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Policymaking 2.0? An analysis of the usage of Artificial Intelligence and Big Data in policymaking on the basis of the policy cycle framework

Master Thesis

by

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July 2022

Acknowledgements

I wish to express my sincere gratitude to my supervisor Sabrina Kirrane for her advice, encouragement, ideas and guidance over the past months, which was very important in order to pursue the master thesis besides my job. I would also like to thank the team of the WU Executive Academy for the support during the last two years.

I am very thankful to my fellow students, from whom I learned a lot due to fruitful discussions and collaboration in the modules as well as in the group assignments, which was valuable help during the MBA programme. Furthermore, I would like to thank my foundation board and in particular the president of the board for giving me the opportunity to pursue the MBA programme alongside my work for the foundation.

Finally, I would like to thank my family, friends, and colleagues and in particular my wife Irina for continuously motivating and supporting me through my MBA journey and beyond.

Kurzbeschreibung

Künstliche Intelligenz (KI) und Big Data spielen mittlerweile eine wichtige Rolle in der Wirtschaft und in unser aller Alltag. Doch auch im öffentlichen Sektor findet sich der Einsatz neuer Technologien zur Verbesserung der Erbringung von Leistungen für die Bürgerinnen und Bürger. In der Politik selbst – und insbesondere in der Politikgestaltung – scheint die Anwendung allerdings noch weniger im Fokus zu stehen, obwohl auch in diesem Bereich der Einsatz von KI und Big Data Potenziale zu Verbesserungen bietet und es einige Beispiele dafür gibt. Auch die Forschung beschäftigt sich immer stärker damit. Diese Arbeit analysiert daher anhand eines integrativen Reviews bisheriger empirischer und theoretischer Arbeiten den Einsatz von KI and Big Data im Politikgestaltungsprozess, mit dem Ziel darzustellen, wie neue Technologien in der Politikgestaltung unterstützen können.

Anhand des Politikzyklus-Konzepts, welches den Prozess der Politikgestaltung in verschiedene Phasen einteilt, analysiert diese Arbeit, welche Möglichkeiten der Einsatz von KI und Big Data bietet bzw. wie sie in der Politikgestaltung unterstützen können und welche Herausforderungen damit verbunden sind. Zur Konkretisierung werden in weiterer Folge einzelne KI- and Big-Data-Methoden, Technologien und Techniken analysiert und aufgezeigt, wie und in welchen Phasen sie eingesetzt werden können. Für jede dieser Technologien wird schlussendlich auch ein konkreter Anwendungsfall dargestellt, der den Einsatz noch besser ersichtlich machen und die konkrete Einsatzmöglichkeit aufzeigen soll.

Schlüsselbegriffe: Künstliche Intelligenz, Big Data, Politikgestaltung, Politikzyklus

Abstract

Artificial Intelligence and Big Data play a key role in business and in our daily lives. The public sector uses new technologies to improve service delivery to citizens. However, in politics, and especially in the policymaking process, it seems that the application is less in focus, although AI and Big Data offer opportunities for supporting the respective tasks, as can already be seen in some use cases. Furthermore, we can find more research on that topic over the last years. This thesis analyses the use of AI and Big Data on the basis of an integrative literature review method with past empirical and theoretical research with the aim to illustrate how new technologies can support policymaking.

Based on the policy cycle concept, which divides the policymaking process into different phases, this thesis analyses which possibilities the usage of AI and Big Data offers respectively, how they can support policymaking and which challenges are related to that. In order to be more specific, we analyse also several AI and Big Data methods, technologies, and techniques and outline how and in which stages of the policymaking process they can be applied. For each of the technologies we illustrate use cases which should point out possible applications in practice.

Key words: Artificial Intelligence, Big Data, Policymaking, Policy Cycle

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ADM	Automated decision-making
ABM	Agent-based modelling
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
API	Application Programming Interface
ARIMA	Auto-regressive integrated moving average
BDA	Big Data Analytics
CMS	Content Management Systems
CSS	Cascading Style Sheets
EU	European Union
HTML	HyperText Markup Language
ICT	Information and Communications Technologies
IE	Instituto de Empresa
IT	Information Technology
LDA	Latent Dirichlet Allocation
MIT	Massachusetts Institute of Technology
ML	Machine Learning
MLA	Machine Learning Algorithms
NEGP	National Education Growth Plan
NLP	Natural Language Processing
OECD	Organization for Economic Cooperation and Development

OGD	Open Government Data
PPBS	Planning Programming Budgeting Systems
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organization
U.S.	United States of America

1 Introduction

“Every day, everywhere, AI is gaining popularity.”

This quote by the former United States of America (U.S.) Secretary of Defense Henry Kissinger, former Google Executive Chairman Eric Schmidt and Daniel P. Huttenlocher, computer scientist at the Massachusetts Institute of Technology (MIT) in their recent book ´The Age of AI and our human future´ (2021) summarizes the current development and discussions we face in one short sentence. Certainly, one can find a wide range of opinions on Artificial Intelligence (AI). On the one hand, it is seen as something bringing a bright future through improving health, prosperity, and access to information, on the other hand, it is linked to dystopian scenarios (West and Allen, 2020).

AI is not a very new discipline, but it has received much more attention from the sphere of politics compared to previous decades (Kuziemski and Misuraca, 2020). Reading the media, one can find articles on AI almost every day, be it in the field of business, education, defence, research, social media or arts and culture. When it comes to politics and administration, the primary discussions are often about the influence on elections or about the application in delivering public services.

On the contrary to AI, Big Data is a quite new phenomenon (Desouza and Jacob, 2017), and some argue, that it is still in its infancy with many unanswered questions regarding its true value (Boyd and Crawford, 2012; Desouza and Jacob, 2017). However, due to the technological progress with an increase in AI technologies as well as in the availability of large amounts of data, it is necessary to discuss possible opportunities for politics and administration. Similar to AI, the discussion should not only be on improving public services of governments, but also about supporting the policymaking process (Zuiderwijk, Chen, and Salem, 2021).

Globally, we have seen the fast developments of AI in the private sector in the last years, but its usage in public administration processes and internal operations could bring improvements regarding efficiency and effectiveness of policymaking as well as service delivery and therefore increase the quality of governance and public service (Kuziemski and Misuraca, 2020). However, with applying AI to enhance policies and services, governments have been slow (Margretts and Dorobantu, 2019)

The same accounts for Big Data, which can provide the public sector with several strategies and techniques to boost productivity and increase efficiency as well as effectiveness (Manyika at al., 2011). The European Union (EU) e.g. set the goal to tackle societal challenges through making policymaking more data-driven (European Commission, 2016). That is why we should increase the attention to governments as ´user´ and not only ´regulator´ of AI and Big Data technologies.

According to a survey by the Center for the Governance of Change of the Instituto de Empresa (IE) University, 51% of Europeans support reducing the number of national parliamentarians and giving those seats to an algorithm. The numbers vary between countries and generations, e.g. on the one hand high approval in Spain (66%), Italy (59%) and Estonia (56%) and among Europeans aged 25 – 44, on the other hand a majority rejection in countries like Germany, the Netherlands, the UK and Sweden and among the population above 55 years old (Jonsson and de Tera, 2021). A difference can also be seen between China (75% in favor) and the US (60% against) (Jonsson and de Tera, 2021). Although the survey is based only on 2,769 adults from 11 countries, these numbers additionally underline, that the topic of using AI in policymaking should be of high relevance for research.

My personal interest in this topic has particularly come through my former positions working in the Strategy and Policy Planning units of the Austrian Foreign Ministry (2016 – 2017) and of the Austrian Federal Chancellery (2018 – 2019). My experience and very personal impression was, that there is a lot of room for improvement in using the possible opportunities of Information and Communications Technologies (ICT) especially in the field of AI and Big Data and even in the consideration and reflection on it in Austria's public administration and among policymakers.

So far, policymaking is a very human and political process which changes only slowly. John Pollock, contributing editor of the MIT technology review, once said that

> *“we are running the 21st century using 20th century systems on top of 19th century political structures….”* (Janssen and Wimmer, 2015).

Therefore, it is of interest, to assess whether new technologies can be applied and in what way they could support and improve the policymaking process.

1.1 Problem formulation

Although AI is not a very young topic, and you can find literature back to the 1950s, publications that deal with the impact of using AI for public governance are still rare compared to AI research in general (Zuiderwijk, Chen, and Salem, 2021). Furthermore, when it comes to AI and public policy, the focus of the discourse is more on the governance by AI and less on the governance with AI (Kuziemski and Misuraca, 2020). Craglia, Hradec, and Troussard (2020) also argue, that

> *“there is an increasing gap between the speed of the policy cycle and that of technological, and social, change”*.

The work with large, high-dimensional data sets has been common in research in physical and life sciences, but beyond these fields it has been much more limited, including policy analysis (Schintler and Kulkarni, 2014).

In addition, previous research focuses in many cases only on one of the fields, either on AI (e.g. Kuziemski and Misuraca, 2020; Zuiderwijk, Chen, and Salem, 2021) or Big Data (e.g. Höchtl, Parycek, and Schöllhammer, 2016; Giest, 2017; Desouza and Jacob, 2017; Mureddu, Schmeling, and Kanellou, 2020), and only few on both (e.g. Pencheva, Esteve, and Mikhaylov, 2018; Craglia, Hradec, and Troussard, 2020). However, the fields cannot always be clearly delimited.

Moreover, previous papers rarely combine the examination of the policy cycle framework, the general usability of AI and Big Data as well as the application of technologies together with use cases including applied tools.

1.2 Research questions

Considering the explanations above, this leads us to the following research question for this thesis:

Q1 *How can AI and Big Data be used in the policymaking process, within the framework of the policy cycle, and what are the opportunities and challenges?*

- ***RQ 1.1*** *How can AI and Big Data be applied in the different stages of the policy cycle framework?*
- ***RQ 1.2*** *What technologies, methods, and techniques can support the tasks of the respective cycles of the policymaking process?*
- ***RQ 1.3*** *What are possible use cases and tools for the application of AI and Big Data in practice?*

1.3 Objective of the master thesis

This master thesis aims to aid to the understanding of the opportunities and challenges of using AI and Big Data in policymaking, and to elaborate some technologies and techniques as well as some specific use cases.

The contribution of this thesis is to provide policymakers with research of the following: if and how new technologies can support to better fulfil the tasks of different steps in policymaking. Since the topic is quite broad, the research only scratches the surface of several technologies and techniques, though, it could give policymakers a compact overview and it outlines some questions for future research.

1.4 Research design and methodology

In order to achieve the research objective and analyse the research questions, we summarize past empirical and theoretical literature in order to provide a more comprehensive understanding of the topic. Therefore the thesis is based on an integrative literature review (Broome, 1993). With this research method, representative literature on a topic is reviewed, critiqued, and synthesized in an integrated way to generate new frameworks and perspectives on the topic (Torraco, 2005) but also to achieve direct applicability for practice and policy (Whittemore and Knafl, 2005).

We follow this method due to the increase in literature on our chosen topic, which brings the need for making a review, critique, or reconceptualization of the growing knowledge base (Torraco, 2005).
Although one can find examples of literature reviews such as Valle-Cruz et al. (2019) or Zuiderwijk, Chen, and Salem (2021), we want to combine the literature on AI as well as Big Data and their respective methods and tools in policymaking.

Firstly, we analyse major publications on ´public policy´, ´public policymaking´, ´policy process´ for the theoretical foundation of the policymaking process.

Secondly, the research was conducted in the database ´Google Scholar´, which includes e.g. ´Elsevier ScienceDirect´, ´Springer´, ´Wiley-Blackwell´, ´Taylor & Francis´ or ´Sage´. The specific searches in the databases oriented on the titles and abstracts and were conducted with the following terms: ´public policy´ or ´policymaking´ or ´policy cycle´ or ´government´ and ´artificial intelligence´ or ´big data´. Certainly, there is a wide range of papers covering the usage of AI and Big Data and their different applications. At this stage, we limited the selection to literature from public policy and administration published in the English language, excluding e.g. papers which explore AI and Big Data from a technical perspective (computer science or engineering).

Thirdly, literature on technologies, methods and techniques, as well as use cases were primarily chosen out of references from selected public policy and administration literature from step 2, which also includes papers from other fields rather than public policy and administration.

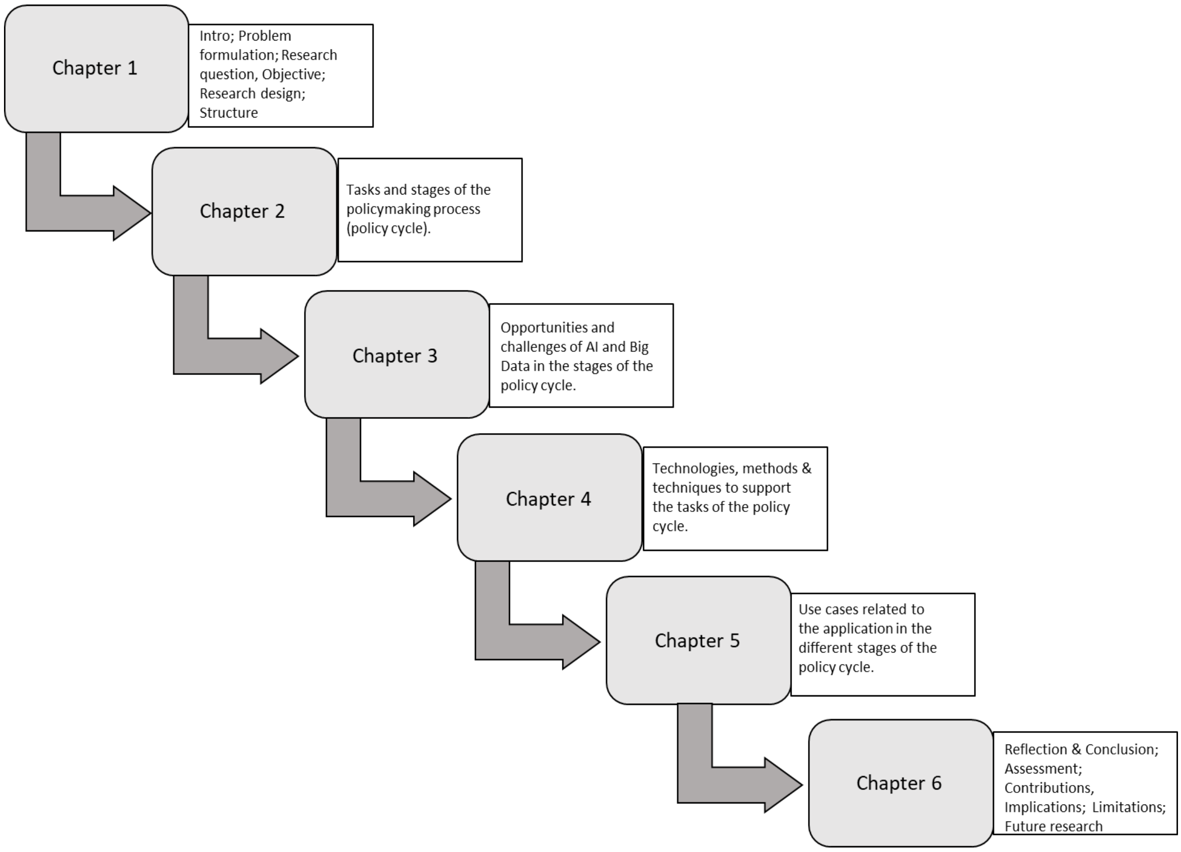
Generally, we selected the literature related to the research questions, including empirical and theoretical research and diverse study methodologies.

1.5 Thesis structure

The steps of the course of investigation in this thesis can be seen from Figure 1.1. After outlining the research topic and questions as well as the research design and methodology in chapter 1, we discuss what public policymaking is and how we can structure it in chapter 2. We examine its process and tasks through considering the framework of the policy cycle. Based on that, we review in chapter 3 the general potential of AI and Big Data in the different stages of the policy cycle.

In order to get more concrete, we elaborate in chapter 4 how certain technologies, methods and techniques can support in fulfilling the tasks in the respective stages of the policy cycle. In chapter 5, we analyse use cases of the different technologies to show concrete fields of application. Finally, we reflect and draw a conclusion in chapter 6.

Figure 1.1: Course of investigation



2 Public Policymaking

The assessment of the usage of AI and Big Data in policymaking requires us to outline what is meant by policymaking and how it works. Policymaking relates not solely to politics or public administration. On the one hand, the process to adopt internal policies in private organizations can also be described as policymaking. On the other hand, private groups also play a role in establishing policies that can affect the broader public. In this thesis, we focus on politics, and more specifically, on the public sector, i.e. the government and not on policymaking in private organizations or groups. This chapter will define, what public policy is, how the policy process works and presents the concept of the policy cycle, a method which divides the policymaking process into different stages. We want to assess, how the method of the policy cycle describes the way of policymaking and if this concept can be employed to explore the usage of AI and Big Data and the application of their technologies, methods, and techniques.

2.1 What is Public Policy?

Herein, we focus on public policy in general terms and not in a specific policy domain (such as agricultural policy, economic policy, educational policy, energy policy, environmental policy, foreign policy, health policy, innovation policy, security policy, social policy, etc.) and analyse policymaking as a political activity. Generally, promoting or working on new policies comes with the conviction that a government has to react to a real problem and that the proposed policies are the best option to deal with this problem (Birkland, 2019). A policy includes an objective and one or more policy instruments to serve the objective and to create an outcome (Maetz and Balié, 2008), which influence on the targeted and non-targeted groups of a population (Mwije, 2013). Policies serve for the implementation of programmes of reform and change, though it is also a policy to keep the status quo respectively not to do something (Howlett, Ramesh, and Perl, 2009; Birkland, 2019).

Table 2.1: Definitions of the term ´policy´

Definition	**Author(s)**
"A relatively stable, purposive course of action followed by an actor or a set of actors in dealing with a problem."	Anderson, 1975
"Policies are revealed through texts, practices, symbols, and discourses that define and deliver values including goods and services as well as regulations, income, status, and other positively or negatively valued attributes."	Schneider and Ingram, 1997
"A policy is a plan of action to guide decisions and actions based on a set of preferences and choices. The term may apply to the work of government, private sector groups and individuals."	Maetz and Balié, 2008
"Policy is a law, regulation, procedure, administrative action, incentive, or voluntary practice of governments and other institutions."	Centers for Disease Control and Prevention, 2015
"A statement by government of what it intends to do, such as a law, regulation, ruling, decision, order, or a combination of these. The lack of such statements may also be an implicit statement of a policy not to do something."	Birkland, 2019

Different actors, such as individuals, groups or parties, private enterprises and the government can adopt policies. As can be seen from Table 2.1, scholars such as Anderson (1975) or Schneider and Ingram (1997) connect policies not only to government action and instruments, but beyond. Maetz and Balié (2008) explicitly cite the private sector and individuals as actors for the application of policies additional to governments. For the intended analysis in this thesis, we follow the definition of Birkland (2019) which describes policy as *"a statement by government […]"*, because the government is a legitimized body to set policies that affect the general public. In the case of government, a law, regulation, ruling, decision, order, or a combination of these kinds are used to adopt a policy (Centers for Disease Control and Prevention, 2015; Birkland, 2019). If a policy gets adopted by the government, the term ´public policy´ is used (Mwije, 2013).

Table 2.2: Definitions of the term ´public policy´ adapted from Birkland (2019)

Definition	Author(s)
"Anything a government chooses to do or not to do."	Dye, 1972
„A set of interrelated decisions taken by a political actor or group of actors concerning the selection of goals and the means of achieving them within a specified situation where those decisions should, in principle, be within the power of those actors to achieve."	Jenkins, 1978
"The term public policy always refers to the actions of government and the intentions that determine those actions."	Cochran et al., 2010
"Public policy is the outcome of the struggle in government over who gets what."	Cochran et al., 2010
"Public policy consists of political decisions for implementing programs to achieve societal goals."	Cochran and Malone, 2010
"Stated most simply, public policy is the sum of government activities, whether acting directly or through agents, as it has an influence on the life of citizens."	Peters, 2010
"The sum total of government action, from signals of intent to the final outcome."	Cairney, 2019
"It affects a greater variety of people and interests than do private decisions."	Birkland, 2019

One can find many definitions of ´public policy´, but as can be seen from Table 2.2 most of the listed descriptions of the several authors have in common, that ´public policy´ is referred to actions of government or the sphere of politics. Apart from Birkland (2019), who emphasizes, that a ´public policy´ affects more people and their interests compared to private decisions. Jenkins's (1978) definition of public policy does not solely relate public policy to decisions of governments and defines policymaking as a dynamic process with not only one, but more interrelated decisions (Howlett, Ramesh, and Perl, 2009). What makes the policymaking process very complex, is the fact, that these different interrelated decisions are often made by various decision makers, e.g. within the government (Howlett,

Ramesh, and Perl, 2009). Furthermore, the process also depends on the respective political system and structure of a nation or supranational organization.
Dye (1972) provides a much simpler definition by describing public policy as any decision of a government to do or not to do something. Although with this simplification you would treat all decisions equally, whether it is an ordinary or a significant one, it clarifies some aspects. On the contrary to Jenkins, the definition of Dye underlines that governments are the main actor of public policymaking, especially because of their authority to decide on behalf of citizens (Howlett, Ramesh, and Perl, 2009). Further, the definition of Dye includes ´negative´ or ´non-decisions´, meaning that the decision of a government to do nothing is also a choice like a ´positive´ one, provided that the decision is deliberate (Howlett, Ramesh, and Perl, 2009). This is also related to the assumption of a conscious choice of a government, meaning that an unintended consequence of a decided policy is not public policy (Howlett, Ramesh, and Perl, 2009). For Howlett, Ramesh, and Perl (2009), Dye's definition is key *"to understand public policy as an applied problem-solving process"*, nevertheless it falls short to explain the characteristics and complexity of public policymaking.

Birkland (2019) argues, that despite different definitions of ´public policy´ as we have outlined in Table 2.2, there is consensus that public policymaking affects more people and interests than private decisions do. In addition to this criterion, we find it also important, that public policies are reactions of legitimate state bodies and organs since we could find policies e.g. of big corporations, which may affect more people and interests than some policies adopted by governments do. Such a definition would also include a major actor of lawmaking, namely the parliament as legislative. But for our further analysis of the application of tools and techniques in policymaking, we focus on the policy processes for actions of governments since they have the most resources and capacities for public policymaking and most of the literature reflects the usage of technology in policymaking of governments so far.

2.2 The policy process and cycle

Public policy is a very complex and dynamic matter due to the high amount of decisions made by different individuals and groups with many stakeholders influencing these decisions.

According to Knill and Tosun (2008), we can point out main characteristics of policymaking: Firstly, multiple constraints such as shortage of time and resources, public opinion and the constitution influence policymaking. Secondly, policymaking consists of various policy processes (e.g. different departments within the government might compete with each other or their tasks overlap). Thirdly, these processes build an infinite cycle of decisions and policies which are mostly related to each other. Given these characteristics and to simplify public policymaking as well as to acquire better insights into the process, the framework of the policymaking cycle is used as a common method.

The procedures which lead to the creation of a public policy show the repetitive pattern for what the term policy cycle can be applied (Savard and Banville, 2012). When describing the policy process, many publications refer to Lasswell´s work on the ´policy orientation´ (Birkland, 2019). The idea to describe the policy process by sequencing it in several stages goes also back to Lasswell, who introduced seven stages: ´intelligence´, ´promotion´, ´prescription´, ´invocation´, ´application´, ´termination´ and ´appraisal´ (Jann and Wegrich, 2007), though we could already find a definition of stages in Simon (1947). Lasswell´s cyclical model has been criticized due to its fragmented approach to explanatory factors (Savard and Banville, 2012) and as can be seen in Table 2.3, different variations regarding the stages have been put forward over the last decades.

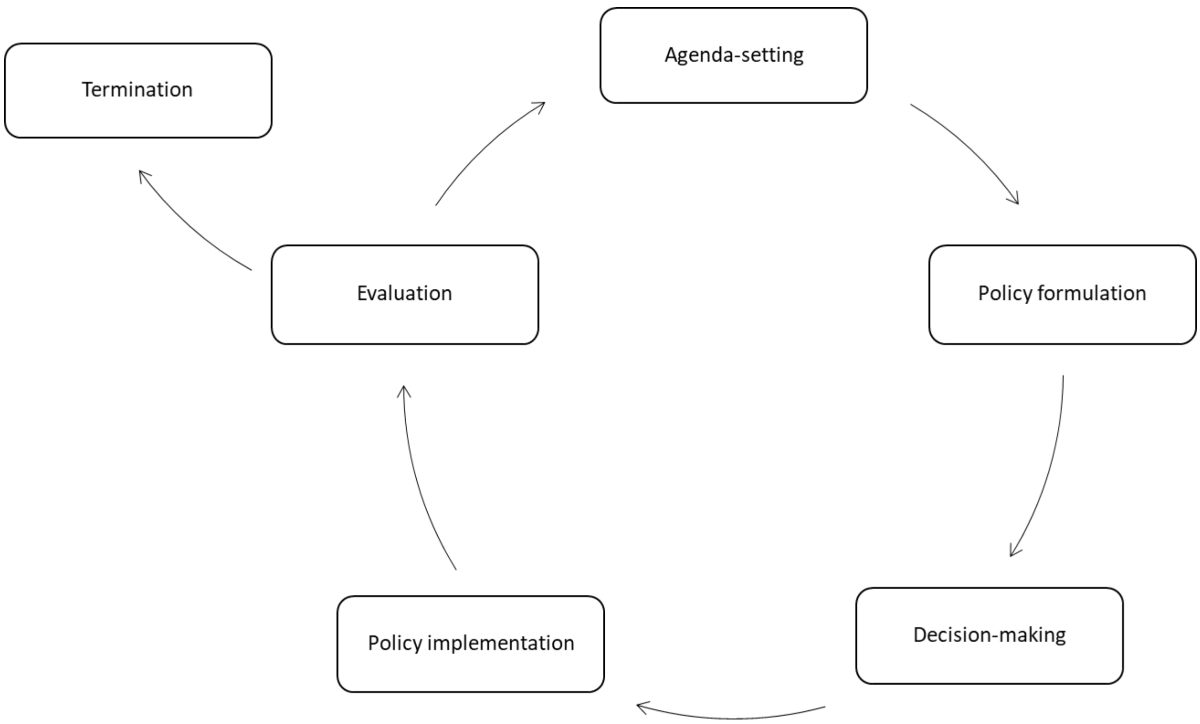
The most applied policy cycle framework differentiates between ´agenda-setting´, ´policy formulation´, ´decision-making´, ´policy implementation´ and ´evaluation and termination´ (Jann and Wegrich, 2007). One of the key advantages of the model is that it provides an easy understanding of a multidimensional process through dividing the complexity of the policymaking process among different stages, which offers us the opportunity to analyse each stage alone or relative to each other (Howlett, Ramesh, and Perl, 2009). Another advantage is that it can be applied to policymaking at different levels, from local governments to international actors (Howlett, Ramesh, and Perl, 2009).

2.2.1 The stages of the policy cycle

At the present time, the most common model of the cycle among scholars consists of five stages (Savard and Banville, 2012), dividing the policy process into ´agenda-setting´, ´policy formulation´, ´decision-making´, ´policy implementation´ and ´evaluation´, the latter could also lead to ´termination´ (Jann and Wegrich, 2007), as shown in Figure 2.1. Therefore, we review these five stages more in detail.

Figure 2.1: The five stages of the policy cycle

Reference: Schito, 2022



2.2.1.1 Agenda-setting

The policymaking process starts with recognizing a policy problem and the need that the state has to intervene to solve it. A significant step when it comes to agenda-setting is to bring an issue from recognizing it to the formal political agenda to consider public action (Jann and Wegrich, 2007). As not all the policy problems will get the same level of attention of legislators and executives, setting the agenda is a powerful task (Knill and Tosun, 2008) and it is important how the agenda-setting works and how choices are made between different topics. The question on whether a problem will be recognized and added to the agenda might also depend on characteristics of a country, culturally, politically, socially, economically, or ideologically (Howlett, Ramesh, and Perl, 2009).

Jann and Wegrich (2007) provide four different categories when it comes to policy initiation and its actors: ´outside-initiation´, ´inside-initiation´, ´mobilization´, ´consolidation´. ´Outside-initiation´ means that social actors from outside try to put an issue on the agenda of the government with broad public support. When interest groups are successful in lobbying their topics without public recognition due to direct access to the government, we speak of an ´inside-initiation´ pattern. The third pattern, ´mobilization´, means that after the agenda-setting has been finished, the government needs to get support from the public for successful implementation (Knill and Tosun, 2008). When the government fosters topics the public already supports strongly, it has been described as ´consolidation´ (Howlett, Ramesh, and Perl, 2009).

In modern societies, the media and more recently social media play an important role in agenda-setting by offering the public a way to raise issues. This can lead to reactions of the government not to lose legitimacy and credibility by ignoring issues raised by the public (Jann and Wegrich, 2007). As agenda-setting depends on many factors such as actors/stakeholders, institutions, ideas, resources and the interaction of them in different situations, it is anything, but a rational choice, and it can always be questionable how relevant the chosen topics are for the wider society (Jann and Wegrich, 2007).

2.2.1.2 Policy formulation

The second stage of the policy cycle framework contains the transformation of recognized problems, demands, or expressed proposals into government programmes. The process before the decision of the government or parliament is marked by formal and informal negotiations and bargains between various actors, dependent on the respective political system and therefore not a rational model of decision-making (Jann and Wegrich, 2007). The formulation of policies can be influenced by the relationship between the government and social actors (Savard and Banville, 2012). Core functions of policy formulation are planning, analysis, policy design and consultation (Knill and Tosun, 2008). Policy formulation has substantive (referring to the nature of the problem) or procedural (referring to institutional and tactical issues) political constraints (Howlett, Ramesh, and Perl, 2009).

2.2.1.3 Decision-making

When the government decides to implement a policy or decides not to do so, this action is referred to the stage of decision-making (Howlett, Ramesh, and Perl, 2009). Although the passing of a law is the role of the parliament respectively the legislative, literature argues that the executive such as the government dominates as it has more resources and that ministerial bureaucracy is an important player especially in formulating a policy (Knill and Tosun, 2008), but also in deciding on a policy action (which is not always a law, but also a regulation, order, etc.). Though, you have differences among the democratic countries regarding the role and power of the different political actors.

2.2.1.4 Implementation

This stage describes the execution or enforcement of a predetermined policy by responsible actors in the public sector, but also beyond. In earlier models of the policy cycle, implementation was not categorized as a distinct stage, and it was assumed, that the policymaking process ended with a passed law. Due to a study by Pressman and Wildavsky in 1973 on the implementation of an unemployment programme in a state in the United States of America (U.S.), which showed the problem of a gap between decided policies and their application into practice (Knill and Tosun, 2008), the importance of implementation as a separate stage in the policy cycle has grown (Jann and Wegrich, 2007).

Pülzl and Treib (2007) describe the different approaches by means of three categories: Initially, implementation is seen as a hierarchical top-down approach, assessing how the goals and objectives are achieved through implementation. Later, this approach is challenged because of evidence underlying that implementation is not a hierarchical process which leads directly from the decision at the top to the implementation by a certain player, this perspective is the bottom-up approach (Jann and Wegrich, 2007). Hybrid models combine both kind of approaches (Knill and Tosun, 2008). Despite the type of policy and choice of the instrument also the question of horizontal (interaction within national level) or vertical implementation (interaction with different subnational levels) plays a role for a successful application (Knill and Tosun, 2008). In order to translate policies into practice and put solutions into effect (Howlett, Ramesh, and Perl, 2009), bureaucracies have a key role, and the success of policies often depends on the abilities of bureaucrats. Though, civil servants' personal preferences in terms of ideology, interests, thought, etc. can impact implementing a policy (Savard and Banville, 2012) such as drifting away from the initial intention of the political decision (Knill and Tosun, 2008).

2.2.1.5 Evaluation and termination

The last stage of the policy cycle focuses on the outcomes of policies and the termination of policies when a problem has been solved or an adopted measure has been failed (Jann and Wegrich, 2007). Evaluation research has been spread around in countries of the Organisation for Economic Cooperation and Development (OECD), especially related to measures in welfare states and general reform policies (Jann and Wegrich, 2007). The main point for evaluation is whether the intended objective has been reached with the output of the implemented policy (Knill and Tosun, 2008).

Efforts to establish evaluation as a way of politics-free policymaking have been broadly criticized since results of evaluation have been challenged as largely depending on a founding value on which an evaluation is based (Jann and Wegrich, 2007). Further, evaluation is a normal part of politics, as actors such as the public, media, opposition parties, (audit) courts or interest groups oversee government policies. Evaluation has been established as key for rational evidence-based policymaking, but one has to take into account the specifications of political processes when carrying out the evaluation. Assessing the output of a policy is dependent on the interests, values, and position of a certain actor. In addition, as governments may avoid concrete definitions for fear of blame and critique, policy goals and objectives are often defined insufficiently (Jann and Wegrich, 2007).

However, evaluation can help to improve policy-learning and could also result in the termination of a policy. Through feedback loops, policy evaluation can enable decision-makers to learn from each implemented policy, to identify problems and to start the policymaking process once again, which leads to an endless policy cycle (Knill and Tosun, 2008).

When it comes to policy termination, the idea that after a problem has been successfully addressed by a policy or after assessing the ineffectiveness of an implemented policy, it should be terminated, is in the real political life a challenge. Empirical findings come to the conclusion, that an implemented policy is rarely terminated (Jann and Wegrich, 2007). Policy reversals are often related to big budget cuts, changing coalitions or governments (Jann and Wegrich, 2007) or supra-national policy harmonization (Knill and Tosun, 2008).

In research literature you can also find policy cycle models in which evaluation is part throughout every stage of the policy process (Centers for Disease Control and Prevention, 2012; Jann and Wegrich, 2007).

2.2.2 Different models of the policy cycle

As mentioned above, one can find different models of the policy cycle framework in the literature. In Table 2.3 we show the cycles by several authors which vary regarding the stages respectively the number of stages. We also group the stages of the different cycles under the five stages of the most applied policy cycle framework. This shows, that on the one hand there is a broad accordance regarding the last stages of the cycle (´implementation´, ´evaluation and termination´), on the other hand we can find more variations regarding the tasks of ´agenda-setting´, ´formulation´ and ´decision-making´, with some models consisting of various stages in these three policy cycle phases. This reflects the complexity in the process of policymaking, especially when it comes to setting an agenda or to formulating a policy before making a decision.

The clustering of the different variations under the five main stages of the most applied policy cycle framework is difficult since a clear demarcation is not always possible, and one has to see all the stages always interlocked. As an example, Jann and Wegrich (2007) argue that combining the stages ´formulation´ and ´decision-making´ under one stage of the policy cycle is expedient because a clear separation between the formulation of a policy and the decision taken is often not possible.

Nevertheless, the grouping of the several variations which can be seen in Table 2.3 also gives a good picture of the respective tasks of the different phases in the policy process. For our thesis, it is not important how many stages the policy cycle is composed of or how the stages are named, but which tasks occur in the policy process in order to assess in the following chapters if and how AI and Big Data technologies can support policymaking. Nevertheless, we apply the most common policy cycle consisting of five stages to structure the policy process and its tasks for the further elaboration.

Table 2.3: A selection of models and stages of the ´policy cycle´

Author(s)	Agenda-Setting							Formulation													Decision-making								Implement-ation			Evaluation and Termin-ation			
	Intelligence	Problem emergence	Agenda-Setting / Issue search / Problem Identification	Issue identification	Initiation	issue filtration	Issue definition	Policy Discussion	Design	Promotion	Policy Analysis	Policy Formation	Formulation	Consideration	Estimation	Foreceasting and projecting outcomes	Setting objectives and priorities	Policy instrument development	Policy option analysis	Consultation	Coordination	Prescription	Choice	Policy Acceptance	Adoption	Decision (making)	Selection	Provision of means	Invocation	Implementation	Application	Evaluation	Termination / Maintenance / Succession	Appraisal	**Number of stages**
Simon, 1947	✓								✓														✓												3
Lasswell, 1956	✓									✓												✓							✓		✓		✓	✓	7
Anderson, 1975			✓										✓												✓					✓		✓			5
Nachmias and Felbinger, 1982			✓					✓				✓												✓				✓		✓		✓			7
Brewer and deLeon, 1983					✓										✓												✓			✓		✓	✓		6
Hogwood and Gunn, 1984			✓			✓	✓									✓	✓		✓											✓		✓	✓		9
Bridgman and Davis, 1998				✓							✓							✓		✓	✓					✓				✓		✓			8
Jann and Wegrich, 2007*			✓										✓													✓				✓		✓			4
Howlett, Ramesh, and Perl, 2009			✓										✓													✓				✓		✓			5
Jordan and Adelle, 2012		✓	✓											✓												✓				✓		✓			6

*Jann and Wegrich (2007) combine the stages of policy formulation and decision-making.

In order to underline our clustering in Table 2.3, but also to make it more transparent, we included an index with short descriptions of the several stages of the different authors. One can see that sometimes only different names are used for the same description, but sometimes also tasks of the five stages approach are split into more stages, e.g. Nachmias and Felbinger (1982), Hogwood and Gunn (1984) or Bridgman and Davis (1998) (then Althaus, Bridgman, and Davis, 2007).

2.2.2.1 Agenda-setting phase

Intelligence: Identifying a problem and collecting data on the problem (Thakur).

Problem emergence: Getting a specific problem for discussion or even consideration by policymakers on the agenda (Benson and Jordan, 2015).

Agenda-setting: See description in 2.2.1.1

Issue search: Identifying and anticipating problems and opportunities (Commonwealth of Learning, 2012).

Problem identification: Identifying and specifying public policy problems (Anderson, 1975).

Issue identification: Emerging of a new issue through a certain mechanism (Andrews, 2014).

Initiation: Initial sensing of a problem (Howlett, Ramesh, and Perl, 2009)

Issue filtration: Determining whether an issue is appropriate to political mechanisms and administrative processes or requires a fundamental analysis (Commonwealth of Learning, 2012).

Issue definition: Perceiving, exploring, articulating, and defining an issue (problem, opportunity, or trend) which is on the agenda in terms of causes, components, and consequences by interested parties (Commonwealth of Learning, 2012).

2.2.2.2 Policy formulation phase

Policy discussion: Identification of the right way to meet the defined problem (Höchtl, Parycek, and Schöllhammer, 2016).

Design: Generating alternative solutions to the problem (Thakur).

Promotion: Changing of support from various groups for competing policy alternatives (Pielke, 2004).

Policy Analysis: Analyzing relevant data and research as well as assessing options for likely consequences (Edwards, 2021).

Policy formation: Formulating and translating a policy into legislative executive language (Höchtl, Parycek, and Schöllhammer, 2016)

Formulation: See description in 2.2.1.2

Consideration: Considering different policy options for the selection of the best course of action (Benson and Jordan, 2015).

Estimation: Systemical investigation of a problem and assessment of options and alternatives (Brewer and deLeon, 1983)

Forecasting and projecting outcomes: Examination and anticipation of the future and alternate futures in consideration of different assumptions about behavior and key variables (Commonwealth of Learning, 2012).

Setting objectives and priorities: Developing and prioritizing the objectives of a policy (Commonwealth of Learning, 2012).

Policy instrument development: Identifying the appropriate instrument to implement a policy (Andrews, 2014).

Policy option analysis: Identifying, defining, comparing different options for review and final decision (Commonwealth of Learning, 2012).

Consultation: Enabling the participation of stakeholders and potentially affected citizens (Edwards, 2021), which can permeate the entire process (Andrews, 2014).

2.2.2.3 Decision-making phase

Coordination: Coordinating a policy position through the mechanisms and machinations of government (processes) (Andrews, 2014).

Prescription: Consensus on the rules to be enforced (Pielke, 2004).

Choice: Selection of the ´best´ solution amongst the different solutions using some criterion (Thakur).

Policy Acceptance: Adoption of a policy (Höchtl, Parycek, and Schöllhammer, 2016).

Adoption: Decision on one of the proposed alternatives, including taking no action (Anderson, 1975).

Decision-making: See description in 2.2.1.3

Selection: Choosing between policy alternatives that have been generated and their likely estimated effects on the problem (Brewer and deLeon, 1983).

Provision of means: Deciding on the required personnel and financial means for the implementation of a policy (Höchtl, Parycek, and Schöllhammer, 2016).

2.2.2.4 Policy implementation phase

Invocation: Initial testing of the policy (Auer, 2017)

Implementation: See description in 2.2.1.4

Application: Final implementation of the policy (Auer, 2017)

2.2.2.5 Evaluation and termination phase

Evaluation and termination: See description in 2.2.1.5

Policy maintenance and succession: Accepting the results of the evaluation and review and making decisions on the implementation of corrective actions (Commonwealth of Learning, 2012).

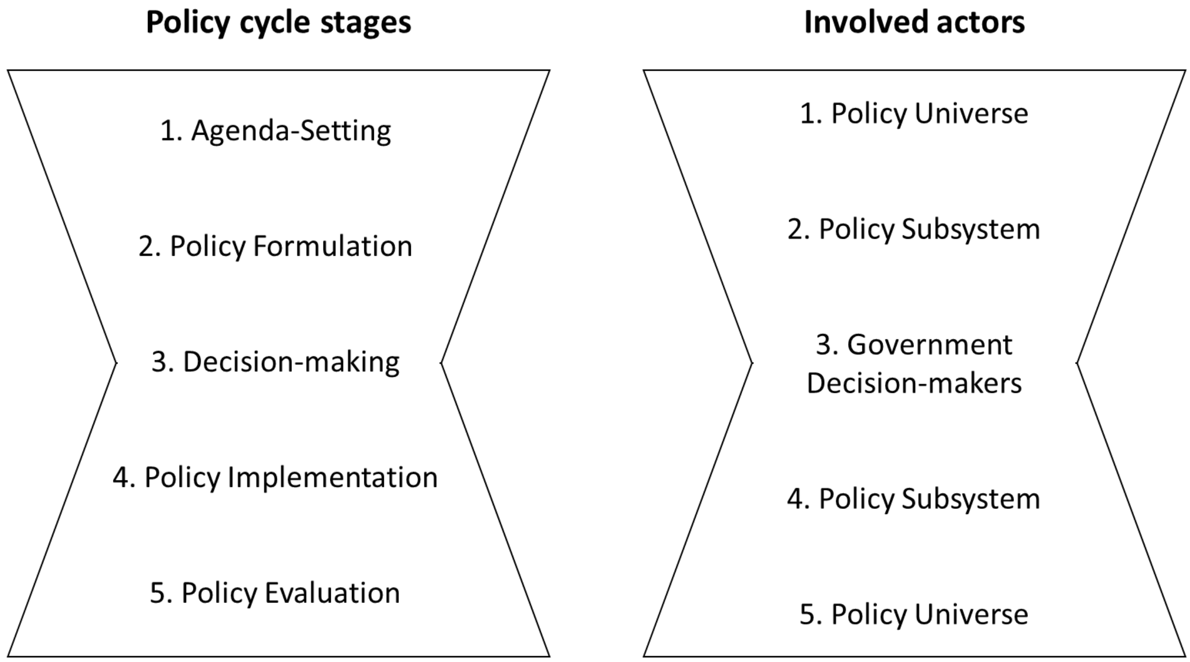
Appraisal: Evaluating the policy using the initial objectives (Lasswell, 1956).

2.2.3 The actors of the policy process and cycle

In order to analyse the policymaking process, it is also important to outline who are the actors or stakeholders in the policy process. Therefore, we also apply the most common five stages model as outlined above. Howlett, Ramesh, and Perl (2009) use an hourglass to illustrate the involved players and groups them into ´policy universe´, ´policy subsystem´ and ´government decision-makers´, as can be seen in Figure 2.2. The ´policy universe´ is involved in ´agenda-setting´ and ´evaluation´. In these two stages, almost everyone can play a role, e.g. through pushing a topic via social media or through commenting an implemented policy of the government. During the stages of ´formulation´ and ´implementation´, the circle of those involved becomes smaller. In these two stages, the government can or has to include certain stakeholders, or actors such as interest groups try to influence the policy process for their part. ´Decision-making´ is the stage in which solely the legitimized body, mostly the responsible actor in government decides on the action.

Figure 2.2: The actors involved in the policy cycle

Reference: Howlett, Ramesh, and Perl (2009)



2.3 Critique

According to Birkland (2019), the critique on the framework of the policy cycle challenges the sequencing of the policy process in different stages and argues, that the framework is oversimplifying and unrealistic. Furthermore, the policy cycle model is not able to reflect the complexity of the policymaking process and the fact that policies are scarcely developed in a linear progression (Kay, 2006). In practice, there is not such a linearity in policymaking as the cycle with its sequential approach might indicate (John, 2012). The complexities in the policy environments include many stakeholders coming from different perspectives and the occurrence of many unexpected events (Edwards, Howard, and Miller, 2001). The model also does not cover causation, explaining *"what, or who, drives a policy from one stage to another nor why this should be the case"* (Schito, 2022) and also lacks an explanation of how the content of a policy could have an impact on policymaking (Howlett, Ramesh, and Perl, 2009).

Even though the criticism is justified, and the framework simplifies strongly, it gives the policy process a structure for analysis and research (Jann and Wegrich, 2007), and therefore gives us the opportunity to better explore the usage of AI and Big Data in policymaking.

2.4 Summary

In order to analyse the usage of AI and Big Data in public policymaking, it has been necessary to outline some of the main literature on public policy and to clarify how we define it. For this thesis, we focus on policies and policymaking related to governments, which have the power to affect a major part of the population. Since policymaking is very complex and dynamic involving many different governmental and non-governmental stakeholders with various capacities of power (Schito, 2022) and various interests, it is appropriate to use a model which presents different stages of the process. The policy cycle model is by far not able to map politics compared to how policymaking takes place in practice, though it gives us a possibility to follow the way of a government action and also to see the role of different stakeholders, the tasks and the status of knowledge during the process.

Therefore, we follow this approach since it makes the very complicated political process more comprehensible and gives us a structure to elaborate along the different stages in chapter 3 how AI and Big Data can support policymaking.

3 Artificial Intelligence and Big Data in policymaking

In this chapter, we assess the usage of AI and Big Data on the basis of the policy cycle model for each of the five stages. Before that, we have to define what we understand under AI and Big Data.

3.1 What is Artificial Intelligence?

When we look back in the history of AI, one of the key scholars in the field of theoretical computer science was Alan Turing. He invented the ´Turing Test´ in 1950 to see if computers can develop human-like intelligence. The first scientist who used the term ´artificial intelligence´ was John McCarthy a few years later (West and Allen, 2020). The definition of AI varies among the literature. Some definitions relate AI to intelligent behaviour and human skills and define it as studying how it is possible that computers can do things which people are currently better at (Rich and Knight, 1991) or as the field studying the synthesis and analysis of intelligently acting computational agents (Poole and Mackworth, 2010). AI can be seen as computational intelligence meaning that a machine has the capacity for learning, rationalizing, and processing intended instructions or performing actions (Poole, Macworth, and Goebel, 1998). Some theories go so far as seeing AI as technology which can think and act like a human respectively rationally (Russell and Norvig, 2010).

AI can be described as narrow or general, which also refers to weak or strong AI. Whereas narrow AI means tasks which are repetitive or based on patterns, general AI intends to create a machine that can perform the same intellectual tasks as a human brain (Tito, 2017). The American author and futurist Ray Kurzweil even speaks of a ´singularity´, which means the point when a machine-based super intelligence surpasses human intelligence. De Spiegeleire, Maas and Sweijs (2017) classify AI in their report for the Netherlands Defence Department in artificial narrow intelligence for machine intelligence that equals or exceeds human intelligence for specific tasks, artificial general intelligence for machine intelligence that meets the full range of human performance in any task and artificial superintelligence meaning machine intelligence that exceeds human intelligence in any task. You can also find definitions which not only refer to humans, but beyond. Valle-Cruz et al. (2019) e.g. describe AI as the field of computer science which includes different techniques for creating algorithms and intelligent machines that simulate individual and collective behaviour of any kind of living and without the help of human beings.

Since there is an ongoing process of evolution due to the technological advances, we lack a concluded concept or definition of AI (Valle-Cruz et al., 2019). The development of general AI is still unclear, whether and when it might have the same intelligence and abilities of humans or even surpasses them in the way of an artificial superintelligence (Holdren and Smith, 2016). Therefore, this thesis concentrates on the narrow AI. Further, given the fact that this thesis focuses on public policy as we have outlined in chapter 2, we consider a definition of AI from policymaking circles, where AI is described as

> *"systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals"* (European Commission, 2018; High-Level Expert Group on Artificial Intelligence, 2019).

The United Nations Educational, Scientific and Cultural Organization (UNESCO) (2021) defines AI as

> *"systems which have the capacity to process information in a way that resembles intelligent behaviour, and typically includes aspects of reasoning, learning, perception, prediction, planning or control"*.

3.2 What is Big Data?

Although Big Data is today very often used as a term, its definition is difficult (Manyika et al., 2011). Initially, it has been referred to the 3 V´s: ´volume´, ´velocity´ and ´variety´ (Laney, 2001). This definition means, that Big Data cannot only be understood as large and many datasets (´volume´) but also fast changing and almost real-time data (´velocity´) and huge heterogeneity (´variety´) (Craglia, Hradec, and Troussard, 2020). According to Gartner, one of the main information technology and research companies, Big Data is

> *"high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision-making, and process automation".*

Other definitions use additional Vs for quality and certainty of data (´veracity´), for filtering data (´value´) and for presenting complex data (´visualization´) (Nativi et al., 2015). Those definitions focus mainly on a technical perspective (Craglia, Hradec, and Troussard, 2020) and the characteristics define the structure of Big Data, but there are also definitions from a more social and political perspective looking at Big Data as transforming our daily life into a collection of data (Mayer-Schönberger and Cukier, 2013; van Dijck, 2014). Some literature takes another path regarding the definition (Desouza and Jacob, 2017), arguing that Big Data is not primarily about a change in the structure of data, but a change in our thinking of research and analytics (Boyd and Crafword, 2012; Mayer-Schönberger and Cukier, 2013), resulting in a move away from ´causal theories´ towards ´simple correlations´ (Desouza and Jacob, 2017). Further, Big Data is often used as an umbrella term to include different characteristics of a data-intensive approach such as ´data analytics´ and ´data science´ (Mergel, Rethemeyer, and Isett, 2016).

Since none of the several definitions are broadly accepted, we use a basic description which argues that Big Data contains datasets which are too large for normal processing systems and require new technologies (Provost and Fawcett, 2013), referring not only to the ´volume´, but also to the characteristics of ´variety´, ´velocity´ and ´veracity´ (Giest, 2017). Poel, Meyer, and Schroeder (2018) argue, that the definitions with the three or four V´s are not that precise in the context of policymaking since the efforts which are described as Big Data in the policy sphere do not always include high ´volume´, ´velocity´, ´variety´ and

´veracity´. Though, the 4 Vs and their characteristics gives us a basis to assess the usage of Big Data technologies and tools in the stages of the policy cycle.

3.3 AI and Big Data in the Policy Cycle

In order to analyse the usage of AI and Big Data in policymaking in a systemic and consistent way, we use the policy cycle framework with the five stages ´agenda-setting´, ´policy formulation´, decision-making´, policy implementation´ and ´evaluation and termination´ as illustrated in chapter 2. The overarching goal is to describe the opportunities and challenges of applying AI and Big Data in supporting the respective tasks of each stage of the cycle.

Figure 3.1: Opportunities and challenges of the usage of AI and Big Data in the Policy Cycle

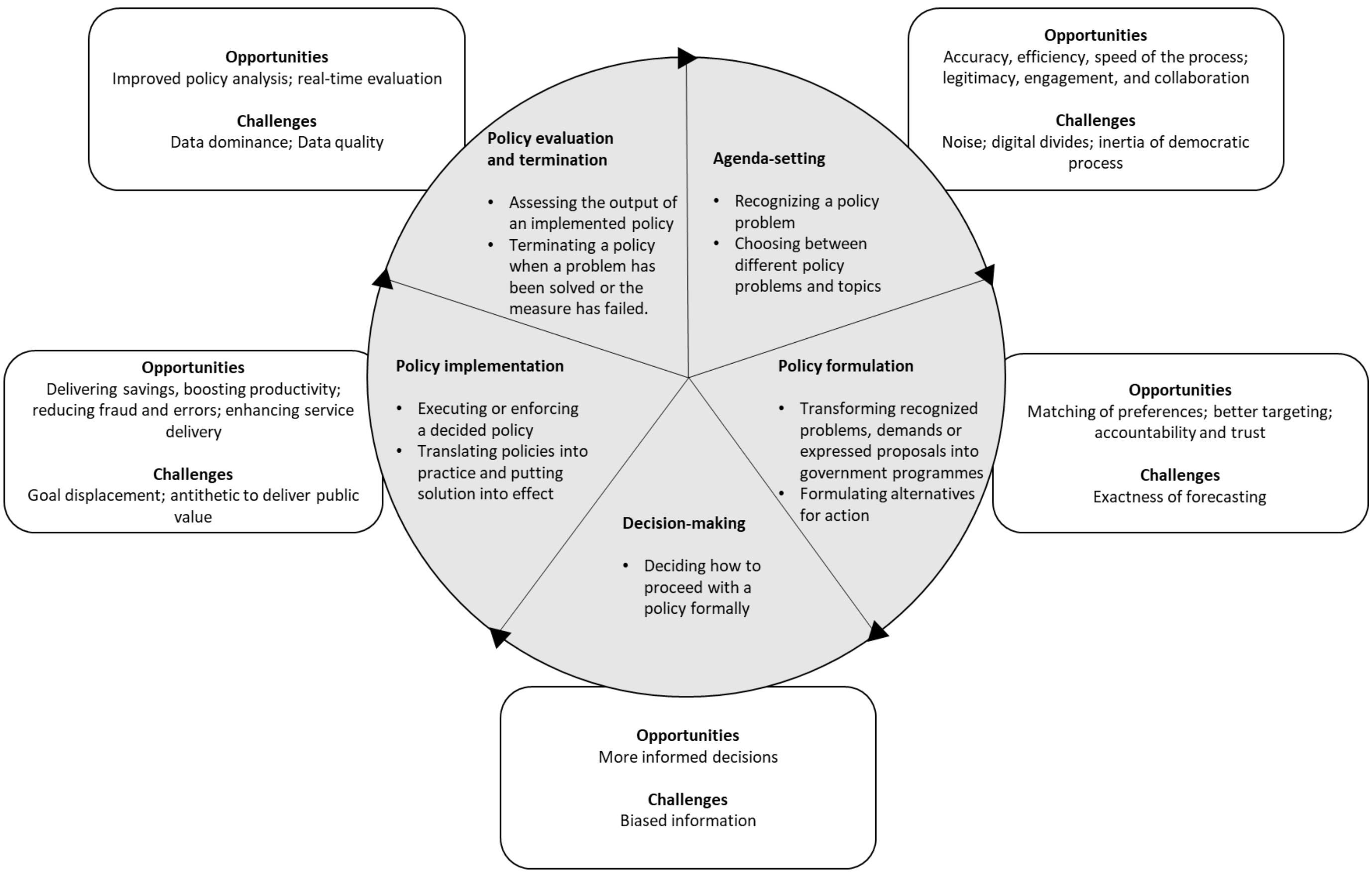


Table 3.1: Opportunities and challenges of the usage of AI and Big Data in the Policy Cycle

<table>
<tr><th rowspan="2">Stages & tasks
Authors</th><th rowspan="2"></th><th>Agenda-setting</th><th>Formulation</th><th>Decision-making</th><th>Implementation</th><th>Evaluation & Termination</th></tr>
<tr><td>Recognizing a policy problem; Choosing between different policy problems and topics.</td><td>Transforming recognized problems, demands or expressed proposals into government programmes; Formulating alternatives for action.</td><td>Deciding how to proceed with a policy formally.</td><td>Executing or enforcing a decided policy; Translating policies into practice and putting solution into effect.</td><td>Assessing the output of an implemented policy; Terminating a policy when a problem has been solved or the measure has failed.</td></tr>
<tr><td rowspan="2">Pencheva, Esteve, and Mikhaylov, 2018</td><td>Opportunities</td><td colspan="2">Accuracy, efficiency, and speed of the process; matching of preferences; legitimacy and collaboration; accountability</td><td></td><td>Efficiency and effectiveness; detection of irregularities</td><td>Greater level of granularity; holistic measurement of outcomes; experimentation; real-time evaluation</td></tr>
<tr><td>Challenges</td><td colspan="2">Noise, digital divides, cumbersome nature of democratic process</td><td></td><td>Goal displacement; antithetic to delivering public value</td><td>Dominance of data; data quality</td></tr>
<tr><td rowspan="2">Valle-Cruz et al., 2019</td><td>Opportunities</td><td>Accuracy, efficiency and speed; legitimacy and collaboration</td><td colspan="2">Accountability and trust</td><td>Cost saving; productivity gains; reduced fraud; better service provision</td><td>Improving policy analysis; real time monitoring; experimentation with new service models</td></tr>
<tr><td>Challenges</td><td>Noise, digital divide, cumbersome nature of democratic process</td><td colspan="2">Noise, digital divide</td><td>Goal displacement; loss of responsibility</td><td>Data obsolescence; data homogeneity; lack of theoretical frameworks in data analytics</td></tr>
</table>

3.3.1 Agenda-setting

As outlined in Figure 3.1, the main tasks in the phase of ´agenda-setting´ are to recognize a policy problem respectively to choose between different policy problems or topics. One of the key aspects is therefore how certain topics catch the attention of the public and policymakers (Valle-Cruz et al., 2019). For this process, you can find different streams of communication between politicians, policymakers, interest groups, and the public today (Subroto, 2012). According to Pencheva, Esteve, and Mikhaylov (2018), Big Data and advanced analytics have the potential to increase the accuracy, efficiency, as well as the speed of agenda-setting through making use of a big amount of unstructured data, analysing the policy preferences of citizens and a variety of sources. Through better possibilities of collaboration between citizens and governments, Big Data may also increase the engagement and therefore also the legitimacy of ´agenda-setting´.

A downside and limitation of using AI and Big Data in the early policy stage might be that public policy data have irregular and heterogeneous properties, particularly at the beginning of the policy process (Schintler and Kulkarni, 2014), making it difficult to get meaningful insights not only technically, but also leading to deployment of resources to less important problems and policies. There could also be limits regarding greater social inclusion, as people who require empowerment the most may have the least access to technology creating a digital divide. Further, the cumbersome nature of the democratic process could prevent people from participating (Pencheva, Esteve, and Mikhaylov, 2018).

´Agenda-setting´ can be divided into the governmental or institutional agenda, meaning topics stressed by the formal branches of government, and the systemic or public agenda, meaning topics emphasized by the public for action (Jann and Wegrich, 2007). For both, the media plays a key role since it has the power to frame issues and spread relevant information, but due to the rise of digital media and online publics, the complexity of the dynamic of issuing agendas has further increased (Höchtl, Parycek, and Schöllhammer, 2016). Especially social media offers anyone the possibility to initiate or react on a debate (Höchtl, Parycek, and Schöllhammer, 2016).

Tito (2017) outlined two possibilities of affecting ´agenda-setting´ by supporting governments in aggregating and analysing the interests of the public by using AI:

a.) *"[…] source information from social media platforms to identify problems and gauge public sentiment."* This could help the government to monitor better the opinion of the public engaging in agenda-setting (Collins, 2015).

b.) *"[…] forecasting emerging social and economic conditions, allowing policy solutions to sit one step ahead of problems."* Through using artificial neural networks, forecasting of conditions with complexity and uncertainty should make predictive agenda-setting more likely.

To both we have to add that not only social media, but also news articles through automated and large-scale analysis could make it possible to predict future events (Höchtl, Parycek, and Schöllhammer, 2016). Further, during periods of crisis, one of the key capabilities of AI tools - synthesizing large amounts of data and detecting patterns – can be very supportive, since generated insights in near real time through machine learning (ML) allow public servants and policymakers to act quickly (Patel et al., 2021).

3.3.2 Policy formulation

After deciding on the policy agenda, the task is to transform a recognized problem into a government action and for that, policymakers have to handle different policy options lying on the table (Valle-Cruz et al., 2019), as can be seen from Figure 3.1. These options can be created through laws, regulations, and other instruments (Tito, 2017). A difficulty for policymakers can be preventing a gap between the objective of a new policy and unintended consequences after its implementation. In order to design a policy which closely matches preferences (Stritch, Pedersen, and Taggart, 2017; Taeihagh, 2017) and to develop various scenarios and to predict their outcomes more accurate (Cook, 2014), Big Data can help (Tito, 2017). Though, we have to consider that predictions can be inexact.

For this forecasting e.g. of projected costs, benefits, and outcomes of the policy options, AI allows insights on smaller subsets of the population and certain regions (Patel et al., 2021). AI can be used by governments to identify for example individuals, entities, regions which need assistance most urgently or which have the highest risk in a certain matter more easily (Tito, 2017). Through gaining this information, a more targeted policy formulation to address a certain challenge, wasting less unnecessary resources and tailored, localized policies are possible (Tito, 2017). Some authors even argue that due to this possibility for central governments, it could have the potential to supplant some tasks of local governments, which focus with their policies on their respective region (Tito, 2017). Further, applied analytics could improve the understanding between government and citizens and therefore increase the accountability of the government (Pencheva, Esteve, and Mikhaylov, 2018). It can also be helpful already in the formulation stage to learn from failures or the effectiveness of previous policies through the application of technologies (The Economist, 2016; Tito, 2017).

3.3.3 Decision-making

After policy formulation, the government decides if and how it acts on a policy matter or not (Howlett, Ramesh, and Perl, 2009). This decision-making process normally follows a certain procedure including a period of debate and voting in a dedicated chamber or committee and is historically very political (Tito, 2017; Patel et al., 2021). Through using AI in the previous steps, policymakers can be better prepared to make more-informed decisions due to better insights (Patel et al., 2021). However, we have to take into account that also the information we get from applying new technologies is not automatically objective and unbiased. Tito (2017) argues that for now this phase of the policy cycle will not change much, but in the future proposed policies could be crafted by AI and policymakers may feed in various parameters in an algorithm for consideration and comparing the outputs of the different set of parameters. Though, this opportunity might be already used in the policy formulation stage. As mentioned in chapter 2, some scholars argue that the stages ´policy formulation´ and ´decision-making´ cannot be separated clearly and should therefore be combined. For the combination of ´policy formulation´ and ´decision-making´ in the policy cycle, we have seen literature already for a long time on rationalization by using techniques and tools, such as the ´Planning Programming Budgeting Systems´ introduced by the U.S. government and in similar ways used by European countries (Jann and Wegrich, 2007). This has been described as a way of rational planning and decision-making due to defining goals, budgetary output targets and applying a cost-benefit analysis to political programmes.

3.3.4 Policy implementation

As can be seen from Figure 3.1, the main tasks of the fourth step of the policy cycle are the execution of decisions taken in the previous steps (Valle-Cruz et al., 2019) through developing processes and procedures to bring the previous formulated policy into action (Savard and Banville, 2012; Centers for Disease Control and Prevention, 2015). According to Pencheva, Esteve, and Mikhaylov (2018), the advantage of Big Data in the stage of ´policy implementation´ can be grouped into strategy and operations. On the strategic level, Big Data can help to achieve the wanted policy outcome for example through data-driven precision governance or with collaborative approaches (Pencheva, Esteve, and Mikhaylov, 2018). However, most of the literature is about Big Data on the operational level and how it can improve the efficiency and effectiveness (Pencheva, Esteve, and Mikhaylov, 2018). The implementation process can be achieved more efficiently when using AI for automation and near real-time analysis of feedback from the field (Patel et al., 2021). Another impact of Big Data might be on the budgetary process for a new policy, increasing the efficiency and effectiveness towards a more outcome-oriented budgeting (Höchtl, Parycek, and Schöllhammer, 2016; Manyika et al., 2011). Through improved monitoring of the operational performance and spending, budget targets can be achieved better (Pencheva, Esteve, and Mikhaylov, 2018). This could also lead to a change in funding decisions through linking those more on the impact of policies instead of the power of government agencies, which also would strengthen a problem solution approach rather than *“maintaining the administrative apparatus”* (Höchtl, Parycek, and Schöllhammer, 2016). The focus on budgetary efficiency and effectiveness is very important, though it should not displace the intended goal and the public value of an implemented policy.

Furthermore, the transformation of the policy implementation step by AI might also be through supporting targeted communication to different audiences or more dedicated policy interventions for several subsets of the population, helping to maximize the impact through tailoring the governments measurements (Tito, 2017). Since the way governments communicate with the public have a huge influence on the reaction of the people (Tito, 2017), governments can improve their approach of interacting and connecting with different audiences (Tito, 2017; McCormick, 2016) by better understanding the effectivity of the different types of communication. Craglia, Hradec, and Troussard (2020) go even so far, that AI enables to redesign a policy to implement it in various ways according to different circumstances like certain areas or groups of the population *“to maximize efficiency of resources, effectiveness of outcomes and fairness in implementation”*. Furthermore, new policies could be tested and observed more or less in real-time with the produced data already during the implementation or daily produced census data (Höchtl, Parycek, and Schöllhammer, 2016).

3.3.5 Policy evaluation and termination

As can be seen from Figure 3.1, the policy evaluation stage should serve to assess whether the initial objectives of a policy intervention were reached (Subroto, 2012) and to consider whether the intervention has to be changed or cancelled (Tito, 2017). An important role in the evaluation process is research and analysis on an implemented policy (Pencheva, Esteve, and Mikhaylov, 2018) and Big Data could improve that (Decker, 2014). Advanced analytics enables more granularity, and additional the possibility of observing individual and aggregate variables simultaneously (Pencheva, Esteve, and Mikhaylov, 2018). Further, a holistic measurement of policy outcomes is supported through the capacity to handle time-series data from multiple and diverse sources (Jarmin and O'Hara, 2016). Both enable public managers to assess the long-term effects and benefits of policy interventions on citizens, society and the budget (Pencheva, Esteve, and Mikhaylov, 2018). In this step of the policy cycle, AI could lead to promising improvements since policy evaluation is highly data-based and through AI, policy evaluation can be done near-term with less human planning as currently required (Tito, 2017). The speed of the policy evaluation will increase as a result of policy assessments in real-time through AI, further data-based findings will allow policy iterations (Poole and Mackworth, 2010).

As mentioned above, you can find models of the policy cycle, in which evaluation is not only the last stage, but proceeds during the whole policy process as part of each stage (Tito, 2017; Jann and Wegrich, 2007). Höchtl, Parycek, and Schöllhammer (2016) even suggest a new approach for a redesigned policy cycle (´e-policy cycle´) considering the possibilities through ICT and especially the various analytical capabilities of Big Data, such as real-time processing which enables evaluation immediately when data arrives. Because of this, evaluation can not only happen at the end of the policy process, but at any stage giving the opportunity to reiterate, reassess and considerate permanently (Höchtl, Parycek, and Schöllhammer, 2016).

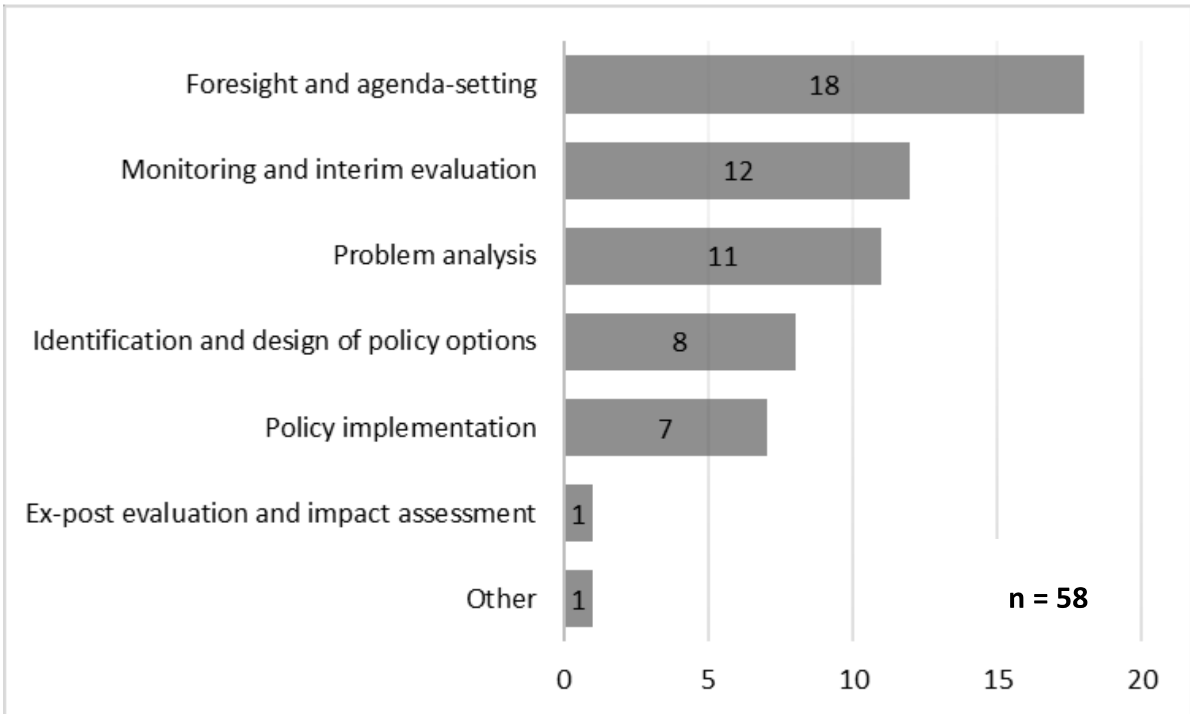
Some scholars warn of the disadvantages of using AI and Big Data in the policy evaluation stage. Cook (2014) argues that focusing on data-driven policy interventions may result in a dominance of data over theory in the policy process. Strongly concentrating on evaluative processes could decrease the probability of understanding the underlying causes while addressing primarily immediate problems (White and Breckenridge, 2014). Furthermore, according to Kettl (2016) it is often the case that there is no connection between data for policy decisions and data for policy implementation which makes an overall evaluation of the policy difficult.

3.4 Data-driven initiatives in the policy cycle

A study carried out for the European Commission from 2014 – 2016 by Technolopis, the Oxford Internet Institute of the University of Oxford, and the Centre for European Policy Studies analyzed Big Data initiatives for policymaking in consideration of the policy cycle. The study is based on desk research supplemented by follow-up queries with 58 data-driven initiatives of governments, national agencies, and non-governmental organizations (Poel, Meyer, and Schroeder, 2018). As can be seen from Figure 3.2, the study concludes that the amount of the examined initiatives using Big Data is different among the stages. The majority of the initiatives can be found in the early stages of the policy cycle, such as ´foresight and agenda-setting´, ´problem analysis´ and ´identification and design of policy options´.

Figure 3.2: Data-driven initiatives in the policy cycle

Reference: Poel, Meyer, and Schroeder (2018)



3.5 Summary

As outlined above, we can see that the usage of AI and Big Data offers opportunities in the policymaking process in supporting the respective tasks of the stages. Though, the potential varies between the different stages of the policy cycle, as can also be seen from Poel, Meyer, and Schroeder (2018) and one has to take into account also possible challenges as outlined in Table 3.1. In order to assess the usage a step further and to see the possible application in the various policy cycle stages, we have to look at the different technologies, methods and techniques.

4 Technologies, methods and techniques

In this chapter, we present technologies, methods and techniques which can be applied to serve the tasks of the respective stages of the policy cycle, adapted from a comparative analysis of tools and technologies for policymaking of Kamateri et al. (2015) and further review of past literature, clustered according to their main scope of application in the policymaking process.

Table 4.1: Technologies, methods and techniques in the policy cycle adapted from Kamateri et al. (2015)

<table>
<tr><th rowspan="2">Main scope of application</th><th colspan="2" rowspan="2">Policy cycle stages and their tasks / Technologies, methods, techniques and their features</th><th>Agenda-setting</th><th>Formulat-ion</th><th>Decision-making</th><th>Implement-ation</th><th>Evaluatio & termin-ation</th></tr>
<tr><td>Recogniz-ing a policy problem; Choosing between different policy problems and topics.</td><td>Transfor-ming recognized problems, demands or prop-osals into govern-ment prog-rammes; Formulat-ing alter-natives for action.</td><td>Deciding how to proceed with a policy formally.</td><td>Executing or enforcing a decided policy; Translating policies into practice and putting solution into effect.</td><td>Assessing the output of an imp-lemented policy; Terminat-ing a policy when a problem has been solved or the measure failed.</td></tr>
<tr><td>Analysis and prediction</td><td>Big Data and predictive analytics technol-ogies</td><td>Processing high volumes of data, analyzing unstruct-ured data, uncovering hidden patterns, and predicting future events.</td><td>✓</td><td>✓</td><td>✓</td><td>✓</td><td>✓</td></tr>
</table>

Analysis and prediction	Semantics and Linked Data	Linking together published information on the web, understand-ing public opinion and predicting reaction on a decision.	✓	✓	✓	✓	✓
Analysis and prediction	Sentiment analysis (opinion mining)	Extracting sentiments from unstruct-ured text, discovering opinions, and pred-icting events through text analysis.	✓	✓	✓	✓	✓
Analysis and prediction	Time-series forecasting	Predicting develop-ments and outcomes, making more informed decisions		✓	✓		
Collaboration	Argument-ation and eParticip-ation techniques	Involving citizens into policy-making process and getting better understat-ing of debated topics.	✓	✓	✓	✓	✓

Real-time information	Real-time data analytics	More precise and in-time policy actions and responses through scanning and analyzing information quickly.	✓	✓	✓	✓	✓
Real-time information	Visualization/Geovisualization	Making large amounts of unstructured data visually representative and interpretative and showing patterns	✓	✓	✓	✓	✓
Simulation	Agent-based modeling (Simulation Tools; Serious games)	Simulating the impact of policy decisions in social systems and analyzing behaviors.		✓	✓	✓	

4.1 Analysis and prediction

The first group includes technologies, methods and tools which serve to make better analysis out of data as well as to predict future events.

4.1.1 Big Data and predictive analytics technologies

Government entities usually have access to large volumes of public data in different domains and the storage as well as analysis of this data contributes to making better decisions due to having more information and to improve addressing the needs of citizens (Gamage, 2016). Public availability of data has increased over the last years, so have the digital sources of the data. Through open data, information shall be freely available and additionally in a standard machine-readable format (Kamateri et al., 2015; United Nations, 2010). Open data offers the potential to get better insights for decision-making, but only if one has the relevant technologies to handle a large amount of data. Since traditional data management and processing techniques have difficulties to handle large and complex data sets, Big Data analytics tools have emerged in order to analyze unstructured data, uncover hidden pattern, exploit social media or make fast decisions on high data volumes (Kamateri et al., 2015).

For making predictions of future events, Big Data predictive analytics can be used. The advantage for government entities of using Big Data and predictive analytics can be to get a better understanding of citizens opinion on government actions or their concerns, and based on that develop models and forecasts on future developments (Kamateri et al., 2015).

The ability to make more usage of large amount of often unstructured data and to get a better understanding of people's thoughts on e.g. planned or implemented policies, but also what topics people concern, can be useful for policymakers in each of the five policy stages. The prediction of future events can especially be applied in the stages of ´agenda-setting´, ´policy formulation´ and ´decision-making´.

4.1.2 Semantics and Linked Data

In order to enhance data mining through the usage of metadata, semantic technology gives us the opportunity to put machine-processable semantics of data in documents and contents. With that, different pieces of information published on the web can be linked together and can enable us to directly reference to a certain piece of information (Kamateri et al., 2015). In recent years, there has not only been data from eParticipation tools or social media platforms, but also governments have increased the availability of data on the web through Open Government Data (OGD) portals, including statistics, reports or geospatial information (Kalampokis, Hausenblas, and Tarabanis, 2011). Like ´social data´, ´meaning data´ created and shared by citizens through social media platforms is defined as subjective, whereas OGD is defined as objective, i.e. non-biased and without personal prejudices (Kalampokis, Hausenblas, and Tarabanis, 2011).

Though, also the decision which data is published and used can be biased and can follow personal preferences of decision-makers. Kalampokis, Hausenblas, and Tarabanis (2011) i.e. propose a two-phased approach to support participatory decision-making and to support policymakers in understanding public opinion as well as predicting the reaction on a decision. The approach of the authors is to integrate the subjective social as well as the objective government data.

Due to the availability of opinion data of citizens in the web and web 2.0, but also due to the trend of making nonpersonal OGD more available, linked data can be important for policymaking by providing useful information and context, something which can be supportive in each stage of the policy cycle.

4.1.3 Sentiment Analysis

The intensive use of the web offers people the opportunity to express their opinion easily. In the numerous communication channels and platforms, one can post texts or statements, but can also read the opinion of other users. Sentiment analysis tools (or opinion-mining tools) can gather, identify, extract, and determine the attitude of large quantities of texts through computational study (Kamateri et al., 2015). Among the tools you can find approaches such as natural language processing, computational linguistics, text mining, and text analysis (Kamateri et al., 2015).

As outlined in 3.3.1, the media and social media play an important role especially in the policy cycle stage ´agenda-setting´. Text analysis gives policymakers the opportunity to discover the topics which are discussed and put forward not only in the news, but also in the different social media platforms. Further, as outlined in Table 4.1, through text analysis events can be predicted, not only in the field of foreign policy (Leetaru and Schrodt, 2013; Leetaru, 2011), but also in domestic politics (Höchtl, Parycek, and Schöllhammer, 2016). A negative respectively highly critical example offer authoritarian states such as China or Singapore, which use it to get information about the policy preferences of their citizens and to get warned if a political unrest is in the making (King, Pan, and Roberts, 2013; Harris, 2014).

In the case of social media, sentiment analysis extracts sentiments from unstructured text. According to Kamateri et al. (2015), the classification of statements is a challenge in sentiment analysis, which gets addressed through different techniques with two main approaches. On the one hand, tools which are based on lexical resources and natural language processing and on the other hand, tools that use ML algorithms. Stylios et al. (2010) show in their experimental study, that through the application of text and data mining of user opinions in social media, the publics stance on governmental actions can be identified and that those techniques can help to empower the participation of citizen in the policymaking process.

Sentiment Analysis tools can give policymakers the opportunity to get to know the opinion of citizens' on certain issues, on government policy proposals or on other governmental interventions and therefore the possibility of decisions which are more socially accepted (Kamateri et al., 2015). Since the knowledge of the citizens' opinion is always of interest for politicians, sentiment analysis tools can be helpful in each stage of the policy cycle.

4.1.4 Time-series forecasting

For policymakers, forecasting the developments of economic and social systems is important in the policymaking process, though, this is something very difficult and complex due to uncertainty, non-linearity and different external elements which can have an impact (Magdalena, Logica, and Zamfirou, 2015). Time-series forecasting enables its users to analyse time-series data with statistics and modelling to make predictions and therefore support decision-making. Although predictions are rarely totally exact, forecasting of more or less likely outcomes enables a more informed decision-making (Tableau, n.d.).

For time-series prediction, one can find different techniques. Among the most accurate and often used models for time-series forecasting regarding social, economic, foreign exchange, and stock problems, are artificial neural networks (Khashei and Bijari, 2010). Magdalena, Logica, and Zamfirou (2015) e.g., show in their paper the application of neural networks for forecasting public expenditure. Alternatively, there are also auto-regressive integrated moving average (ARIMA) models which have dominated many parts of time-series forecasting for more than half a century (Khashei and Bijari, 2010).

The ability to predict certain developments and outcomes can be useful in the stages of ´policy formulation´ and ´decision-making´.

4.2 Collaboration

The second group comprises techniques which can be applied for collaboration in the policymaking process.

4.2.1 Argumentation and eParticipation techniques

The involvement of citizens in the policy process is not a new phenomenon, but due to ICT, policymakers have an important vehicle which can be adopted for that. Therefore, when governments want to consult citizens on policy issues, eParticipation has become more and more important. According to Kamateri et al. (2015), one can find primarily web 2.0 based tools with different social networking features and therefore enabling various types of involvement. These tools include discussion forums, message boards, wikis, electronic surveys or polls, e-petitions, online focus groups, and webcasting. However, analysing, evaluating, and responding to the volume of data gained from the citizens participation is challenging and technology which can support should be easy to use on the one side and on the other side be able to organise the content in a proper way (Wardeh, 2013).

In order to combine those two tasks, argumentation tools can be used, which are able to present and defend a point of view and provide complex information in an organized and easily accessible way (Macintosh, Gordon, and Renton, 2009). Argumentation tools support by giving a large number of people the possibility to participate, debate, and contribute their arguments and proposals and visualise them in a graphical network, making it easier for policymakers to analyse and to get a better understanding of the debated topics (Kamateri et al., 2015).

As can be seen from Table 4.1, interaction between citizens and policymakers can be an advantage in every stage of the policy cycle, but such tools can also be used to interact with certain stakeholders, e.g. also when it comes to enforcing a policy.

4.3 Real-time information

In this group, we list techniques which give their users the opportunity to get more reliable and timely information through the usage of real-time data.

4.3.1 Real-time data analytics

One of the key requirements to be able to make more precise policy decisions and to improve data-driven decision-making is a proper data infrastructure, combining new and existing data sets. One of the challenges can be the fact, that data often gets collected individually by different government departments and levels (national, regional and local) (Fingerhut, 2021).

The topic of data infrastructure in the public sector has been given a boost due to the Covid-19 pandemic and therefore we want to outline one technique as part of the field of data infrastructure respectively databases. Since the outbreak of the Covid-19 pandemic in 2020, we have seen how governments worldwide have tried to implement data infrastructure and analytical capacity to make more precise and in-time policy actions and responses (Fingerhut, 2021). Real-time data can be used for data dashboards, a decision-making tool for policymakers to scan and analyze information quickly (Fingerhut, 2021).

Management and visualization (which we elaborate in 4.3.2) of real-time data can be a powerful technique for policymaking in each of the policy cycle stages. Though, when combining data, we have to take into account that real-time data is a reflection at a given time and different data changes at different speeds.

4.3.2 Visualization

Especially governmental agencies or organizations collect large amounts of data and due to the internet, the volume of data – structured and unstructured – has even increased over the last years. In order to make large amounts of ´raw´ and unstructured data visually representative and interpretative as well as to show patterns, relationships, and observations, which might not be visible in a ´raw´ or unstructured way, visualization tools can support (Kamateri et al., 2015).

Visualization enables one to make more usage of data and to explore as well as analyze it better (Osimo and Mureddu, 2012). Among the different data visualization tools, one can not only find the ones to visualize and analyze ´raw´ data, but also those with additional features like data annotation, data handling, and statistical computations (Kamateri et al., 2015). The tools can be clustered into static or interactive ones, the first ones being figures or maps as a static image, the latter ones offering different functions for interaction such as zooming (Mitchell, 2005).

Some scholars like Chang (2010) see geovisualization also as part of data visualization and such tools have been used to visualize a combination of societal statistics and geographic data (Kamateri et al., 2015). Kamateri at al. (2015) outline in their comparative analysis that visualization respectively geovisualization tools have been applied in different policy domains, presenting data in the field of social, economic, environmental, health, demographics, arts, labour market, innovation, etc.

Since a high amount of unstructured data and the need for its visual representation can play a role in each stage of the policy cycle, visualization tools are useful in the whole policy process through providing better information out of data.

4.4 Simulation

The fourth group outlines a technology which can be used for the simulation of complex systems by modelling and reproducing.

4.4.1 Agent-based modelling

Policymaking is a difficult matter, because it has to set rules for society. Social systems are highly complex since they consist of interacting individuals, motivated not only by their own beliefs and personal goals, but also by the circumstances of their social environment (Kamateri at al., 2015). In order to simulate social systems and analyse how individuals interact, a simulation technique can be used, as we have outlined in Table 4.1. This method works with agent-based modeling (ABM), a system which consists of interacting and autonomous ´agents´ representing humans. The dynamics of the system emerge from the interactions of those individual agents’ behaviours.

For policymakers, the usage of such tools can help to simulate the long-term impact of policy decisions, which is of importance for the policy cycle stages of ´policy formulation´ and ´decision-making´, as we have outlined in chapter 3. ABM can be an alternative to the Empirical Statistical Models which are fitted to past data and the Dynamic Stochastic General Equilibrium Models which assume e.g. a complete market (Çevikarslan, 2020).

Serious games can also work with ABM, which have as main purpose to train or experiment in a low-risk environment compared to games which are only for entertainment (Olejniczak, Wolanski, and Widawski, 2018). They enable people to slip into a role of key stakeholders of the real world. Olejniczak, Wolanski, and Widawski, (2018) argue in their paper, that most of the used methods for predicting policy response are based on the rational choice model which has limitations in anticipating real responses on policies and that serious games can be used especially in the stage of ´policy formulation´ to test a new policy in a safe environment. It can also be an interesting method for the ´implementation stage´, since serious games give the opportunity to put oneself in the role of critical stakeholders and to experience certain problems which can occur while implementing a policy.

4.5 Summary

In chapter 4 we have shown different technologies, methods and techniques related to AI and Big Data and how they can be used in the policymaking process. As can be seen from Table 4.1, most of them can be helpful in each of the five stages of the policy cycle and can support in the respective tasks of the stages. Though, two of the technologies, ´agent-based modelling´ and ´time-series forecasting´, have their potential in the middle stages of the policy cycle. In order to make the usage in the policymaking process more concrete, we will show some use cases in chapter 5.

5 Use cases and tools

In this chapter, we outline one use case for each of the technologies, methods and techniques listed in chapter 4 and cluster them by policy domains. Some use cases are already being realised in practice, some are prototypes or have a high readiness level for the application in the policymaking process. Furthermore, we want to outline also the models, platforms and tools used in the respective examples. Among the selection of the use cases there is at least one for every stage of the policy cycle.

Table 5.1: Possible and applied use cases of the technologies, methods and techniques in policymaking

Domain	Use case	Main scope of application	Stages	Technologies/ methods/ techniques	Models, platforms, or tools
Economy	Assessing economic impacts	Analysis and prediction	Formulation Decision-making	Semantics & Linked Data	Automated Reasoning and Knowledge Graph; Vadalog (Bellomarini et al., 2020)
Education	Predicting need for School infrastructure	Analysis and prediction	Formulation Decision-making	Big data and Predictive Analytics	Catchment Planning Model (Ministry of Education, 2019)
General	Expert Scouting	Analysis and prediction	Agenda-Setting Formulation	Sentiment Analysis	EurActory, PolicyLine, CurActory' (Androutsopoulou et al., 2016)

General	Open Government Brainstorm-ing	Collaboration	Formulation	Argumentation & eParticipation	Debategraph (Noveck, 2009)
General	Visual analytics of petition data	Real-time information	Agenda-setting	Visualization	LDA topic modeling, LDAvis (Hagen et al., 2019)
Health	Forecasting epidemic or pandemic spreads	Analysis and prediction	Formulation Decision-making	Time-series forecasting	R (Duan and Zhang, 2020)
Health	Monitoring utilization of health care	Real-time information	Implement-ation Evaluation	Real Time Data Analytics	HTML, JavaScript, CSS, bootstrap, jquery and Highcharts (Tuozzolo, 2017)
Health	Simulating epidemics or pandemics	Simulation	Formulation Decision-making	Agent-based modeling	Own agent-based simulation environment implemented in JAVA (Bicher et al., 2021)

5.1 Economy

The first use case is related to the field of economic policy.

5.1.1 Assessing economic impacts

The analysis of the economic impact of restriction e.g. due to a pandemic is important to decide on policy actions. Semantics and Linked Data tools can be used for such an assessment or application scenario.

Bellomarini et al. (2020) use the example of Italy in their paper, a country that was affected very hard during the first months of the outbreak of Covid-19 in 2020. They show how the application of ´Automated Reasoning and Knowledge Graph technology´, which puts data in context with linking and semantic metadata, can address the impact of the pandemic on the network of Italian companies and support the usage of legal instruments to protect strategically relevant companies from takeovers. This can be important due to the complex shareholder structure in the global economic system. In times of crisis, the dynamics in the company network can increase. In order to understand the influence regarding ownership and control, the shareholding structures of the companies in Italy can be combined in a graph or network with shareholders (companies and people) as nodes and ownerships as links, conglomerates will be shown as groups of companies close in the graph. Therefore, the authors used the Vadalog system (Bellomarini et al., 2020).

Such assessments can be helpful in order to design an effective policy and to get more precise information for deciding between different policy options.

5.2 Education

The second use case is from the educational policy domain.

5.2.1 Predicting requirement for new schools

In order to forecast the short, medium and long-term demand of net school places, the Government of New Zealand has been using a prediction model.

For their National Education Growth Plan (NEGP), the Ministry of Education has developed the so called ´New Zealand Catchment Planning Model´ for forecasting the demand of student places and the distribution of education infrastructure, based on 39 growth areas which are called ´catchments´. The model uses data with information from the education sector, local authorities and from government agencies, but also current and projected housing development activity at a catchment level (Ministry of Education, 2019). So far, the NEGP focuses only in the areas with high growth for state and state integrated school infrastructure to 2030, but the Ministry has planned to expand this framework across all regions and their respective catchments. The chosen 39 catchments with high growth are the same areas which were identified under the National Policy Statement on Urban Development Capacity (NPS_UDC), which is based on assessments of housing supply and demand.

This use case demonstrates the possibility of creating more targeted policy actions and also the advantage of more information for decision-making.

5.3 General

The following three use cases are not related to a specific political domain.

5.3.1 Expert scouting

Analyses, assessments, or opinions of experts are relevant for the policymaking process. The EU has therefore developed a method in its project ´EU-Community´ for a more specified scouting of content on policy issues created by experts.

Sentiment Analysis tools cannot only be used to exploit the political content created of the general public on the internet and web 2.0 such as social media, but also for collecting higher quality political content on existing or planned public policies (Charalabidis, Maragoudakis, and Loukis, 2015). According to the authors, this can be achieved through crawling regularly the most relevant external sources of knowledgeable and credible people regarding EU policies and also relevant documents of different types, updating the corresponding databases, and processing the retrieved data as well as assessing the reputation, credibility and relevance. The databases then process user queries and present the results visualized. According to Androutsopoulou et al. (2016), a platform was designed consisting of two components which are accessible by users (‘EurActory’ and ‘PolicyLine’) and one component including the database which stores and crawls the information (‘CurActory’).

This approach can support better consideration of external information and knowledge resources of non-governmental actors such as scientists for designing and implementing public policies in the complex policymaking process (Charalabidis, Maragoudakis, and Loukis, 2015), but it might also be the case that certain issues come on the agenda in the first place through this method.

5.3.2 Open Government Brainstorming

In order to collect ideas for an open government policy, the White House had a brainstorming phase in 2009 as part of the Open Government Initiative. In total, over 1000 ideas were gathered for a more transparent, participatory, and collaborative government.

For mapping the arguments, ´Debategraph´[1] was used, a web-based and collaborative idea visualization tool for running citizen engagement in public policy and to facilitate debates on complex topics. With this tool, the redacted proposals on the three main topics transparency, participation, and collaboration from the White House´s Open Government Brainstorm were translated into interactive debategraphs which give the opportunity to rate, address, and edit the different proposals collaboratively. Further, it enables citizens to add supportive or opposing arguments to the proposals (Noveck, 2009).

This use case shows the possibility of involving citizens in the phase of ´policy formulation´ with argumentation and eParticipation tools.

[1] https://debategraph.org/

5.3.3 Visualization of petition data

In 2011, the Obama administration in the U.S. launched the e-petitioning platform ´We the people´ with the aim of increasing the participation of citizens. The collected data comprised the title and text of the petition, signatures and their accumulation, some characteristics of the signers and issue categories as well as metadata. Data of past petitions has been made available as Open Data for the public, also providing an Application Programming Interface (API) for facilitating data access and editing. Since such initiatives come with a high volume of unstructured data, it is a challenge to use it for the policymaking process (Hagen et al., 2019).

In order to exploit the potential of the data for policymaking, Hagen et al. (2019) suggest in their paper the extraction and visualization of textual Big Data with a prototype. For extracting emerging topics from petitions and presenting the topics, Latent Dirichlet Allocation (LDA) topic modeling and LDAvis[2] was used. Further, to assess the usability of the prototype visualization and to get better impressions of their potential for policymaking, six experts were interviewed. The interviews showed that the experts were positive about the potential of the usage despite the respective technical knowledge (Hagen et al., 2019).

Since petitions often bring topics to the agenda, this use case is an example of using technology in the phase of ´agenda-setting´ to see which topics citizens concern.

5.4 Health

The following three use case are related to health policy, a domain where we can find already a lot of examples.

[2] https://github.com/cpsievert/LDAvis

5.4.1 Forecasting of epidemic or pandemic spreads

In order to react within a reasonable period and make the right decisions to tackle a pandemic such as we have seen with Covid-19, a prediction of the spread is important.

We can find many papers where the ARIMA model has been used to analyse data sets and predict the daily new cases. In their paper, Duan and Zhang (2020) analysed two data sets with the ARIMA model in order to predict the daily new confirmed cases for a 7-day period for Japan and South Korea. Therefore, the authors used the daily new confirmed cases data of Covid-19 outbreaks in Japan and South Korea of a certain time-period with no missing values and applied the statistical software tool R[3]. The advantage of the analysis of regularly new data with the ARIMA model is a timely prediction of the changes of Covid-19 to provide better information to the policymakers, certain departments and other institutions on the development and changes of the pandemic (Duan and Zhang, 2020).

Such a forecast can help to make better decisions, especially in times of crisis, and to react in advance to the forecasted developments.

5.4.2 Monitoring utilization of health care

In the U.S. state of Louisiana, ´Medicaid´, a programme which is federally funded and provides health coverage to residents within certain groups based on income and resource limits, was expanded in 2016.

In order to monitor if the expansion resulted in more access to medical care, the Department of Health created a dashboard using HyperText Markup Language (HTML), JavaScript, Cascading Style Sheets (CSS), bootstrap, jquery and highcharts.com[4] (Tuozzolo, 2017), which shows the number of citizens covered by the ´Medicaid´ programme and what services are received. The real-time data on ´Medicaid´ utilization has been available on the

[3] https://www.r-project.org/
[4] https://www.highcharts.com/

county level and has given the citizens, media, and legislators information about the local effect of the expansion which might have also positively contributed to the public support of this programme. Furthermore, the dashboards enabled the staff of the Department of Health to prioritize the quality measures and to address gaps in the utilization of health care. The department also created additional dashboards, e.g. one in response to the Covid-19 pandemic, mapping results of Covid-19 tests, real-time ventilator, intensive care unit, and total bed capacity to show the rapid spread of the disease (Gee and Muncy, 2020).

Such dashboards using real-time data can support the implementation of a policy but also the evaluation of an implemented policy, as it is the case in this example.

5.4.3 Simulating epidemics or pandemics

Health crises, such as the Covid-19 pandemic, are a major challenge for policymakers in order to keep the cases of infections under a certain limit and to ensure medical care for the population, while taking into account economic and social side effects.

Due to the pandemic the world has faced since 2020, simulation tools have got more attention. In the case of Austria, there have been many examples and research projects using ABM in order to provide a solid basis for decisions of policymakers (see dwh). One of the examples is an agent-based simulation of Bicher et al. (2021) to evaluate the contact-tracing policies against the spread of SARS-CoV-2 in Austria. The authors used a specially developed agent-based template implemented in Java[5] in which the model agent with certain demographic and disease-related feature represent each Austrian citizen statistically and in which the transmission of the disease occurs through contact between interacting agents inside of locations, such as households, workplaces, and schools (Bicher et al., 2021).

[5] https://www.java.com/

The model enables one to simulate the changes of behaviour of the agents and the transmission of the disease due to the introduction of certain policies such as tracing or reduction of contact strategies, which can support in formulating a policy action as well as deciding between different policy options.

5.5 Summary

In chapter 5, we listed several examples, one for each of the AI and Big Data methods and techniques we outlined in chapter 4 in order to show possible or already applied use cases for the policymaking process. Most of the use cases are related to the stages of ´policy formulation´ and ´decision-making´, something which reflects the elaboration in chapter 3 and 4 regarding the potential of using AI and Big Data and their technologies. However, the used models and tools might have the potential to support in other stages of the policy cycle as well. All the use cases show their main scopes of application in policymaking: ´analysis and prediction´, ´collaboration´, ´real-time´ information´ or ´simulation´, which can support the very complicated and still human process with better and faster information as well as more participation.

6 Reflection and conclusion

In conclusion, this master thesis provides an analysis of the usage of AI and Big Data in policymaking based on an integrative literature review.
Firstly, we have outlined in chapter 2 what we understand under public policymaking and have elaborated the concept of the policy cycle. Although this concept is not totally perfect in illustrating the very complex process of policymaking with many stakeholders involved, it enables us to show different tasks divided into several stages of the policymaking process. Through our presentation of the different policy cycle models in 2.2.2, we provide a comprehensive view of the several tasks in policymaking of governments.

The policy cycle framework and the tasks of the five stages build the basis for the further general analysis of the opportunities and challenges of using AI and Big Data related to the main tasks in the policymaking process in chapter 3. We then elaborated in chapter 4 the different technologies, methods and techniques, based on the analysis of Kamateri et al. (2015), but also further research and clustered them under consideration of their main scope of application in policymaking: ´Analysis and prediction´, ´Collaboration´, ´Real-time information´, and Simulation´.

For each of the technologies, methods, and techniques we have listed in chapter 5 use cases clustered into policy domains in order to give stakeholders examples for a practical implementation and outline some of the models, platforms and tools. Also, this analysis shows the differences of the potential for the several policy cycle stages and underlines our clustering of the main scopes of the technologies in the policymaking process.

With this thesis, we provide a review of the recent public policy and administration literature on the usage of AI and Big Data and break down the opportunities and challenges into the different stages of policymaking and pave the way for future research to further analyse the concrete opportunities and challenges of each of the technologies related to the tasks of the stages. Due to the rapid developments of new AI and Big Data tools and the increase in the availability of data, it will be even more important to continue research in order to understand the potential for supporting policymaking.

6.1 Assessment of research questions

Q1 *How can AI and Big Data be used in the policymaking process, within the framework of the policy cycle, and what are the opportunities and challenges?*

The answer to these research questions is presented in chapter 2 and 3. We outline the different tasks in the policymaking process and analyse the opportunities and challenges of the usage of AI and Big Data on the basis of the policy cycle model.

- ***RQ 1.1*** *How can AI and Big Data be applied in the different stages of the policy cycle framework?*

  We answer this question in chapter 3 and show that there are possibilities of use in each of the stages of the policy cycle, although the potential can vary.

- ***RQ 1.2*** *What technologies, methods, and techniques can support the tasks of the respective cycles of the policymaking process?*

  The answer is presented in chapter 4 by showing several technologies, methods and techniques and how their features support in the different policy cycle stages. We outlined that most of the technologies, methods and techniques have the potential to support each of the stages, and that all of them can support ´policy formulation´ and ´decision-making´.

  RQ 1.3 *What are possible use cases and tools for the application of AI and Big Data in practice?*

In order to answer this sub-research question, we illustrate a couple of use cases in different policy domains and how they can be applied in the stages of the policy cycle in chapter 5.

6.2 Theoretical contributions

Firstly, through our grouping of the different models of the policy cycle under the five phases in Table 2.3, we illustrate the different tasks which can be part of the policymaking process and show, that all of them can be assigned into one of the five stages of the most common policy cycle framework.

Secondly, most of the research on AI and Big Data and their potential usage in policymaking focuses on only one of the two fields. In this thesis, we analyse and combine both fields since they are strongly connected and complementary when it comes to applying certain technologies and tools.

Furthermore, there is few academic literature combining an elaboration of the policy cycle and its tasks, the general opportunities and challenges of AI and Big Data, different technologies as well as use case. This thesis therefore addresses this gap in the literature and provides information with combining the above-mentioned research topics. However, the ´Comparative Analysis of Tools and Technologies for Policy Making´ of Kamateri et al. (2015) provides the basis especially for chapter 4 and the selection of the different technologies.

Thirdly, due to the literature review and discussion of it, the thesis reflects the status of the current research and provides through the above-mentioned combination and clustering of issues a linking of interrelations and therefore a better understanding of the topic.

6.3 Practical implications

The practical implication for stakeholders, especially policymakers, of this thesis is an analysis of the certain tasks of the policymaking process and how AI and Big Data applications can support in fulfilling these tasks.

First, the analysis relates the possibilities and challenges of both, AI and Big Data, to the respective tasks of the policymaking process.

Secondly, it should give policymakers a better understanding of the features of the technologies and for what use case they can be applied in the different phases of policymaking.

The findings underline the potential of using AI and Big Data technologies much more in the policymaking process, though one has to take into account the respective challenges and obstacles.

6.4 Limitations and directions for future research

This thesis is subject to several limitations, which are related to the general aim of reflecting the current status of research on this topic and to give a general overview to stakeholders like policymakers. Generally, the integrative literature review method has the risk of inaccuracy, bias, and lacking rigour (Whittemore and Knafl, 2005).

Scope

Due to the decision, that this thesis analyses both, the usage of AI as well as Big Data in policymaking, the scope is quite big which leads to the fact that deeper research on the different technologies, methods and techniques or a broader elaboration of the use cases was not possible. This might cause limitations to the practical usability for policymakers of the examination. Also, most of the public policy literature does not focus on specific technologies in the policy cycle, therefore future research should not only be done to combine AI and Big Data in policymaking, but also in order to make the usage of different technologies more concrete for each of the stages.

Sources

We tried to cover a lot of public policy literature on the usage of AI and Big Data, primarily using Google Scholar and Elsevier, however, it is in all probability that we missed valuable research on that topic, and we are aware that the selection of the sources might be prone to be biased or subjective. Also, due to the limitation primarily on public policy and administration literature, we did not go deeply into ´Information Technology´ (IT) details, however, we integrated parts in chapter 4 and 5. Further research should review literature on AI and Big Data in policymaking on a larger scale, and should also include more papers from the field of IT.

Ethical and legal questions

The usage of AI and Big Data in the policymaking process raises a lot of ethical, political and legal questions. Since we speak of the field where rules for the society and decisions which can affect every citizen are made, such questions have even more importance compared to the application in the business sector. Since we focused on the opportunities and challenges related to the tasks of the policy cycle, we did not cover explicitly the questions, how the usage has to be seen from an ethical and (constitutional) law perspective.

Geographic limitation

Most of the literature we used is related to Europe and the Anglosphere, since we wanted to focus on liberal democracies, especially when it comes to the use cases. Nevertheless, a review of papers related to non-democratic countries would also be important for future research to compare findings, taking into account, that the potential usage differs for ethical and regulatory reasons.

Empirical analysis

Due to the broad scope of the thesis and the aim, to give an overview of this topic, we limited the research to reviewing the literature, also in chapter 5 with the use cases, which could be conducted in more depth, and we did not execute qualitative interviews. However, some of the papers we used include qualitative research methods. We consequently encourage other researchers to test the examination in a qualitative survey with a large sample of participants from various fields and in different countries. Further future research should be done on more use cases, e.g. it would be interesting to compare successful and unsuccessful use cases and to identify what hinders a more intensive application of new technologies in policymaking.

Continuous developments

Although the scope of research of our thesis is quite broad, we have consciously selected it together with the research objective in order to assess the current status on the topic. However, this led to the limitations outlined above. Since this field is continuously evolving and is still lagging behind compared to the business sector, there are many opportunities for future research.

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