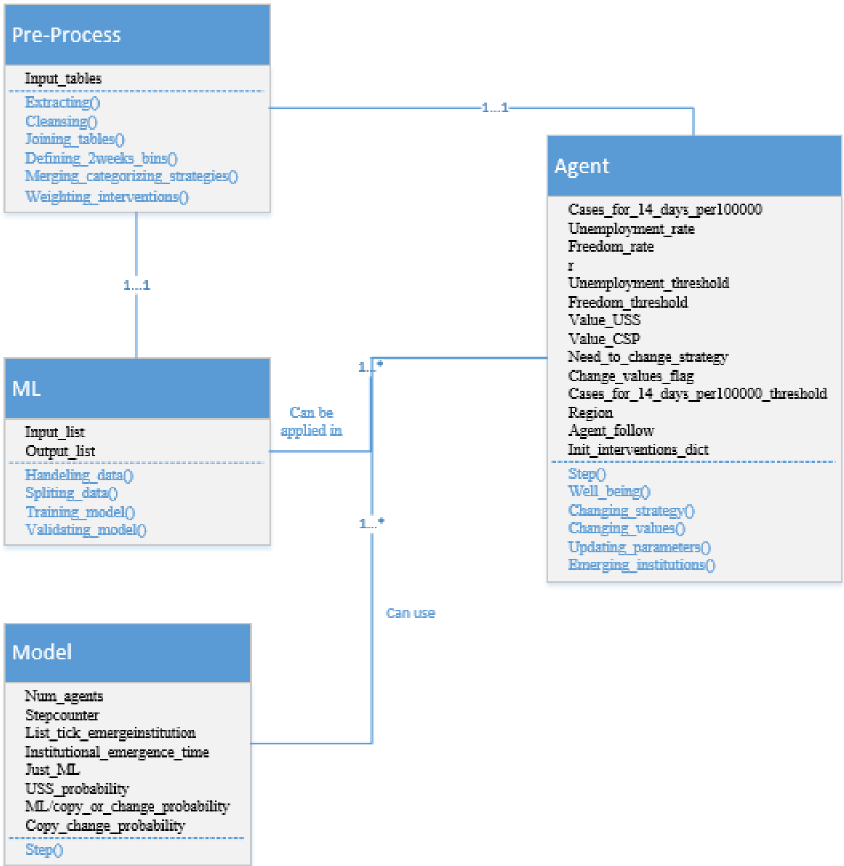


Figure 9. Class diagram of the model

Appendix D: More Explanation on Input Variables and Parameters

Decease_freedom: based on the real data (https://freedomhouse.org/report/freedom-world), the differences in freedom between 2019, 2020, 2021 in average is 1-2, therefore each two weeks in average 0.04-0.08 is the decreased value. Therefore, we assume random uniform (0.03, 0.09) as decreased freedom parameter for each agent to cover the tolerances. In the scale of model parameters, it is between 1.4-4.2 (0.03-0.09 * 100 /2.15).

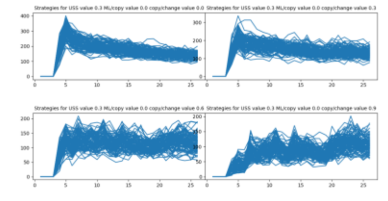
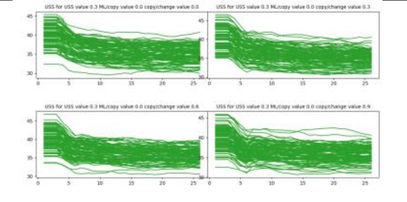
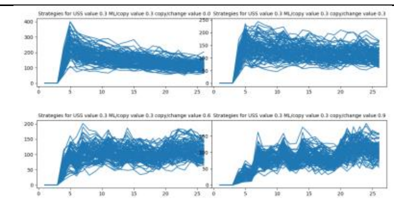
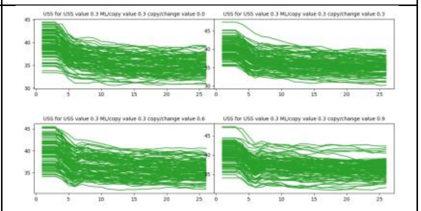
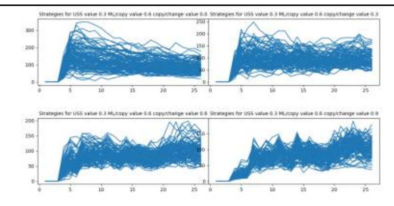
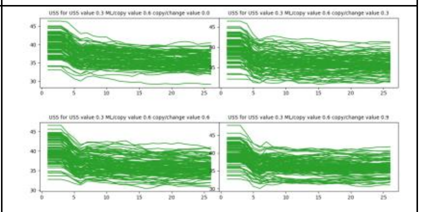
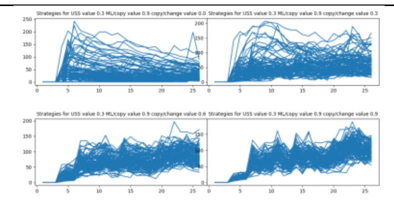
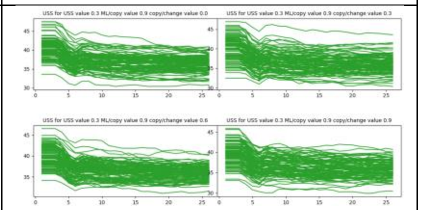
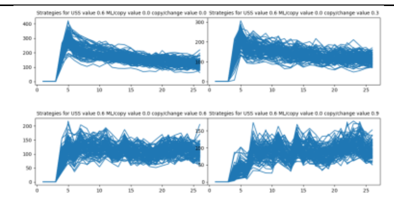
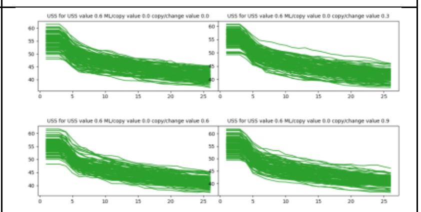
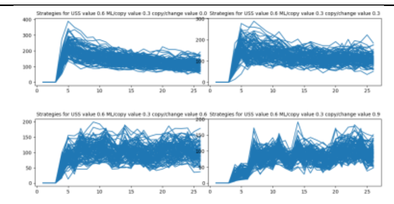
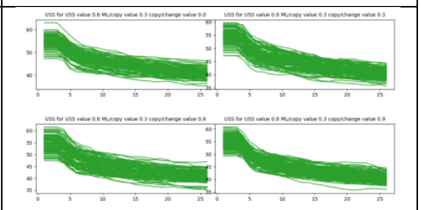
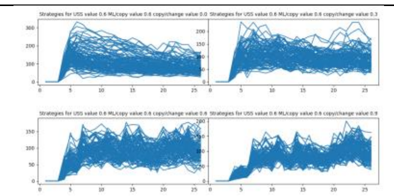
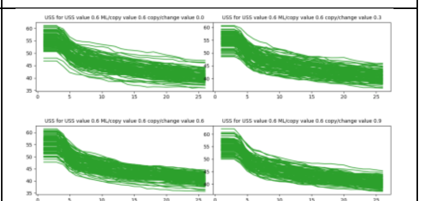
Increase_unemployment: based on the real data (Monitor 2020), the differences in unemployment relative to 2019 in total is 1.1, therefore each two weeks in average 0.04 is the increased value. Additionally we have analysed https://databank.worldbank.org data, between 2019 and 2020 (the data for 2021 was not available on the time of analysing), we calculated the differences between unemployment rates of countries which we have available data, then divided the numbers per 24 to calculate the difference of unemployment in each two weeks, the average of differences in each two weeks for all the countries is 0.04 (same as what is mentioned for the first resource). Therefore, we assume random uniform (0.03, 0.05) as increased unemployment parameter for each agent to cover the tolerances. In the scale of model parameters, it is between 1.2-2.5 (0.03-0.05 * 100 /2.5).

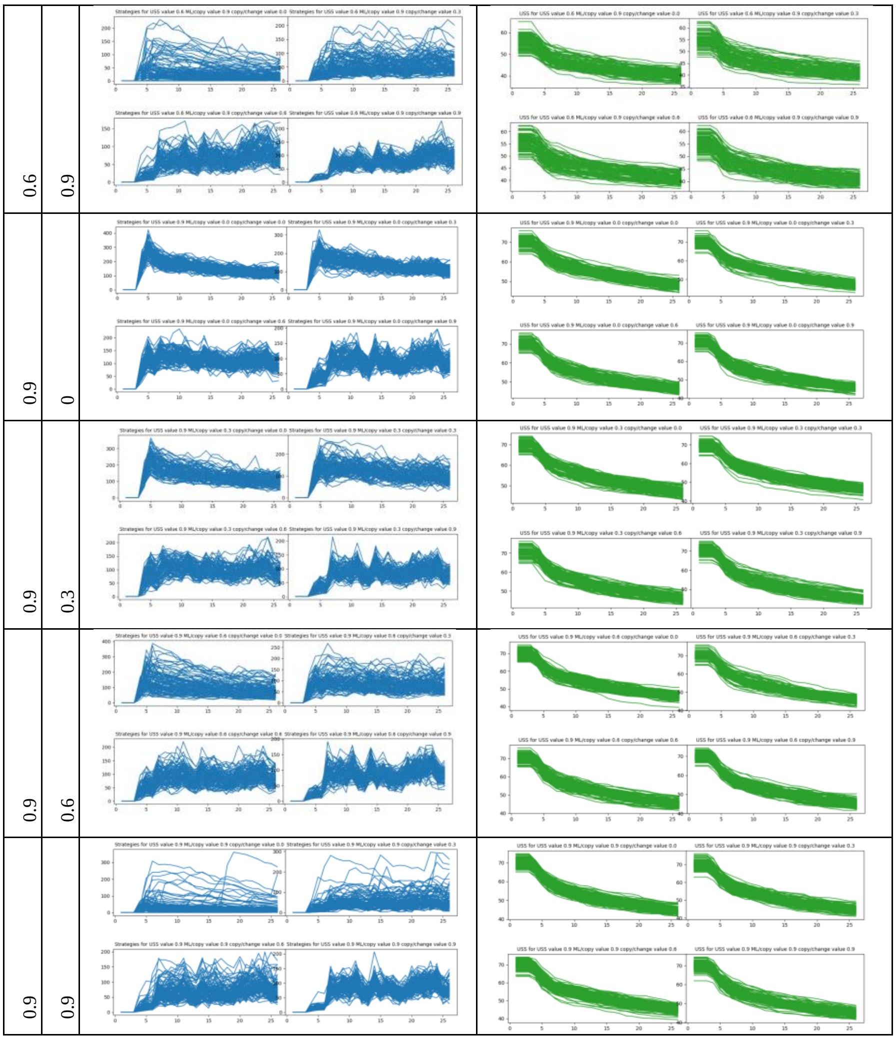
Increase_cases: It shows the increasing number of infected cases (without considering any strategies). Before starting the pandemic ($r < 1$) the new number of infected cases are estimated as a random number between: 1) number of current infected * random integer [0, 5], which shows one infected person can infect 0 to 5 people; 2) or a random number between 0 to 100.

When the pandemic starts (r >= 1), based on the reproduction rate formula, the new infected cases are the current ones multiply to r.

Appendix G: Sensitivity Analysis

Table. 7. Sensitivity result

OSS	ML	Strategy Changes	Value Changes
0.3	0		
0.3	0.3		
0.3	0.6		
0.3	0.9		
0.6	0		
0.6	0.3		
0.6	0.6		



Although the main purpose of sensitivity analysis is to find the parameter ranges, which the model is sensitive to, it can bring more insights into searching the whole parameter domain and their effects on the relationship between accumulated value and shared strategy. The relationship between overall accumulated value and shared strategy over time is an emergent pattern from the model. Since value change and strategy change processes are completely independent in the model.

Following the first goal, the results show that the model is sensitive to ML Degree = 0.9. Since the fluctuations are always observable in this situation in comparison with other ML Degree in all combinations. In other words, the 100 runs do not converge only when ML Degree = 0.9.

Additionally, the model is sensitive to Innovation Degree = 0. Among the four diagrams for different ML Degree values, always a same pattern is observable. However, when Innovation Degree = 0, the same pattern is not observable. In other words, the model does not follow the same way and acts differently in this situation.

The case OSS Degree = 0 is not a real scenario, since the probability to produce a non-conservative country would then be zero. In that case, we are dealing with a simulated world where most of the countries are conservative or extremely conservative and almost none of the agents (countries) are willing to change their values. Therefore, we exclude this case from parameter setups.

Following the second sensitivity analysis goal, the general inverse relationship between accumulated value and shared strategy is observable. Moreover, as we move to simulated worlds with higher initial degree of OSS, the ranges of strategy changes are higher. This shows that a world with more open countries is going to have stricter strategies. On the other hands, a simulated world with mostly conservative countries changes their strategy less.

Additionally, the sub-scenarios with higher initial OSS degrees have a wider range of accumulated OSS over time. The cause is that the agents (countries) with higher OSS are much more likely to change their values.

Moreover, we explore the effect of ML on the relationship between accumulated value and shared strategy. Based on the sensitivity analysis, we have three ML degrees: 0 (no intelligence), 0.3, and 0.6. In this cases, we do not discriminate sub-scenarios based on initial OSS degree. Therefore, the start points for original accumulated OSS are mostly near the average. With increase in the ML degree, the ranges of shared strategy changes are wider. It can be interpreted in this way: in reality, we may have more unexpected peaks of infected cases or other parameters, which cause countries to suddenly choose stricter strategies.

Finally, we explore the impact of Innovation degree on the output (i.e. relationship between accumulated value and shared strategy). Again, we have three different probabilities: 0.3, 0.6, and 0.9. With increase in the copying, the ranges of shared strategy changes are lower. When the level is higher, the probability to go for copying is higher. Therefore, when we have more countries, which copy other countries 'strategies (with similar initial values), the shared strategy will converge. Moreover, the ranges for strategy changes are less in these situations.

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6 Outlook

Institutions can facilitate the functioning of social, technological, and ecological elements in our society. Yet, institutions change over time, and the dynamics have a significant impact on the foundation and well-being of societies. This research aimed to study the dynamics of institutions using ABM to explain how institutional change relates to individual behaviour and interaction by linking macro-level patterns and micro-level reasons.

This thesis, therefore, addressed the question: **How can ABM contribute to understanding the dynamics of institutions?**

This final chapter discusses and reflects on the role of ABM in explaining the dynamics of institutions.

6.1 Reflections

6.1.1 How Agent-based Modelling can be Used to Study Institutional Change?

Based on the experiences gained in this research, ABM can be used both inductively and deductively to study institutional dynamics as reflected on below.

ABM as a Deductive Approach vs. Inductive Approach

ABM as a deductive approach to study hypotheses on institutional dynamics. High-level institutional patterns show the trends of institutional change over extended time horizons. However, it is difficult to postulate which dynamics at a lower level have led to these patterns (e.g., rapid change of rules at the establishment phase of a social system). These macro-level patterns or trends show the overall characteristics of institutional change rather than specifications of micro-level reasons. Although these patterns already contribute to a better understanding of institutions, hypothesising links between these patterns and bottom-up causes and deductively exploring them in simulations brings valuable insights into institutional dynamics. Chapter 2 of this thesis provides a proof of this claim.

The guidelines proposed in Chapter 2 explained how ABM could be used deductively to reproduce high-level institutional patterns and consequently understand the underlying mechanism. These guidelines were drawn based on the model that was developed to explain an already observed historical pattern: U-shape change of institutions over the lifetime of commons. As a summary of the guidelines for using ABM, a model is first developed to reproduce a specific institutional pattern. To increase the reliability of the model outcomes and increase the degree of generalizability, modellers must verify and validate the model using independent datasets (different from the one where the pattern was initially observed). The U-shape case used an existing validated ABM of CPR management to reproduce the institutional pattern extracted from the historical dataset. After this step, the modeller conceptualises hypotheses and configures model parameters. In the U-shape case, the hypotheses were drawn from the literature and by a historian. By running different experiments for different hypotheses, the ABM is then able to confirm whether the hypotheses hold in an abstract validated setting. This modelling methodology can help institutional analysts to deduce the plausibility of the underlying mechanisms that have led to institutional patterns by comparing emerging patterns from the ABM to existing theories/hypotheses or observed institutional patterns in datasets.

ABM as an inductive approach to develop theories about institutional change. Besides providing a means to test existing theories and hypotheses, ABM can also provide insights into the dynamics of institutions without the need to reproduce certain patterns. In such situations, ABM helps researchers develop institutional theories inductively either through abstract models or data and case-driven ones.

Chapter 3 presented an example of an abstract model that investigates the role of wealth inequality on the cooperation to shape and preserve institutions that are established for the management of commons. Although the model used was previously validated with empirical data, it did not make use of any real-world data. By experimenting with different wealth distributions in a simulated society, we showed that wealth inequality generally has negative effect on cooperation. Furthermore, the results showed that at low inequality, common-pool resources perform better in terms of average wealth and availability of the resource. In similar unequal situations, when cooperation is higher, the average wealth and amount of resource are higher. Moreover, when cooperation is high, there are fewer agents who cheat or do not vote, and the first institution emerges later in time. In similar cooperative situations, cheaters and non-voters are less when inequality is less.

Chapter 5 showed how a data-driven ABM can be used in an inductive setting to explain the relationship between the emergence of institutions and the value dynamics of the society. The model focused on the particular case of the COVID-19 pandemic and postulated some relationships about how the values of countries and their prioritization influences the change of institutions that the governments define to manage the crisis.

In the inductive approach, agents, actions, and interactions are the heart of the system. They are the ones who collectively define, change, follow, or even disobey institutions. These agents have both homogenous and heterogeneous specifications. These specifications, and sometimes their combination, make agents unique which is a crucial factor in the institutional course. The availability of institutional data (e.g. the regulations in the pandemic case) however, can bring in a more tangible and concrete dimension to the dynamics of institutions that could further help policy making.

Using Data in ABM of Institutional Change

Data-driven vs abstract ABM. It is important to reflect on the use of data for institutional modelling further. Data-driven or case-based models as Boero and Squazzoni (2005) define them are specifically associated with a case and related data. Theoretical abstractions (Boero and Squazzoni (2005)) or abstract models, on the other hand, allow modellers to explore wider domain space. Each one of these approaches have benefits and drawbacks for the institutional analysis domain.

Data-driven models are usually bonded to a specific case, a set of data, and time. Therefore, the insights that they provide are more tangible as previously touched upon. Besides providing policy relevant insights, data-driven institutional models can be argued to have reliable insights as generalization does not have to be a goal in such cases, very similar to case-based empirical research. However, abstract models provide more degrees of freedom to explore hidden causal relations by looking at the full parameter spectrum. At the same time, abstract models are sometimes the only way to look at institutions that can emerge for situations that do not exist yet. It is also important to note that looking at long-time dynamics of institutions, may also benefit from abstract models as the details of the past, especially over centuries are not always available. So, the question on whether to use abstract ABMs or data-driven ones always boils down to the choice between generalizability and preciseness. Nonetheless, the level of abstractness and the amount of data used are not a 0 or 1 decision and there is a full spectrum of abstractness and data that a model can benefit from.

Data availability. Institutional data can be considered as data that directly connects to institutions. Such as the data that specifies the conditions under which a certain regulation hold. However, other forms of (quantitative) data may also be used in simulations that are indirectly associated to institutional dynamics such as the income distribution of a population. Institutional data is mostly qualitative and can therefore, mainly be incorporated into models through conceptualization. Another difficulty with institutional data is that existing data is much less available and more expensive to collect. This type of data is mostly collected through interviews and policy documents, which take a rather long process to complete. Even with other indirectly related types of data, given that institutions mostly take longer time horizons to change, data is not necessarily available. For instance, although institutional data was available for the case in Chapter 2 no data was present on the specification of commoners (agents) who lived and established institutions during that specific period. Therefore, as compared to other data-driven agent-based models, institutional data is less available, and this may be another reason why theory-driven models may be more within the reach of institutional analysts.

How to choose an appropriate ABM? As we mentioned before, data-driven and abstract ABMs are the two extreme ends of model. However, there is a range between these two endpoints. Finding an appropriate point for the desired ABM in this range, primarily depends on the availability of institutional data.

Besides the availability of data, another factor plays a role in choosing the degree of using real-world data in ABM. This factor is the 'purpose' of the study. Does the modeller want to study one specific institutional case (e.g., the trend of institutional change in gross lands in South Holland)? Or is it a general phenomenon related to institutions (e.g., impact of sanctioning on the longevity of common-pool resources)? Is she curious about the unseen or unexpected results?

A modeller should consider all these questions before choosing an appropriate ABM. The nature of the research question determines the degree of being data-driven. Nevertheless, suppose a situation when a modeller wants to study one specific case where the related data is insufficient, if not absent. Can the modeller still use an ABM? Yes. Is it a data-driven ABM? It depends on how much available data is there and how much freedom the modeller wants to give to the model to explore the domain space. Therefore, the crucial question changes from 'How much data do we have?' to 'How much data do we need?'.

Furthermore, the degree of model abstractness is rather fuzzy. An ABM can belong to data-driven and abstract models simultaneously but with different degrees. The modeller and the modelling questions are the ones to determine the degree of abstractness and the amount of data to use.

For instance, the case in Chapter 5 of this research has a higher data-driven degree than the abstract. First, we wanted to be as close to reality as possible and second, give a chance to the model to search a wider space and find likely unexpected results (and preserve the generalisation degree). Therefore, we used a real dataset on the COVID-19 government measures and real-world data on COVID-19 cases to inform our model. Besides some other parameters, the initial amount was a random number in a specific range—the specific ranges derived from real-world data.

Smart ABMS for Studying Institutional Change

In recent years, more researchers have been using machine learning techniques in ABM (Chu et al., 2009; Sun & Müller, 2013; Laite et al., 2016). Although adding a higher degree of intelligence to the models can be beneficial, some modellers criticise the black-box nature of ML techniques. As Albert Einstein said, "If you cannot explain it, you do not understand it well enough". A black box ML is an algorithm that does not show the process inside it. And the use of the algorithm only knows the input and output. This feature makes ML techniques hard to track. Contrary to this belief, (some) ML techniques can be transparent and interpretable (e.g., Decision tree or Bayesian network).

It is worth mentioning that one should pay attention to the model's functionality. Simplicity is good until it compromises functionality. Sometimes the nature of institutional data and the system's complexity bring the opportunity to use ML.

On the other hand, each ABM fulfils one or more than one specific purposes (Edmonds et al., 2019). The purpose of an ABM determines the whole process of conceptualising and modelling. Therefore, it is essential to see how modellers apply and find an appropriate ML in ABMs with different purposes. Therefore, in Chapter 4 of this research, a literature review was conducted, as a guideline, for using ML techniques in ABM based on the specification and the actual purpose of the corresponding ABM.

For instance, the model in Chapter 5 which explored the relationship between value change and institutional change during COVID-19 was of an 'explanation' type (Edmonds et al., 2019). For this complex case, the results must capture reality. Agents should have the ability to choose strategies in combating the pandemic similar to the real country's strategies. On the other hand, the institutional data (as mentioned before) was diverse and from different sources, and with different levels of granularity. Agents on the other hand needed a degree of intelligence to act like real countries (in this perspective). Therefore, based on the result of the review in Chapter 4, a decision tree was used to extract rules that model the agents' decision-making. This decision tree trained based on real-world data before simulation and then applied it to the agents' decision-making during simulation.

Although validating ABM is still an open topic, validating one ML model is more straightforward, especially with supervised algorithms. There are defined desired output and the output we get from the model. The measurement criteria are also defined. In an unsupervised algorithm also, the validation process is clear (by defining one goal function).

Conceptualising Institutional Change

ABM, especially abstract models, does not aim to reproduce the exact reality. They help bring more insights to answer the research questions by exploring various parameter settings and conditions (Danielisová et al., 2015). So, the models may not fully match reality. The last point, by itself, grabs the attention to the fact that the modeller may prune some detailed information during the conceptualisation.

Modellers may skip many details in conceptualisation, especially when the degree of generalising is high, and they decide to use abstract ABMs. Using an abstract model by itself forces us to ignore some detail in agents' specifications, the context, interaction, or even institutional changes.

Additionally, sometimes it is not possible at all to conceptualise some aspects related to institutions. E.g., feeling or image about the institutions.

Furthermore, "Everything is a trade-off." (First law of software architecture by Richards & Ford, 2020). It is applicable for institutional conceptualisation. Although we may skip some details, we can reach a valid, defendable outcome in an approachable way. Moreover, sometimes focusing too much on details can build a heavy model that is neither easy to use nor reusable.

Monitoring and Sanctioning. In complex institutional systems, like common-pool resource systems, both users and the environment are tightly interconnected. In those situations where resources share amongst a group, institutions need to prevent individuals from overusing the resource (Hardin, 1968; Ostrom, 1990). Therefore, self-governing institutions come up with rules to prevent overuse. Ostrom (1990) mentioned that these institutions should have monitoring and sanction to restrain cheaters who neglect institutions.

However, recent studies on the institutional governance of common-pool resources bring more attention to cooperation and participation between commoners instead of having a strict sanctioning system (Travers et al., 2011; De Moor & Tukker, 2013). In supporting this claim, in chapter 2 of this research, our model revealed the negative impact of sanctioning on the longevity of CPRs. Institutions without sanction showed more effectiveness, leading to longer CPR long. Moreover, the ABM corroborated that collaboration between agents in developing institutions by participating in frequent meetings positively affects the longevity of CPR. Commoners' changing and adjusting institutions more frequently led to a stable and longer CPR lifetime.

Nonetheless, as users are always free to follow institutions or cheat, the modeller should conceptualise the institutional system in a way that agents can cheat.

Context. Institutions are context-specific. Working in different contexts has different requirements. Therefore, conceptualising institutions in each context can be different. Conceptualising institutions should be a Domain-Driven Design (DDD). DDD is a software design approach that focuses on the specific domain and its requirements. ABM is also a software by nature that fortunately gives us, as a modeller, such freedom to conceptualise in our desired manner. Therefore, the modeller needs to be aware of the content and have or be able to gather the required knowledge. Focusing on domain and context is essential when a modeller works on a case-based data-driven model.

6.1.2 Reflecting on Institutional Change Insights

A social shock can be detrimental for the survival of commons. The observed pattern that we studied with a model showed that the frequency of institutional changes over time with a high frequency of changes during the initial phase, followed by a period of relative stability, and concluding with another phase of frequent changes.

This pattern can be explained by the institutional learning phase, characterized by a trial-and-error approach, followed by a period of stability during which the commoners exhibit contentment with the existing institutional setting. Eventually, the pattern enters a phase of rapid change triggered by a social shock, such as escalating taxation or external pressure on the commoners.

The CPRs' longevity has been positively impacted by a reduced emphasis on sanctioning. Institutions that lack sanctioning mechanisms have demonstrated greater effectiveness, resulting in longer-lasting CPRs. This trend can be explained by the fact that agents incur greater losses over each interval, consequently, expressing dissatisfaction more frequently with the existing institution, prompting efforts to alter it.

Frequent interaction among commoners can have a positive impact on the longevity of CPRs. Collaborative efforts among agents to develop institutions through regular meetings positively influence the CPRs' lifespan. Commoners' frequent changes and adaptations to the institutions result in greater stability and longevity of the CPRs.

Wealth inequality has negative effect on collective action in CPR management. Our results demonstrate that inequality and cooperation are inversely related, with greater inequality leading to lower levels of cooperation. Moreover, our model reveals that CPRs perform better, in terms of average wealth and resource availability, under conditions of low inequality. Conversely, when cooperation is high, resources perform better even under unequal conditions, resulting in higher average wealth and greater resource availability.

In times of crisis, there exists an inverse relationship between value change and institutional change. A higher average openness to change values across the world leads to less stringent shared strategies, while a greater emphasis on conservation values results in stricter shared strategies, on average.

6.2 Relevance of This Thesis

6.2.1 Scientific Relevance

Contributions to the social simulation literature: This research provides computational sociologists new guidelines on how to use ABM (inductively or deductively) as a tool to explore dynamics of institutions.

The proposed framework in Chapter 2 of this research can provide a means to show how ABM can deductively help historians to find hidden micro reasons behind historical data by generate certain patterns and then backtracks those patterns to find underlying causal mechanisms.

The case study in Chapter 3 Investigates how ABM can be used as an inductive approach. The model focuses on bottom-up actions and interactions of individual agents, which can lead to emergent patterns at macro-level.

This research also provided a guideline for modellers on the ways significant, real-world, and diverse datasets can be used to inform ABM through ML approaches (Chapter 4 and 5). In particular this is a concrete guideline on applying ML techniques in ABM by considering the specific ABM purpose. This guideline can benefit modellers and the ABM community in considering the most appropriate ML technique that fulfils a specific modelling challenge for a modelling purpose. Using ML not only adds more intelligence to an ABM, makes ABMs more efficient, accurate, data-driven, understandable, and implementable; but also provide the opportunity to learn from the past and apply it for the future.

Contributions to institutional studies: This research makes a significant contribution to the field of Institutional Economics by providing new insights into the dynamics and changes of institutions. By using advanced modeling and simulation techniques, this study provides a new perspective on how institutions emerge and evolve over time. The findings present in this research add to the existing body of literature on institutional dynamics and contribute to a better understanding of the complex interplay between individual agents and the collective institutions they form. The new insights provided by this research can help policymakers, institutional analysts, and scholars alike to better understand the factors that shape the emergence and evolution of institutions, and to develop more effective strategies for managing and regulating them.

6.2.2 Societal Relevance

This study provides valuable insights for policymakers, especially in the area of institutional dynamics. By using simulation and advanced modeling techniques, this research offers an explorative tool to understand institutional changes, assess their impact on real datasets, and evaluate their performance over a longer time. Policymakers and policy analysts can use the findings of this study to better analyze and comprehend policy problems and implement effective policies.

Furthermore, this research contributes to the protection of CPRs by identifying impactful parameters that influence their longevity. By exploring institutional dynamics, this study sheds light on the successful governance of CPRs and the parameters involved. The insights gained from this research can be used as practical recommendations to improve CPR protection and extend the longevity of valuable resources.

Commoners can also benefit from the outcomes of this research, particularly by improving the protection of their CPRs from overuse. Encouraging collaboration between agents in developing institutions and participating in frequent meetings can have a positive impact on the longevity of CPRs. Additionally, adjusting institutions more frequently can lead to a stable and longer CPR lifetime. On the other hand, this research suggests that commoners should pay less attention to sanctioning since it may have a negative impact on the longevity of CPRs. Institutions without sanctioning have proven to be more effective in extending the longevity of CPRs.

6.3 Future Works

This research faced some limitations that opens up pathways for future work. First, the models we developed and used were abstract. Therefore, some concepts and details in the settings were missing. It is worthwhile to explore whether more detailed models would provide more insight or are required in discovering underlying mechanisms from macro-level patterns.

Although we modelled triggers that eventually change institutions in this research, another interesting line that the researcher can follow is to model types of institutional change. By categorising institutional change into predefined standard types, ‘Creation’, ‘Displacement’, ‘Layering’, ‘Drift’, ‘Conversion’, ‘Exhaustion’ (Mahoney and Thelen, 2010), one can more easily study the journey of dynamics of institutions. This topic is mainly discussed in political institutions outside the scope of this research. However, it could be beneficial for future research. One example of different types of institutional change is: ‘conversion’, which takes place when the application of existing institutions changes due to strategic redeployment. In other words, the institutions must reinterpret for a new situation. In this type of change, the implementation and application of institutions change (Hacker et al., 2013).

Although we considered some types of agent heterogeneity in our models, one can model various types of agents that try to change institutions (e.g., the actors of change proposed by Mahoney & Thelen (2010)). This would allow one to study their influence on the dynamics of institutions and the relationship between types of institutional change and the portion of specific actors of change in society. These actors mainly differ based on their actions and intention to obey institutions and preserve/change institutions. One example of actors of change is 'insurrectionaries', who try to find a way to abolish existing institutions by not obeying them. Not only do they not wish to preserve institutions but also they do not obey the rules. They try to replace existing rules with new rules. One way to model these factors could be the "obey the rule" factor that can appear in the behaviour of an agent against an institution. At the same time "preserve institution" factor can be modelled in the form of influence (positive/negative) on neighbours or impact on the voting process to establish institutions.

Ostrom (1990) demonstrated that monitoring and graduated sanctioning are crucial elements for the longevity of successful institutions. While this research considered the effect of sanctioning on the longevity of common-pool resources, there is a need for further investigation into the role of various monitoring and sanctioning mechanisms in promoting the success of common-pool resources. These mechanisms should be explored in future studies.

To sum up, this research investigates the application of ABM as a tool for studying institutional dynamics. Our study employs advanced modelling and simulation techniques to aid in the understanding of institutional dynamics and changes. The research aimed to address gaps in the existing knowledge of institutional change, and the findings contribute towards the ongoing efforts to develop a more comprehensive understanding of this complex phenomenon. We anticipate that the guidelines and frameworks presented in this study will serve as a valuable resource for future research in this field. We hope that the readers will find this thesis informative and useful for their future research.

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List of Publications

The followings list presents my publications during PhD, some of which formed the chapters of this dissertation.

Journal Articles

Aleebrahimdehkordi, M., Melnyk, A., Herder, P., & Ghorbani, A. (2024). Examining the Interplay Between National Strategies and Value Change in the Battle Against COVID-19: An Agent-Based Modelling Inquiry. *Journal of Artificial Societies and Social Simulation, 27(1), 1-18.*

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