Predictive economic algorithmic policymaking in the public sector.

A case study of the Netherlands.

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Preface.

Dear reader,

I would like to thank dr. Sarah Giest of Leiden University for guiding me in this topic. In addition, the support of my partner, family and family-in law has been of great importance to me. Finally, I hope the reader feels enticed to investigate further where this research might have fallen short. The interest that initiated this work will hopefully spark the same interest in this topic to the readers of this paper.

-Sebastiaan Klaassen

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1. Introduction.

In the Netherlands algorithms are more pronounced in society than one might initially expect. The Dutch taxation system is one of the institutions that has gained a notorious reputation for using algorithms and even led to the resignation of the entire cabinet, deemed the 'kindertoeslagenaffaire' [child benefit scandal] (Belastingdienst gebruikte algoritme, 2021). As a reaction to increases in tax fraud, a self-learning algorithm was deployed (Belastingdienst gebruikte algoritme, 2021). The minority group (7,3% of the base that claims child benefits) of household incomes of less than twenty thousand euros per year formed a majority of 82,3% in the 1000 riskiest households in terms of fraud likelihood (Belastingdienst gebruikte algoritme, 2021). This algorithm used a multitude of variables, of which the variable of income and (second) nationality are now hotly debated (Belastingdienst gebruikte algoritme, 2021).

1.1 The Relevance.

The extent to which the scandal has influenced the perception of algorithms in society and policymaking warrants the investigation of this subject in terms of societal relevance. The research relevance, on the other hand, is not the debating of the negative effects on society per se. Rather one should investigate why the algorithm failed in its purpose. Using nationality was outlawed in 2015, yet second nationality was still in use until 2018 (Belastingdienst gebruikte algoritme, 2021). Inferring from this, one could see the relevance of such controversial variables for the algorithm.

Algorithms can evoke as many emotions as they have purposes. Software algorithms are a vital source of power in today's world, where code tells the computer what to do, and is essentially performative (Williamson, 2015 p.84). These models calculate outcomes that matter for social regulation, nudging behaviour of a community, and replacing complex and implicit social regulation (Christianini, 2019 p.645). Therefore, algorithms are an unmistakeably large part of our lives. It is where society finds use in developments, that research has arguably the greatest potential. One may find algorithms to be a threat to equality and transparency, whereas the other may find them to represent the future of a technology-human symbiosis and societal progress. However, such value judgements need to consider the contextual application of an algorithm.

1.2 The Case.

The advent of algorithmic policymaking in the Netherlands is discussed. More precisely, the application of predictive economic algorithmic policymaking in the public sector. The method of data collection is mostly constrained to primary and secondary textual sources. Textual analysis was thus employed, in combination with the method of process tracing which utilises within case analysis to discover causal mechanisms (Beach & Pedersen, 2013 p.3). Even though the algorithmic policymaking is assessed from a public policy (governmental) perspective, references, and uses of examples from corporates are being used as well to illustrate that stakeholders like big banking are needed in this development too. There is no specific policy under review. The lack of predictive economic algorithmic policymaking is assessed, and evidence will be compiled to enable evaluation of its constraints.

The case selected (the Netherlands) includes the stakeholders of (big) banking and the Dutch government as they are both subjected to the constraints in predictive economic algorithmic policymaking. The use of algorithms in public policy making, with resource allocation efficiency, public spending allocation and predicting macro-economic trends available are deemed most important (Van Veenstra, 2021 p.400). The research challenge is to identify what is causing something not to happen (e.g. a constraint causes a policy not to be made) in a niche subject, arguably a gap in the literature concerning constraints on predictive economic algorithmic policymaking.

1.3 The Question.

What constraint poses the biggest obstacle to overcome to implement more predictive economic algorithmic policies is evaluated. The literature review will present the views of authors who argue for an opacity, legislative, no organisational readiness, technical or ethical constraints. The case description will lay out the context of the case of the Netherlands. The analysis will provide one with the argumentation that confirms the hypothesis.

The research question is formulated as ‘what is the main constraint in using predictive economic algorithmic policymaking in the public sector?’. The research question is approached from the policy design lens theoretical angle to evaluate the procedure (data gathering, modelling, and evaluation) in a data-driven policymaking context (Giest, 2017 p.5). The mentioned phases of algorithmic policymaking are based on the pipeline model by Robyn Gulliver (2021 p.269). The hypothesis is that ‘technical constraints are at the core of predictive economic algorithmic policymaking in the public sector’. This thesis is explanatory and argues it are indeed technical constraints that limit predictive economic algorithmic policymaking in the Netherlands, and that ethical, legislative, and organisational readiness limitations are merely symptoms of the disease. One is implored to see the applicability of the findings made here to similar cases in terms of algorithm types, organisation types and countries.

2. Reading Guide.

The introduction (section 1.) has put forward the general approach of the study and how algorithms that are used for the policies offer potential, but face setbacks of implementation due to an array of constraints stemming from insufficient technology. One is now in the reading guide (section 2.) The literature review (section 3.) will lay out how the theoretical context of algorithms in (economic) policymaking have great potential but are subject to constraints. These constraints are grouped per phase of the algorithm's lifecycle. The data gathering phase, the modelling phase, and the evaluation phase. The research design (4.) describes the research methods and how the variables and sources of interest are identified. The case description (5.) will feature the Dutch landscape one travels when designing algorithms for policymaking. The case analysis (6.) builds on the foundation amassed in the previous sections to enable an adequate analysis of the role of predictive economic policymaking empowered by algorithms, divided into each phase of the policymaking process where technical constraints occur; the data gathering phase (6.1), the modelling phase (6.2), and evaluation phase (6.3). In the conclusion (7.), the reader will be presented with a short summary, remarks, and suggestions for future research in this era of research, thereby allowing for nuanced suggestion for future economic and societal potential. The discussion (7.1) will touch upon shortcomings of work. Lastly, the bibliography (8.) allows one to explore further research if one so desires.

3. Literature review.

What is the main constraint to using predictive economic algorithmic policymaking in the public sector? It will be explained that it is a technical constraint that limits usage of predictive economic algorithms in the public sector. This literature review consists of those authors that argue for implementation and amelioration of the predictive algorithmic policymaking. Here one finds the discussion on what a predictive algorithm is, and then the constraints that limit the production and usage of algorithms.

This literature review has been constructed in such a way that the debate is applicable in the context of the Netherlands. This becomes clearer in the case description, which lays out the algorithmic landscape of the Netherlands.

The constraints that limit the use of these algorithms can be opacity, legislative, ethical, technical, and organisational readiness related. These are grouped based on when these constraints occur in the algorithmic policymaking process. Opacity, legislative and no organisational readiness are grouped into the data gathering phase of the procedure. The technical constraint occurs in the modelling phase of the procedure. The ethical constraint is the largest in the evaluation phase of the procedure. The literature review investigates the debate around these constraints and will assess these in the respective procedural order mentioned and will thereafter conclude what is to be the main constraint that should be investigated to ensure possible economic and societal progress.

The last paragraph of the literature review concludes the debate by weighing the arguments of those who argue for any of the constraints to have supremacy in the debate. The conclusion there is that technical constraints are at the root of the legislative, ethical, opacity, and the no organisational readiness constraint.

The use of concepts such as model, algorithm and machine learning will be used as they have been used in their respective texts. These things are regarded to be the same unless it is stated elsewise, in which case context will be given to indicate how the definition differs.

3.1 What is an Algorithm?

Since the 1930s an algorithm is mostly seen a mathematical effort, with the values everchanging and bespoke, yet the goal is usually efficiency in calculation (Coombs, 2016 p.286). A simple algorithm is a decision-making process where a decision is made (buy, sell, activate etc.) when variable x (price, quantity, time etc.) reaches the target or limit, and algorithms themselves can be identified then by their code and by the decisions they make based on operationalised variables (Coombs, 2016 p.282).

Some algorithms are rather separate calculating bodies that might overlap or cooperate when complex situations occur, which makes identification of the algorithm and its sub-parts challenging (Coombs, 2016 p.289). Ambiguities in parameters and variables, as well as large strategies complicate assessments further (Coombs, 2016 p.293). What you measure and how one measures it sway the shaping of reality greatly, as cultural effects have a performative effect on algorithmic governance (Coombs, 2016 p.297).

The idea that standardised algorithms can create equal treatment of citizens and/or create more efficient systems is an idea that has been both developed and scrutinised over time (Ingrams, 2019 p.3). Especially in large and complex systems, expert- and citizen- informed decision-making creates conflicts and harmonisation of paradigms and value systems that are hard to translate directly and correctly into an algorithm (Ingrams, 2019 p.3). The goals in big data processes are publicly discussed and shaped by institutional structures and the processes reveal the value preferences that guide the development and goals of algorithms (Ingrams, 2019 p.4). Such goals (in the public sector) focus on technical prediction to perform better, with Mergeln, Rethemeyer and Iset incorporating the 10 goals of algorithms about prediction (opportunities) (Ingrams, 2016 p.4). These goals are presented in the table below to illustrate what algorithms are.

Goal.	Source.
Signalling functions to further understanding of emerging vulnerabilities.	(Ingrams, 2019 p.4).
Ameliorating prediction precision.	(Ingrams, 2019 p.4).
Diversifying types of public data.	(Ingrams, 2019 p.4).
Provision of real-time data.	(Ingrams, 2019 p.4).
Connecting biology, psychology, and public policy to estimate risk behaviour.	(Ingrams, 2019 p.4).
Creating geospatial data.	(Ingrams, 2019 p.4).
Provide better description of measurements used.	(Ingrams, 2019 p.4).
Enable transparency around (public) opinions.	(Ingrams, 2019 p.4).
Improve data analytics, enabling public value creation.	(Ingrams, 2019 p.4).
Combing micro- and macro- methods to create societal insights.	(Ingrams, 2019 p.4).

Values of variables in an algorithm are arguably divisible into performance (strategic and corporate management and participate forms of governance) and procedural (honesty, integrity, equality, transparency, and lawfulness) processes (Ingrams, 2019 p.6). These public values are not only important to algorithmic policymaking in governmental institutions, but the technical proficiency needed to translate these values, often codified into law, must also be followed up upon by corporations which will have to find a cost-effective way of making such an algorithm.

3.2 Data Gathering Phase.

3.2.1 Opacity Constraint.

Opacity is defined to be the lack of transparency due to trade secrets or politically sensitive information (the lack of transparency due to trade secrets or political reasons (Burrell, 2016 p.1). This can be aggravated by technical illiteracy (Burrell, 2016 p.1). Problematic data is one of the biggest issues facing algorithmic policymaking via class imbalance (underrepresentation) resulting in non-generalisability, too many categories, missing data, and outliers (Thessen, 2016 p.8). Algorithms tend to have a black box effect states Plesner (2021 p.149).

The political legitimation is often based on perceived ‘rational, logical and impartial effective governance’ due to algorithms (Tubumello, 2021 p.5). Algorithms are systematically protected by property- and copyrights which limit transparency and verification of neutrality, which can reproduce bias in the algorithm (Tubumello, 2021 p.7). The calibration bias, goal setting and measures are subject to transparency limits, especially as corporate (economic) models employ cost prediction to be the supreme accuracy measure adds Obermeyer (2019 p.6). Howlett (2015 p.173) also states individual, organisational and system capabilities depend on depends on the quality of the resources (data) that are put into the policy making process.

Suitable data constraints are also the biggest technical hurdle that holds back the creating of algorithms that ought to be more efficient via efforts like customised bundling (Wu, 2008 p.608). Heterogeneity of the number of goods and services offered is more important in positively affecting this optimal pricing scheme than is the heterogeneity of the customers’ valuation function, which makes information gathering algorithms easier to be developed as the corporate sectors should hold the right information (Wu, 2008 p.621). Not sharing this information (opacity) is thus a severely limiting factor. Opacity in (corporate) algorithms can hinder the understandability of the models due to intellectual property, illiteracy and diverging interpretations perpetuates Lepri (2018 p.619). AI companies do not share technical details due to trade secrets Yen (2021 p.4) agrees.

In addition to the usual stratification of the sample (age, sex, education etc.) a sensitivity analysis can be included, as variables like diminishing utility complicate measurement accuracy (Versteegh, 2016 p.9). Logical consistency, for example, is achieved when the coefficient preserves the severity ordering of the levels in each dimension, whilst predictive performance is the difference between the predicted and the actual outcome (can be measured via an absolute error) and limiting censoring maintains the significance of the parameters and therefore the algorithm (Versteegh, 2016 p. 4).

Besbes argues lacking data inputs, due to opacity reasons, creates a trade-off between time spent to understand demand and the time spent exploiting the insights gathered (2019 p.1408). Considering the time spent on the understanding of the demand will enable a better and longer exploitation, one will try to limit regret (percentage loss in performance in relation to the benchmark) (Besbes, 2019 p.1408). The frequentist approach expands applicability, yet the non-static nature of demand complicates the window in which learning the demand function is effective (Besbes, 2019 p.1409).

Investigating supply can be as viable as investigating demand, as limited supply (which is almost always the case) limits the influence of capacity restrictions and therefore reduces the value of projects like dynamic pricing (Feng, 2010 p.2154). Supply uncertainty holds great potential for procurement policy and pricing policy (Feng, 2010 p.2154).

Capacity uncertainty leads to technical constraints in analysing models, making base-stock policies unfit in this specific case (Feng, 2010 p.2155). Choosing the optimal price or the riskless instead of risk aversion, are all three options that form fundamental differences in the development and outcome of algorithms (and therefore policies) by influencing choices whether to go with dynamic pricing or procurement pricing (Feng, 2010 p.2156).

Giest diverges slightly, as she states that governments have the responsibility to combat siloed data to encourage interdepartmental collaboration, as opposed to digital era governance emphasising defragmentation or centralisation to standardize methods and data (Giest, 2017 p.175). The digitalisation of the government should enable the public sector to successfully utilise digital governance structures, resulting in an isocratic government Margetts (2013 p.6) corroborates.

Lastly, to make an algorithm increasingly complex investments are needed, which limits the extent to which technical constraints can be lifted when market incentives are missing (Feng, 2010 p.2162). The state has not made enough efforts to combat the opacity Scheld (2021, p.152) adds, as algorithms and readability of mandatory product information is needed when information overload occurs.

Although divided between the need for more government or corporate transparency, all beforementioned authors of this paragraph see the integration and transparency of algorithms and data as the biggest challenge. From this paragraph one may conclude that the intentional opacity due to property rights and machine learning models by corporations do limit the publicness of algorithmic processes. The ensuing misrepresentations can lead to the lack of providing opportunities or the development of alternative theories for the policy makers. Nevertheless, the need for extensive data inputs from third parties could circumvented via development of machine-learning algorithms that can aggregate data themselves, such as random forest models (Hashimoto, 2019 p.2965). In addition, a more developed algorithm could lift the constraints by more effectively predicting demand in tumultuous circumstances, as price exploration regions expand, and are therefore only lucrative when uncertainty is high (Besbes, 2019 p.1411). It is therefore concluded that technical constraints are at the root of the opacity problem.

3.2.2 Legislative Constraints.

Law, the framework of permissible actions, is in the debate on algorithms mostly defined as data protection. (Gellert, 2022 p.170). The data protection laws can be interpreted differently between knowledge communication and data science perspectives, nevertheless, this thesis looks at data as information that is given (Gellert, 2022 p.157) A discussion on information definitions and aspects will not be held (Gellert, 2022 p.169).

In algorithmic governance social ordering is at the forefront, and therefore is adopted by law, media studies, technical studies, and political science (Wijermars, 2022 p.945). Datafication, and the usage of algorithms makes policy fields overlap (Wijermars, 2022 p.942). The data used in economic sectors is credit score for example, a form of transactional data that is used excessively by corporates and public institutions where models are then applied over multiple policies (Wijermars, 2022 p.942).

The EU is adamant that free speech, cybersecurity, terrorist propaganda dissemination and online financial security are at stake, and therefore states that errors are not permitted (Wijermars, 2022 p.948). Especially the nudging (steering) effect, combined with a lack of transparency, is argued to be detrimental for the perception of algorithms as something beneficial to society as this is hard to detect and regulate (Wijermars, 2022 p.945). The legislation needed to halt the disinformation and manipulation, whilst enabling a more competitive digital single market must be tailored (Wijermars, 2022 p.942). Especially in an international context the complexity of algorithmic infrastructures needed for the cooperation of multi-stakeholder law and policy formation processes require interstate audit systems (Wijermars, 2022 p.945).

The security sense underlying what is usually denoted as DSM (Digital Single Market) or competition law, opens the possibility for the EU to expand its responsibilities and abilities to be actively involved in the situation in term of user-generated content and algorithmic recommender systems in media consumption (Wijermars, 2022 p.948). The General Data Protection Act (GDPR) was instituted to enable insights into automated processing decisions and allows one to challenge the outcomes, by arguing that non-verified or relevant are used (Wijermars, 2022 p.957). The EU Code of Practice of Disinformation (October 2018) is another example to handle disinformation efforts of companies like Google and Facebook (Wijermars, 2022 p.949). Yet, a common issue of legislation, like the 2018 Code of Practice is that the importance of scrutinization of algorithms and verification tools is that no real measurements or specifications are made (Wijermars, 2022 p.955). The takeaway of this is that the EU might limit the extent to which AI could be used at a national level (Van Veenstra, 2021 p.404).

The financial market high frequency trading, especially after the financial crisis is one of the areas where regulation (such as the European Market Infrastructure Regulation of 2012) has made monitoring of the credit cycle and improving transparency possible (Coombs, 2016 p.279). Digital ready legislation would therefore be unambiguous and simple in it enabling of automated processes Plesner (2021 p.146) adds. The general takeaway from this literature is that the developments that enable predictive economic algorithmic policymaking to happen at the EU level and therefore limit progress within the framework of the Netherlands.

The arguments made by authors surround the assumption that legislation will somehow outperform technological advancements in terms of data aggregation and prediction rules. One can inference algorithms are developed in a pace so extraordinary, with algorithms becoming more nuanced and exploratory, that legislation cannot keep up with the exploitation by algorithms. In addition, as algorithms become better at prediction without the usage of variables and systems that could be seen as discriminatory and invasive in terms of privacy (the laws will not form a barrier anymore) whilst the ‘prohibitive approach’ even within the

Netherlands in predictive analytics has not been successful as innovations outpace laws considerably, further showcasing that the law is not adapted to handling the innovations at either the EU or national level (Regan, 2018 p.186).

3.2.3 Constraint of No Organisational Readiness.

Organisational readiness enables members of an organisation to better understand their rights to access, control and share data (Cardon, 2021 p.6). Organisational readiness is indicated by organisational alignment, maturity, and capabilities argues Klievink (2016 p.272). This empowers the creation of data intense bureaucracies (Klievink, 2016 p.272). The organisation is then able to promote collection, combination, analytics, and usage of algorithms (Klievink 2016 p.271). The idea is that a ready organisation can promote the combining of datasets, structures, and data streams, which enlarges the capacity of algorithms to be correct and innovative (Klievink, 2016 p.269). Margetts (2013 p.7) takes a different angle to organisational readiness, stating that digitalisation, more broadly, is defined as centralisation, independent data generation and modelling.

Scaccia explains how the technical applications introduced depend in their success on the motivation to implement technologies, the capacities of the organisation, and the ability to develop specific capacities needed per innovation implementation (Scaccia, 2015 p.484). This is defined as happening within larger framework and strategies for implementations of technologies (Scaccia, 2015 p.485)

The frontline practitioners, administrators and policymakers depend on funding to cooperatively implement new technologies (Scaccia, 2015 p.486). Motivation is defined as beliefs and support of innovation that matches the direction of the new technology (Scaccia, 2015 p.486). This depends on relative advantage, compatibility, complexity, trialability, observability and priority of the innovation are part of the motivation (Scaccia, 2015 p.487).

General capacity is defined as sufficient staffing and effective leadership within the own organisation and the community in the cultural, organisational, and infrastructural sense (Scaccia, 2015 p.486). Innovation-specific capacity is often defined by human, fiscal and technical capacity for swift and concrete changes (though the scope of change might be small)

(Scaccia, 2015 p.487). The interaction of the delivery system (implementation branch of the organisation), the support system (training and innovation), and synthesis and translation system (makes products user-friendly) makes macro-policy, socio-political climate, existing research and theory into outcomes (Scaccia, 2015 p.490).

Empirical guidelines can only identify a (nonlinear) degree of readiness, but this is by no means clear-cut (Scaccia, 2015 p.489). The key variables that influence the process from initial readiness to readiness outcomes are bound within relationships, as training, technical assistance, tools (like manuals and programs) and quality assurance together enable progress (Scaccia, 2015 p.493).

Modern society will require a transparent management style for trust in collaboration between government and society (Ruijer, 2020 p.7). Feedback loops and controls of machine learning may interfere with values such as personal freedoms (Christianini, 2019 p.647).

Giest (2017 p.238) argues that policymakers must comprehend the data, assuming that the data is complete. Illiteracy in big data has shown to be a hurdle, both on the individual and institutional level, with the data readiness depending on the increased alignment, capabilities, and maturity of the organisation (Giest, 2017 p.369). Stakeholders affect the interaction and complexity, whilst political ideology can hold back promising technocratic inputs, creating imbalance of the precision of the performance metrics Giest (2017 p.371) adds.

Ruijer (2020 p.5) sees the organisational readiness as social systems, organisational forms and institutional arrangements interact with the contextual platforms and users where the stable technology enables the implementation of the system to overcome barriers of illiteracy. In policymaking, the innovation occurs when government can use data to model future policy implications and support future decisions as part of evidence-based policymaking (Giest, 2017 p. 171).

ICT's relative power in the development and application of the algorithm gives them a large sway in the direction of a system states Di Guilio (2021 p.2). ICT works on a different plain of interdependence, as most processes are formed by the demands of the technology, forming intra- and inter- organisational relations (Di Guilio, 2021 p.4).

Data analytics projects are usually executed by multi-stakeholder collaborations, but the scope creep occurrence (deviations from the original goal) might complicate and put a strain on all parties involved van Veenstra (2021 p.405) says. Giest (2017 p.173) calls this data culture, which acknowledges that IT needs the right organisational structure of governance, aside from IT resources, internal attitude, external attitude, legal compliance, data governance, and data science expertise. Di Giulio (2021 p.14) emphasises the intra-organisational dimension, as when internal interdependencies are high, the consensus management must be of a higher level to retain political commitment. Inter- and intra-organisational interdependencies, when successfully deploying technology, require therefore more complex governing structures to optimise the advantages of AI to enhance randomisation via machine learning Kalaiselvan (2021 p.1) adds.

These sources, either on the individual-actor or inter-organisational level, state the organisational readiness to be the core of the lack of algorithmic policymaking to be organisational readiness. The arguments that are based on organisational readiness as a limiting factor assume that algorithms are big and demanding construct that are too heavy to be carried by an overtaxed or unstructured organisation. It is however considered that better algorithms need not be more complex or difficult to handle (Thessen, 2016 p.7). More advanced algorithms might be simpler and easier to use, thereby lifting the burden on organisations that are bureaucratically and organisationally not yet ready for complicated algorithms (Thessen, 2016 p.7).

3.3 Modelling Phase.

3.3.1 Technical Constraint.

An algorithm can fail due to modelling failures. The plurality and non-traceability of which makes it impossible to list them all. Lacking parameters, validation, and variable inclusion are examples of reasons for diminishing success rate (explanatory ability) (Manzaneque, 2015 p.276). Sensors, actuators, and controls are needed to measure the difference between the current state and target state to know what to ameliorate (Christianini, 2019 p.652). An algorithm learns how to apply interventions by relying on a ‘reward’ signal via which the programme aims to maximise cumulative rewards (Wiens, 2020 p.26)

Giest (2017 p.367) for one, warns of the fallacies in big data algorithmic policymaking, as the capacity to utilise big data analytics is often lacking, with big data including datasets that are too large for traditional processing systems and therefore require new technologies to be truly utilised. Despite objections based upon the rather unsure future and objectivity of predictive algorithms, finite-time approaches and uncertainty of demand create the need for quick-thinking algorithms (e.g. the learning type) (Seele, 2019 p.11). To elaborate shortly, there are two types of uncertainty: nonparametric (demand is assumed to be broad functional classes) and parametric (demand function under a given parametric structure without parameter values) (Besbes, 2019 p.1408). Models that can combine multiple parameters and algorithms are stochastic approximation algorithms, or they can rely on Bayesian decision theory (prediction outcomes based on previous outcomes and the current situation) (Seele, 2019 p.8). Long trace data is especially critical here, as this enables companies to build fine-grained profiles, creating information asymmetry (Seele, 2019 p.9).

Algorithms deal with the issue of proxy data usage, which can be very useful if it is clear to those using it that it is not reality, especially since proxy models are taken for face value in policy making as argued by Pacheco (2019, p.1127).

Seele (2019 p.6) proposes that financial and insurance products are great examples of societal pillars that heavily depend on algorithms that estimate individual pricing. To work efficiently, algorithms need clear goals or problems to solve, as different needs ask for different types of algorithms. Customised bundling is one of the market incentives that furthers algorithmic complexity by creating pricing schemes that handle issues such as the law of large numbers (where everyone becomes similar when one adds more subjects) and economic factors like deadweight loss (Wu, 2008 p.608). This applies to goods and services that could be bundled and what goods and services can be bought individually (Wu, 2008 p.608). Giest adds that there is a difference between substantive instruments which enable collecting information to enhance performance evidence-based policymaking, whilst procedural instruments are geared towards information and legislation, are at the core of any algorithm (Giest, 2017 p.172).

Machine learning, where an algorithm learns from the outcomes versus its prediction, are essential to complex policies with many variables such tax rate effects being influenced argues Eichner (2012 p.2352). Machine learning could be considered better than other statistical methods because it does not impose unrealistic assumptions, can use proxy data, and reduces annotation efforts (Thessen, 2016 p.1). Machine learning uses data trees, in which data is being split into subsets and then terminal classes, and such trees can be later combined to overcome residual error. (Thessen, 2016 p.9). Especially random forest tree-based methods that combine predictions from all trees by fitting user-selected trees to data sets holds great potential as it combines the fast and calculatable results of the single trees whilst coping with small sample sizes, diverging data types, and missing data (Thessen, 2016 p.10). Thessen (2016 p.22). acknowledges that machine learning methods are limited due to social factors (not enough knowledge and therefore resistance) but that mostly technical factors like test data and software testing are at the core. This might be a method preferred over the 'black box' method of neural network, which are very speedy in computation but with a minor sacrifice in accuracy (Thessen, 2016 p.11).

Training the model is important, as it learns the machine how the dependent and independent variables influence each other, which enables it to cast predictions based on input data (Thessen, 2016 p.4) This can be tested by introducing a dataset to which one knows the answer (target) and when the algorithms infer the right prediction from the inputs it passed the test (Thessen, 2016 p.4). An algorithm can perform function approximation, classifications, clustering (classification without training data, and is therefore very context dependent) and rule induction (inferred rules from observations via feature construction, rule construction and hypothesis construction) (Thessen, 2016 p.5). One logically infers that an algorithm that models perfectly with training data performs best in real life, nevertheless, due to a concept called overfitting, the prediction error might be low, but the generalisation error might be high (real-world performance) (Thessen, 2016 p.7).

In addition, algorithms tend to favour complexity over simplicity, yet this may cause an ungeneralisable model (Thessen, 2016 p.7). Therefore, the consensus is that a simpler model with better data is the best option, which can then be tested against a complex model (Thessen, 2016 p.7). This applies to the number of features in a model as well, as the inclusion of more (irrelevant) features increased the number of combinations the algorithms must study and therefore becomes slower and worse in predicting (Thessen, 2016 p.8). Two proposed solutions are feature selection before one tries to train the algorithm, and future extraction which creates aggregate features (Thessen, 2016 p.8). The technical constraint is the most important as it introduces more parameters and finer granularities, which are needed in complex subjects like ecology and economics (Thessen, 2016 p.4).

The argumentation that follows from the technical constraint corner are based on the limiting factors in modelling like trade-offs in accuracy and speed, proxy variable selection and lacking processing systems. The use of better and more unbiased proxies enables more effective algorithms, which is essential to the future of algorithms as the technical constraints are both the constraint at the base of all the other constraints and their possible solution. It follows then, that these technical issues in modelling are resolvable via new classification systems, inference methods or data trail tracing (Thessen, 2016 p.4).

3.4 Evaluation Phase.

3.4.1 Ethical Constraints.

The deontological approach of Kant is taken, being that ethics are rules and are therefore breakable (Ananny, 2016 p.94). Ethical rules are social constructs and will results then in laws (constructs as well) (Ananny, 2016 p.98). PPA (Predictive Policing Algorithms) are one of the more commonplace implementation areas of predictive algorithms, and even though civil rights organisations in the Netherlands are calling for limitations on the use of policing algorithms they will most likely be part of the future in predictive algorithms and sociotechnical developments Yen (2021 p.2) argues. Area, person, and event are the main variables of interest, and might offer applicability in such algorithms (Yen, 2021 p.3).

Regan (2018 p.178) mentions that the ethical dilemma is mainly a factor due to the third parties involved, who aggregate data with dubious measures and ambiguous definitions that make legal intervention difficult. Translated to the individual level privacy concern, collection awareness and consent to gathering, done only to the extent necessary to complete the task (Regan, 2018 p.182). Regan (2018 p.184) also points to the danger of reidentifying data, which is argued to be quite easy when the amassing of (proxy) data can be done without any limits. The problem that this poses to the development of non-biased algorithms is the perpetuation of old prejudices and the accentuation of social stratifications (Regan, 2018 p.184).

Economic research for the purpose of policy application specifically, often identifies treatment effects that vary across population subgroups, but due to the lack of a standardised socioeconomic standard upon which research can rely to infer, it is hard to identify missing information and interaction variables (Rosch, 2021 p.537). In terms of bias, this means that treatment effects are often correlated to variables of race, affluence, age, education, and gender (Rosch, 2021 p.537). Underpowered studies can also lead to a lack in validity of the research because the policymakers are unable to make the right inferences as measurements of the treatment effect might exaggerate or underestimate the real effect, and especially the non-measurement of (modest) policy-relevant effects complicates the policymaking process (Rosch, 2021 p.538).

In addition, transparency and accountability tools have performative effects, complicating the algorithmic obscurity due to politicisation of terms and complex computational systems (Plesner, 2021 p.152). Big data is made up from collectors (those that determine which data is collected), utilisers (define the purpose of the data) and generators (actors that create data inputs (in)voluntarily) (Zwitter, 2014 p.3). Big data enables understanding of human behaviour, social structures and civic engagement coalescing into algorithms and probabilistic policymaking, which can sway into coercive quantitative informational digital era governance Williamson (2015 p.9) elaborates. Coded infrastructures are the background where automated processes occur that we take for granted, for-profit becomes more engaged is a more active sector every day (Williamson, 2015 p.13).

Data transparency is always limited due to the vulnerability to ambiguity and misuse of the system (Lepri, 2018). Data generation is very much linked to privacy, as data collection of IP addresses is made possible (Zwitter, 2014 p.4). The Group privacy is being breached when health status, sleeping patterns and consumption patterns are de-individualised (Zwitter, 2014 p.4). Most important here is propensity (the risk that one might do something) which is part of predictive algorithms, which are often subject to bias of the programmers (Zwitter, 2014 p.4). The being unaware of the decision the algorithm makes upon your behaviour opens a debate about the ethicality of the variables the algorithm used together with big data (Zwitter, 2014 p.1). The individual moral agency is complicated by the ethicality of impersonal data that are sold on the market for selling and manipulation purposes (Zwitter, 2014 p.1). Algorithmic regulation creates positive and negative incentives via data trails of human behaviour one does not know one creates (Christianini, 2019 p.647). The agent receives a verdict, whilst the agent is not aware of its action, cannot make a choice and is not aware of the causality of the action (Zwitter, 2014 p.2).

The decision to provide contextual information to subjects can create bias in the experimental research as participants align themselves with political mindsets that can be implied (Rosch, 2021 p.534). Programmes that organise experiments can, however, alter the parameters, such as the selection process, information disclosure and budget (Rosch, 2021 p.536). When a study then finds multiple equilibria, the interpretations that can be made, this is often relatively useless for policymaking due to the non-definition of what is the right equilibrium (Rosch, 2021 p.537).

The actions taken are dependent on the closed loop control system and the extent to which the algorithms perpetuate bias argues Christianini (2019 p.652). The commensuration (translating qualities into quantities) reduces, simplifies, and integrates information and can generate unexpected and united reactions extraneous to the goal, or even manipulate internal rules to temper with results (Chirstianini, 2019 p.652). When all is connected more intensively, interactions can emerge (aside from filter bubbles, public opinion manipulation and market flash crashes) and pose the question whether feedback loops should be separate or merge to halt the perpetuation of stigmatisation (Christianini, 2019 p.656). Indeed, the purpose of a system and its maker may not be aligned in such developments (Christianini, 2019 p.653). Uber is such an example, where the Uber algorithm measures customer experience, yet management uses the data trails as proxy variables to measure driver efficiency (Christianini, 2019 p.655).

The violence that can occur via algorithmic bias could be related to calculation power Bellanova (2021 p.123) argues. Here it is then specified that an algorithm only reads code, not a world or a situation (Bellanova, 2021 p.124). Normalising systemic underrepresentation and digital redlining reinforce suppressive (economic) policymaking (Bellanova, 2021 p.125). Even though political and legal big data questions such as data justice and data colonialism are not debated, the point made is that one must think constructively about something as seemingly technical as data. The arguments made in this section point to the limitations of algorithms due to breaches of privacy and bias in algorithms. At the same time, these arguments are bases upon the technical fallacies that result in the large human influence in these algorithms. As algorithm technology develops further, however, the human error and bias are arguably resolvable.

3.5 Conclusion.

The conclusion of the literature review is that predictive algorithmic policymaking is limited mainly due to technical constraints. The other constraints mentioned (legislative, ethical, opacity and no organisational readiness) are not argued to be completely unfounded, yet it is the technical constraint that is at the base of the other constraints.

The variability, variety, value, veracity, volume, and velocity of data make for competitive advantages in economics and politics but also demand more developed systems for analysing such data (Gulliver, 2021 p.270). The data storage data integration and data access (data gathering phase) must cope with technical and legal constraints (Gulliver, 2021 p.273). Data analysis, especially predictive modelling depends on infrastructure to handle the big and complex data, and the proficiency of the algorithms and its designers (Gulliver, p.276). The evaluation stage (data interpretation and data operationalisation) depends on equitable and ethically sound outcomes to inform policy proposals which depend heavily on design support and testing (Gulliver, 2021 p.278). Such efforts are bias reduction, visualisation improvement (making patterns visual) (Gulliver, 2021 p.278). This enables better replication, transparency and management efforts which come paired with digital security issues (Gulliver, 2021 p.279).

Continuously altering weights of the predictors to alter the trade-offs between values, a more well-rounded algorithm can be built (Williams, 2018 p.24). Especially in normative issues, a national network, via auditing in waste management and administrative law elements in organisational infrastructure, actors, and mechanisms can be more effective (Plesner, 2021 p.150). The positive outlook on algorithms is based upon the relative lacking scientific base forming the fundament of the critiques towards predictive algorithmic policymaking (Yen, 2021 p.13). Most authors define some shortcoming of the algorithmic policymaking centred around the abuse, yet the tools themselves are not to blame and could even be the solution (Yen, 2021 p.4).

Database architecture is essential to making algorithms as the increased useability of the data is key (Williamson, 2015 p.15). The data trails reveal interactions and identities, where machine learning and statistical models built from data to predict actions, behaviour and attitudes which can only effectively be gathered from big data (Williamson, 2015 p.16). Linking data semantically for re-use shows more potential than simply publishing data, as this provides problem-solving in the opacity issues via technical means (Van Veenstra, 2021 p.398). Challenges to data use like public sector readiness can lead to hesitancy or too high expectations by the government in terms of transparency, technology and accountability will continue to complicate implementation strategies (Van Veenstra, 2021 p.398).

One of the greatest concerns about the use of big data and algorithms is the involvement of third parties, as they have the knowledge and technical means to design and implement the algorithms, which is dangerous to citizen and state information (Van Veenstra, 2021 p.403). The need for data safety is strong, as algorithmic success can be hindered due to the human biases that are limiting mechanical efficiency and effectiveness (Agyekum, 2019 p.1270). If the political commitment and embeddedness (the degree to which the relationships within a network are based on the trust and reciprocity) are sufficient, one can depend on ICT experts to reinforce auditing of algorithms so they can be more tailored (Di Guilio, 2021 p.6).

More technical approaches to transparency promotion in the systems combat opacity in the system through combatting developments like cryptographic commitments (sealed documents) for which inter-organisational integration is key (Lepri, 2018 p.619). There are several other techniques that enhance transparency (accessibility and understandability of data and processes), such as auditing (detecting and removing biased questions and standardised tests), opacity measuring, usage of proxy variables, predictability increasing programmes, using fair random choice, and elaborate post-hoc interpretations (Lepri, 2018 p.620). Re-encryption could also negate the data safety concerns in policymaking, as this allows data to be stored in both blockchains and proxy cloud servers (Agyekum, 2019 p.17).

The legislative, ethical, opacity and no organisational readiness constraints are not argued to be unimportant. Nevertheless, the transparency, ICT promotion, and lifting of biases depend on technical innovation. This answers the question what the main constraint to using predictive economic algorithmic policymaking is. The conclusion from the literature review is thus that technical constraints are at the base of why predictive economic algorithmic policymaking is limited.

4. Research Design.

4.1 Method.

This research employs explanatory deductive qualitative research methods where in-depth knowledge of the under-researched niche concept of predictive economic algorithmic policymaking are gained. The deductive approach entails that one starts with a concept and theoretical relationships working toward concrete evidence, after which a conclusion is made based on the theoretical lens (Neuman, 2014 p.69). The qualitative approach makes that the sources used are textual in nature. Qualitative studies focus on the situationally constrained interactive processes and thematic analysis where theory and data (documents here) are fused (Neuman, 2014 p.17). Thus, qualitative thematic analysis with a focus on interactive actions, where technological constraints create shortcomings of algorithms was performed.

The research question is presented as ‘what is the main constraint to using predictive economic algorithmic policymaking in the public sector?’. Economic algorithm development processes are studied, which is substantive, as explanation makes use of empirical generalisation and association (technical constraints lead to ethical arguments) to research why the constraints occur (Neuman, 2014 p.38). This is a logical approach as interest in this topic has been sparked due to media attention, which leads naturally into explanatory research.

A policy design theoretical angle is taken where the procedure from data gathering, to the creating of the model, and to the evaluation of the effect of the algorithm are considered in a data-driven policymaking context (Giest, 2017 p.5). Policy design theory argues that governments aim to use (data) evidence tools efficiently and effectively in the formulation stage, implementation, and outcome in policymaking to reach the intended goals (Giest, 2017 p.5). Process-tracing was employed to see how and where the constraints in predictive algorithmic policymaking pops up in the algorithm’s lifecycle, being a causal mechanism discovering within-case analysis of the Netherlands (Beach & Pedersen, 2013 p.3).

The phases that are distinguished in this thesis: data gathering, modelling and evaluation are based on the pipeline model by Robyn Gulliver (2021, p.269). Gulliver (2021, p.269) names six phases. The data storage, data integration and data access phases were fused into the data gathering phase. The data analysis stage is equated to the modelling phase (Gulliver, 2021 p.269). The Data interpretation and data operationalisation are part of the evaluation stage (Gulliver, 2021 p.269). Ethical considerations are a considerable part of management in algorithmic management due to misuse of statistical discrimination and limits in storage and modelling infrastructures (Gulliver, 2021 p.270).

The hypothesis is that 'technical constraints are the core constraint inhibiting predictive economic algorithmic policymaking'. The micro events of algorithmic policymaking find their effects and discussion within the context of macro-explanations. This thesis sees these macro-events as stemming from micro-events, and hovers in the meso-level which is about implementation of algorithms. Of course, the macro-level is more easily studied than the micro-level in this case due to the technical nature of the subject. Yet one cannot, for the same reason, omit the micro-level of algorithms.

4.2 Case Selection.

The selection of this case is justified as the weight of the argument that the constraints and possibilities of predictive economic algorithmic policymaking are exemplified by the relative nicheness of the issue. The case of the Netherlands is also justified as the country is technically, and legally, quite in favour of data protection and the possibilities of algorithmic policymaking (Ministerie van Justitie en Veiligheid, 2021 p.2). As one will discover, Non-Governmental Organisations (NGO's) were not considered of importance since usage of (especially economic) algorithms is mostly found in corporates and the governmental due to technical constraints, whilst the NGOs that do use some automated tools focus merely on crowdsourcing (Loynes, 2020 p.340).

In terms of the larger decision-making process in national political economic policymaking, the budget process is made up of the preparation of the budget in spring, which is then presented on the third Tuesday of September, which is fact-checked and checked for corresponding to the 'regeerakkoord' (governance agreement between of the coalition) by the ministry of finance (Rijksoverheid, 2018). Each budget is then proposed to the second chamber individually as a law, allowing the budget to be changed, on which is voted by the second chamber (parliament) at the end of the year (Rijksoverheid, 2018). This is then approved by the first chamber (senate) (Rijksoverheid, 2018). On January first, the ministries start executing the policies of the budget, and if they need more money they can apply for supplementary budgets (Rijksoverheid, 2018). At the utmost date of December first, the fall report is presented, which gives updates on the budget (Rijksoverheid, 2018). On the third Wednesday of May the ministries present their yearly report (used to create better budgets in the future), which are then approved by the second and first chamber (Rijksoverheid, 2018). The regional and municipality level policymaking were not considered due to the separateness of the levels of governance.

Following, the structure of algorithmic design at a conceptual level, and the guideline for doing so is presented. The ministry of justice and safety published a document march first, 2021 on the guidelines of algorithmic policymaking, where the emphasis is put on only the scale to which algorithms and data inputs have developed in the decision-making process (Ministerie van Justitie en Veiligheid, 2021 p.1). The combination of corporate, systemic, and work floor processes makes for the creation of new guidelines on transparency and risk-perception (Ministerie van Justitie en Veiligheid, 2021 p.2). These guidelines focus more precisely on the awareness of risk, transparency and understandability, data recognition, responsibility, validation, testability, public awareness, and auditing capabilities (Ministerie van Justitie en Veiligheid, 2021 p.2).

Different types of algorithms need different permits for usage (Ministerie van Justitie en Veiligheid, 2021 p.3). Some algorithms are machine learning (a self-learning algorithm) used in artificial intelligence, which can find complex connections, but with the risk of being opaque (Ministerie van Justitie en Veiligheid, 2021 p.3). Other algorithms are simple decision trees, rule-based algorithms, linear regressions, and random forest methods (Ministerie van Justitie en Veiligheid, 2021 p.3). The effectiveness of the algorithms depends on their goal as well, where the Dutch government uses descriptive (what), diagnostic (why), predictive (what can), and prescriptive (what ought to be done) (Ministerie van Justitie en Veiligheid, 2021 p.3). It is logical that predictive and prescriptive models have more impact in policymaking (Ministerie van Justitie en Veiligheid, 2021 p.4).

Economic and financial interest of the state, especially fiscally, is one area in which full transparency might not be warranted (Ministerie van Justitie en Veiligheid, 2021 p.6). The government will not use algorithms from which the results are not traceable and verifiable

(Ministerie van Justitie en Veiligheid, 2021 p.7). The government also uses principle of comply or explain, which means that one must always follow the rules unless one can defend why one cannot (Ministerie van Justitie en Veiligheid, 2021 p.10). In terms of data protection, the Baseline Information security Government, the Business Impact Analyses, and the Decision Prescription Information Security Government Agency are part of the framework that is continuously tested for its adequacy in the planning and control cycles of government algorithms (Ministerie van Justitie en Veiligheid, 2021 p.11). The translation of norms and values into concrete design qualities of the algorithms (anti-discrimination) makes for testability and juridic concreteness (Ministerie van Justitie en Veiligheid, 2021 p.12).

The algorithms are discussed and used in practically all levels of decision-making: the public administration, decision-forming, policymaking, design, control, and communication level (Ministerie van Justitie en Veiligheid, 2021 p.13). An example of an algorithm is one that helps unemployed people by offering personal conversations, which are awarded via an algorithm (Ministerie van Justitie en Veiligheid, 2021 p.16). For such an algorithm to be operational the testing and subsequent evaluation is needed, and if the software changes an evaluation of the case scenarios themselves is needed (Ministerie van Justitie en Veiligheid, 2021 p.19). Changes, increases, decreases, and changes in data dispersion are reason for algorithm monitoring (Ministerie van Justitie en Veiligheid, 2021 p.19). Especially predictive algorithms need a report on the relative weight of the outcome on the decision-making processes via standardised methods, and what the usage of proxy variables meant for the outcome (Ministerie van Justitie en Veiligheid, 2021 p.19). Cooperation with stakeholder parties is to define what data inputs, performance and benchmarks are good enough (Ministerie van Justitie en Veiligheid, 2021 p.21).

4.3 Variables.

Variables/ Concepts	Definition (from theory)	Indicators	Data Sources
Independent Variables			
Data gathering phase:			
1. Opacity constraint.	1. Lack of transparency due to trade secrets or politically sensitive information.	1. Data inputs.	1. (Burrell, 2016 p.1)
2. Legislative constraint.	2. The framework of permissible actions.	2. Data protection laws.	2. (Gellert, 2022 p.170).
3. No organisational readiness.	3. Data intense bureaucracies.	3. Organisational alignment, maturity, and capabilities.	3. (Klievink, 2016 p.272).
Modelling phase:			
4. Technical constraint.	4. Model failure.	4. Accuracy.	4. (Manzaneque, 2015 p.276).

Evaluation phase:			
5. Ethical constraint.	5. Ethical rules.	5. Rule breaking.	5. (Ananny, 2016 p.94).
Dependent Variable			
Use of predictive economic algorithms.	Decision making programme made from code.	Accounts of usages of algorithms.	(Coombs, 2016 p.282).

There is a cluster of concepts around algorithms, but the chosen definitions of the independent variables are based on their use in academia and their importance to algorithmic policymaking. The dependent variable is usage of the predictive economic algorithms. This is defined by reviewing the real-life operationalisations of these algorithms with every implementation considered a success. This definition is taken here to enable operationalisation in both corporate and governmental organisations. The independent variables influencing the dependent variable of successful implementation have their origin in academic theory. All these variables are measured by proxy, via textual analysis, and are independently and objectively evaluated to ensure triangulation effectiveness.

Opacity is defined to be the lack of transparency due to trade secrets or politically sensitive information (the lack of transparency due to trade secrets or political reasons, worsened by technical illiteracy (Burrell, 2016 p.1).

Law constraints were also included to refer to external forces at play and indicate whether local, national, or supranational laws are more restricting as the framework of permissible actions (Gellert, 2022 p.170).

Organisational readiness is defined as staff capacity, willingness to change mentality, organisational alignment, maturity, and capabilities to control and share data (Klievink, 2016 p.272).

Technical constraints are the lack of technical capacity to develop algorithms that can achieve their purpose, which in terms of predictive algorithms can be measured by the accuracy or success rate (Manzeneque, 2015 p.276).

Ethical constraints are more often found in algorithms designed to perform predictive policing but are generally defined to be (yet) unwritten laws, as the deontological approach of Kant states that ethics are rules and therefore breakable (Ananny, 2016 p.94).

4.4 Reliability.

Reliability is the consistency of the measure of a variable over time and space, yielding consistent results (Neuman, 2014 p.212). Reliability might be low, as generalisations are made here to create applicability of these findings to a set of algorithms that are discussed. The context in which the thesis was produced can only be exactly done once. Yet, if multiple studies are done over time, one will most likely not find a massive paradigm shift within the coming months or even years, which means that if the same research is employed the results will not differ drastically. If future case studies of algorithms (in the Netherlands) are done, and the conclusion holds, the reliability is indeed high.

4.5 Validity.

High validity occurs when the measures of indicators that match the concepts in the study are correct (Neuman, 2014 p.215). Face validity (the measures make sense initially) is arguably high, but the future application of the findings will point out the real (predictive) validity where the indicators of the variables are logically consistent (Neuman, 2014 p.216). Discrete variables are used to make research easier. The categories (phases) are made mutually exclusive. If other studies would reproduce this study but alter the measure of the concepts used, the validity is high.

4.6 Sources.

Secondary sources were selected from the Leiden catalogue. This source is selected because the selection option for peer-reviewed online-accessible articles enables easy access to a sizeable and pluriform information platform. Search terms include the likes of: ‘algorithmic policymaking; predictive economic policymaking’, predictive economic policymaking’, ‘economic algorithms’, and ‘constraints of algorithmic policymaking’. Most articles used are from 2000- and onwards due to the relatively recent developments in this area of research. Document analysis to get to know why things happen was employed and used peer reviewed and CPB (Centraal Plan Bureau) [Central Planning Bureau] documents, which is a bureau that makes (calculated) budget plans based upon party preferences (Centraal Planbureau, 2022 p.4). Government documents are used to complement the CPB documents, as they give more insights into the decision-making process in the public sector. The information was analysed using thematization to make sense of the diverse topic in terms of micro-meso- and macro-level analyses and across subfields. The English language was used for literature selection. Only the government documents and the CPB were in Dutch. These sources were used to give insight into the case specifics of predictive economic algorithmic policymaking in the public sector of the Netherlands. These sources were also selected due to their relative trustworthiness over information from websites and online articles.

The research efforts tried to include peer reviewed articles and official documents only, as the lack of modelling and ICT knowledge from the author limited triangulation efforts. Some examples could be considered deviant samples, but they were used to create insights.

4.7 Constraints.

Unfortunately, this thesis faced a suffocating limitation. A multitude of interviews was planned to enable me to generate expert data across institutions. Phenomenology, using participants experiences to understand a phenomenon, was elected to be the suitable solutions to the data constraint experienced in analysing articles. Nobody of the addressed for the interview responded positively, for reasons of ‘time-constraint’, ‘lack of knowledge’ and ‘trade secrets’. Lastly causality was difficult to discover as counterfactuals (no policy, or no algorithms) were very hard to come by.

5. Case Description.

5.1 History.

The Netherlands has a public administration history of being a participatory democracy (all government information is public information, which gives public organisations broad authority to collect and share data) (Ingrams, 2019 p.9). The technological development is high, and the Dutch Public Access to Government Information Act and the Data Protection Act form the basis of the current day legal foundation for algorithmic policymaking (Ingrams, 2019 p.9). An example being article 5(I) of the GDPR stating that personal data must be processed lawfully, fairly, and transparently (yet ambiguity exists in what forms of retro- and prospective transparency exists) and can alleviate notice and consent issues via Article 4(II) (Felzmann, 2019 p.2). Both the Advocacy Coalition Framework (ACF) and the Narrative Policy Framework (NPF) form approaches that incorporate budget constraints and information provision in evidence-based policymaking, where collective policy learning via expert data is essential to societal progress (Mosley, 2017 p.702). This makes the Netherlands an excellent case, as the literature applies to the case legislatively, as it promotes predictive economic algorithmic policymaking.

Public sector data analytics concerns the data retrieval process, analysis of the data, publishing the results as well as re-using the data to address societal challenges (Van Veenstra, 2021 p.397). The Netherlands is the third ranking in the Digital Era Economy and Society Index (Van Veenstra, 2021 p.397). Data availability is increased by the combination of a variety and re-use of government big data, whilst the use of algorithms encounters constraints in the context of the Dutch government, which require improvements in performance in predictive maintenance, logistic optimisation, and personalisation (Van Veenstra, 2021 p.398). Opportunities of data analytics, via anticipatory governance design and delivery and performance managements are juxtaposing the technical challenges such as ensuring data quality and quantity, ensuring interoperability for data re-use (Van Veenstra, 2021 p.398).

5.2 Structure.

The bureaucratic structure in the Netherlands is that the office of the ombudsman, freedom of information offices, and data protection agencies are the institutions that government has established to support public information rights and democratic accountability (Ingrams, 2019 p.10). The institutions that ensure the right usage of algorithms are fortified by the central e-governance standard-setting of the Washington agreement of 2014, supported by the privacy regulations such as the criminal code, the civil code, the telecommunications Act and Telemedia Act (Ingrams, 2019 p.10). Government organisations are pluriform, with the municipality, central government, and province in collaboration with executive or semi-public organisations (Van Veenstra, 2021 p.401). Here only the central government is of importance, as most applications of algorithms are on the physical environment, safety, and security, with great potential for infrastructure and finance (Van Veenstra, 2021 p.402).

5.3 Institutions.

Compilation and analysation of data in the Netherlands revolves around two institutions: Statistics Netherlands, and the Open State Foundation (Ingrams, 2019 p.141). These organisations empower the government to initiate independent analyses by providing valuable (financial) data openly at the local and state level (Ingrams, 2019 p.141). The BRP (Personal Records Database) has more built-in protection, as it is guarded by the Ministry of the Interior and Kingdom and is protected by the Personal Records Database Act (Ingrams, 2019 p.141). In 2000 the Data Protection Act, which was updated in 2016, was instated to provide the largest part of the legislative provision (Ingrams, 2019 p.139). The Data Protection Authority (DPA) is the main line of defence for privacy, yet they are transparent in their approach to get result and the choices they make in doing so (Ingrams, 2019 p.139). The Authority is independent, has discretionary power, and generally advices and enforces compliance with the DPA (Ingrams, 2019 p.139).

EU law has supremacy over Dutch law, with the SyRI (Systeem Risico Indicatie) [System Risk Indication] for example, was outlawed for being too privacy invasive and was ruled not to be transparent and accountable enough (Van Veenstra, 2021 p.404). Scheld (2021 p.153) mentions the standardisation and language guidelines are regulatory measures put in place by the EU. The Committee of European Securities Regulators (CESPR) was made to lay out what 'clear language is' typeface and less jargon are EU's general measures to insure more transparency (Scheld, 2021 p.158).

Both big corporations and the state are under the scope of jurisdiction, as legal infractions were brought before the court in case of the governmental plan to retain phone and Internet data under criminal warrants in 2014 (Ingrams, 2019 p.139). In addition, the GIA specifies the right of public access to information, and the right refuse to release information for reasons of legal matters, security, and privacy (Ingrams, 2019 p.139). The Re-use of the Public Information Act, however, is more focused on efficiency as commercial uses of government data reuse are permitted (Ingrams, 2019 p.139).

The independence of the five high councils of the Netherlands is guaranteed by the constitution, the Court of Audit, the National Ombudsman, the Council of State, and the two legislatures of the national parliament, which are essential to data management in the Netherlands according to the values of the public and technocratic leadership (Ingrams, 2019 p.139). The Court reviews the abiding of data standards, public finance management, and policy formation advise in big data topics like transport, defence, social security, and taxation (Ingrams, 2019 p.139). There are different types of data analytics, such as original reports by organisations in big data, service user digital click streams (such as geolocating), metadata on government performance, regulations, and analytics (Ingrams, 2019 p.140). The Dutch approach is defined by its heavy use of third parties to create capacity for big data algorithmic policymaking (Ingrams, 2019 p.141).

The 2016 FinPro program was used to identify welfare fraud, saving the government millions of euros, making such programs a major investment opportunity (Ingrams 2019 p.141). Despite the potential, compliance and economic efficiency is mostly held back by time preferences, to some extent compromising democratic citizen values of big data (Ingrams, 2019 p.141).

This section demonstrates that the literature applies here in terms of organisational readiness, as the organisational structure does not show any characteristics that would make it sufficiently diverging from the organisational structures in which algorithms are made to question the applicability of the literature.

5.4 Corporate Stakeholder.

In the implementation of big banking macroprudential systems, investigating the role of algorithms in public banking in the Netherlands has been identified as a great example of the possibilities by Liao (2015 p.231). Systemic risk is the risk of the default of the entire system due to the interbank connections, with currently only individual bank regulation in place, macroprudential capital requirements equal to the share of risk could offer great predictive economic algorithmic policymaking potential (Liao, 2015 p.231). More specifically, the balance sheets plus an algorithm in interbank exposure clearing incorporates common banking factors and contagious defaults could increase the health of the banking sector (Liao, 2015 p.232). In the largest Dutch Banks Sample: a 17% default reduction and the likelihood of multiple defaults dropped by 26% and 40% in different capital level deviations under the previously mentioned algorithmic prediction (Liao, 2015 p.232).

This Merton-style network model (derivative investment instruments to calculate financial market developments) looks at both systemic risk from both asset correlation and contagion through interbank exposure (Liao, 2015 p.232). This model is composed of a panel of correlated structural credit risk models in addition to a clearing algorithm on the network of interbank exposure direct cost bank closure (10% of assets) (Liao, 2015 p.235). Even though different models hold diverging results, the systemic loss estimation consists of stage one (being the calibration of the model), stage two (being the simulate systemic joint losses) and stage three (which relates losses to macroprudential capital requirements) (Liao, 2015 p.238). This shows how both public (national) institutions and corporates are stakeholders.

5.5 Street Level Response.

Cardon’s research is introduced here to further fortify the argument that the Netherlands is an excellent case selection, as Cardon interviewed employees in technology adoption with management functions, controlling for age, gender, and diverse sampling (corporations in retail, finance, and education) (Cardon, 2021 p.7). The interviews lasted between 40 and 60 minutes, in which questions about experiences and the future of algorithms in the workplace were asked (Cardon, 2021 p.10). From the 50 in-depth interviews, the 11 most important interviews for the purpose of this paper are the German interviews as these correspond most to the Dutch case in terms of legislation (Cardon, 2021 p.1). Germany is, as is the Netherlands, subject to the GDPR of the EU, which is the strictest form of digital privacy protection in the world (Cardon, 2021 p.8). Clear consent and transparency were deemed essential to the creation of guidelines concerning algorithms and privacy, with especially the German respondents referring to a legal framework (Cardon, 2021 p.13). The Germans responded in a way that was more likely to have concern for wellbeing as opposed to efficiency in the US respondents (Cardon, 2021 p.15).

Algorithms are here introduced as being of importance as they do not only diagnose, rather they provide recommendations in decision-making (Cardon, 2021 p.2). To provide some contextual information, the algorithm under discussion in communication is one that analyses verbal tone, nonverbal communication, expressions, and conversation transcripts (Cardon, 2021 p.3). The research was specifically focussed on privacy of individual (state or condition in which one has agency over the information other parties can access) as the advances in technology are argued to outpace the privacy laws that are being issued (Cardon, 2021 p.4). The responses from the interviewees of the Cardon study indicate that the opacity, datafication (where one is not aware whether one's work aligns with the algorithm's goals), and nudging can be perceived as manipulative and in breach of a trusting relationship (Cardon, 2021 p.5). Full transparency is often denoted as a utopia, in the sense that it is either impossible to achieve, or that it could be abused by people to 'play the game' or by authoritarian regimes to control the citizens fully (Christianini, 2019 p.657). A technical constraint is at the centre here, as a binary system, could mitigates abuse of the system via incentives that are generated by the algorithm (Christianini, 2019 p.659).

Linkage of information, inference mechanism, classification and technical developments may offer further prospects of relief (Christianini, 2019 p.658). The interviewees stated that the management was required to instate rules for making unbiased algorithm that make sure that who decides, who is accountable, who audits and who is responsible is being disclosed (Cardon, 2021 p.6). This organisational readiness enables the employee to better understand their rights of which information can be access, control and share data (Cardon, 2021 p.6).

Awareness of the bias implicit in making an algorithm was unfortunately not high (Cardon, 2021 p.17). The consensus of the interviewees thereafter was that the privacy would be given up under these conditions, if employees were sure to benefit from this too (Cardon, 2021 p.14).

5.6 Usage of Algorithms.

In the Netherlands 98% of the households has access to the internet, which is used for 84% to gather information, 83% for internet banking and 78% for online shopping (Overvest, 2020 p.4). The market response is a 19% of investments going to ICT (Overvest, 2020 p.4). The DDoS-attacks on Dutch banks in 2008, at the same time, exemplify the need for strict digital security, which is hard to do considering a software has millions of lines of code (Overvest, 2020 p.4). Market incentives for security are mixed, as it is costly to provide cybersecurity and is therefore undesirable due to competition but comes at the cost of a company’s reputation (Overvest, 2020 p.9). In terms of government policy (restrictions, standards, and liability), this can be tailored to negative effects of technology on the (market) economy (Overvest, 2020 p.9).

The CPB is an organization that operates at the core of algorithmic policymaking and publishes policy briefs, with an array of algorithms being able to analyse nonlinear normalized systems and resolve prediction difficulties via (econometric) equations of a large size and brute force algorithmic power (Hasselman, 2004 p.3). When a government is formed, the coalition of parties forms a regeerakkoord [agreement of governance] in which the plans are laid down for the next government term, which is in principle four years (Centraal Planbureau, 2022 p.2). These are submitted to the CPB and calculated (in cooperation with institutions like the Dutch Central Bank and the central economic planning bureau), considering the budget plan’s effect on innovation, efficiency and growth in defence, climate, care, social security, and other posts of spending (Centraal Planbureau, 2022 p.4).

Assumptions made for the calculations and the baseline scenario are made public in the document (Centraal Planbureau, 2022 p.6). Even alternative budgets and assumptions are considered in the scenario planning (Centraal Planbureau, 2022 p.21). Predicted variables of interest that the CPB calculated in percentages in a timeframe of one year in the future are plural (Centraal Planbureau, 2021 p.1).

The international economy is mostly denoted by the value of the euro, long term interest rate and the value of a barrel of oil (Centraal Planbureau, 2021 p.1). GNP (Gross National Product), household consumption and investment are under the section of the GNP and spending (Centraal Planbureau, 2021 p.1). Inflation, purchasing power, and the price of imports are under prices, loans and purchasing power are variables of interest (Centraal Planbureau, 2021 p.1). Other variables like savings, employment and local sector statistics are also taken into consideration (Centraal Planbureau, 2021 p.1). For the variable of purchasing power, the source of income, household type and income group are plotted in 20% intervals in a static purchasing power graph (Centraal Planbureau, 2021 p.3).

The CPB spurs the government to help negate the external effects of digital failure due to incomplete information or malfunctioning software that hurt consumers and benefit big corporation via price discrimination and monopolies (Overvest, 2020 p.1). The CPB asks for more regulation in terms of liability rules, education, and governmental oversight in the market, but also to see non-digital and digital products as the same, and to levy tax on the users of the algorithms (Overvest, 2020 p.2).

Not only is the CPB responsible for the working plan, being coordinated with the CPC (Centrale Plan Commissie) [Central Planning Commission] of each year, the request of political parties for budget options questions during cabinet formation, and the second chamber have continuously appealed to the bureau for calculations (Centraal Planbureau, 2021 p.2). Over the 116 publications of 2021 the CPB was instrumental in giving oversight in the economic ramifications of policy options concerning labour shortages and permit allocations (Centraal Planbureau, 2021 p.4). This includes scenario planning, which involves uncertainty around the Covid pandemic (resulting in altered trend-prediction), especially for the yearly risk report on the financial markets (ordered by the second chamber) (Centraal Planbureau, 2021 p.4). In terms of macro-economic prediction, the influence of data, long term innovation in the market, inequality in the market, and the political budget in conjunction with the market cycles are of great importance to ensure stability in taxes and purchasing power (Centraal Planbureau, 2021 p.7).

Corona is also taken into new prediction strategies as the analysis of economic costs and corporate dynamics can only be reported into scenarios as developing and coordination algorithmic models is key in this process (Centraal Planbureau, 2021 p.7). The Data Science

Team is especially keen on limiting the re-enforcing of unwanted patterns in predictive models, how to utilise machine learning on the individual level and to help match jobs with vacancies (Centraal Planbureau, 2021 p.9). The data-driven economy of the Netherlands must deal with big corporations which have a great advantage over small companies and consumers (Aalbers, 2021 p.2). Internalising the negative externalities via standard routes, like property rights or a trading system do not work well in data (Aalbers, 2021 p.4). The data one produces can be aggregated and instantly becomes part of the economy, and this makes for the integrated nature of the economy with the state via (media) legislation (Aalbers, 2021 p.7).

6. Case Analysis.

In the case analysis the literature review conclusion is applied and offers further understanding why technical issues are limiting predictive economic algorithmic policymaking in the public sector in the Netherlands. This is achieved by matching literature on the creation of algorithms to the case description. First opacity, legislation and no organisational readiness constraints limiting data inputs into the algorithm will be argued to have a technical nature. There will be technical constraints mentioned that complicate the data gathering phase. Second, technical constraints in modelling are presented, as the modelling phase is argued to be constricted by technical issues. Third, ethical soundness needed to order and evaluate algorithms is argued to have a technical constraint at the core. Technical constraints that cause the symptom of ethical constraints are presented in the evaluation phase. The conclusion will affirm the coalescence of the evidence into the affirmation of the hypothesis that technical constraints are the core constraint inhibiting predictive economic algorithmic policymaking. One will see that the findings of the case analysis fit within the process-tracing method, the policy design theory, and the pipeline model proposed by Gulliver (2021 p.269).

6.1 Data Gathering Phase.

Firstly, technical constraints are at the root of the data gathering phase, where the opacity, legislative and the no organisational readiness constraint are arguably the most pronounced symptoms. Data collection affects representativeness and comprehensiveness of the analysis and is complicated due to the trade-off between external and internal validity, complicated even further by the need for parallelism (Rosch, 2021 p.533). Key institutional elements of society such as law enforcement, transportation, communication, and resource allocation depend on efficiency arguments which require mountainous amounts of data inputs to allow the algorithms to work (Wijermars, 2022 p.943). The data gathering methods expand the quality of the models that can be selected based on logical consistency, significance of the parameters, and predictive performance (Versteegh, 2016 p.4).

Another way in which the technical performance is arguably fundamental to data gathering is via algorithmic experiments. Three areas of economic experiments are identified. First, one uses experiments to identify causal responses to policies which cannot be isolated in observational data (Rosch, 2021 p.531). Experiments can then be divided to be either field experiment in which randomization of information and interface variables can be altered, and laboratory (artefactual) experiments in which changes can be pilot tested (Rosch, 2021 p.531). Second are the experiments that are used for the direct observation of human behaviour as opposed to secondary sources (Rosch, 2021 p.531). Third, information on participation can be gathered via experiments (Rosch, 2021 p.531). As data inputs are essential to algorithmic pricing, data availability via bigger and better algorithmic programmes enables information aggregation systems to exploit digital traces via more advanced modelling capacities (Seele, 2019 p.4).

Technical issues are of such detriment in the data gathering phase because it is unstructured data, more so than a lack in quantity of data that makes facilitating analysis hard, especially finding comparable control and treatment variables (Rosch, 2021 p.532). Such technical issues can and should be resolved.

As the amount of information going through an algorithm makes human curators culling the information impossible, making one rely on algorithms to manage the quality of its own data inputs via automated curation systems (Wijermars, 2022 p.947). Big Data research has enabled the creation of algorithms that look for corelations themselves which combined with data mining can result in unexpected findings (Zwitter, 2014 p.5). Experimental methods do not work in every field, such as agriculture, due to heterogeneous treatment effects, lacking participant base, and funding issues (Rosch, 2021 p.533). The advice of creating a standard set of demographic characteristics, stratified randomised designs, and pretesting specifically to the agricultural sector might not be fully extrapolatable of course (Rosch, 2021 p.533).

The CPB planning considers alternate scenarios, with trend-prediction coping with a lack of data inputs, especially for the yearly risk report on the financial markets (ordered by the second chamber) (Centraal Planbureau, 2021 p.4). In terms of macro-economic prediction, the influence of data inputs limited by the opacity constraint, the legislative constraint and the no organisational readiness constraint is considerable, yet the scenario planning in combination with cutting edge algorithms is argued here to take precedence.

6.2 Modelling Phase.

Secondly, technical constraints are at the root of modelling phase. Algorithmic pricing (algorithmic pricing mechanism based on data analytics) considers pricing, personalisation, models, inventory management and electronic retail to generate individual and aggregate trends in society (Seele, 2019 p.2). The algorithmic proficiency can be defined by the evidence it creates which in policymaking can be promoted via re-encrypting software in policy updating (Fugkeaw, 2018 p.371). Macro-economic trends are hard to predict due to the large array of variables and the nonlinear nature of real-time changes in the market (Sun, 2021 p.1). Data mining models are one development that enables the forming of standard processes for decision-making based on data which has been implemented in trading, assessments, and cost reductions whilst other models can perform complementary to one another, such as autoregressive moving average (ARMA) which is complemented by datamining in its attempt to predict stock market prices (Sun, 2021 p.2). In a BP neural network, on the other hand, there is an input that is processed by the neurons in the input layer and hidden layer, after which the output layer shows the result, yet the error between the network output and the actual value (which is returned along the originally connected path) is easily affected by unforeseen interference variables (Liu, 2020 p.3). The effectiveness of an algorithm compared to others can be measurable via economic input cost, return on net assets, and economic growth level (Sun, 2021 p.6).

The enormous gains made in the finance sector due to predictive assessments and automated systems may also result in (error) damage in misinterpretation, misclassification, and exploitation of the vulnerable (Wijermars 2022, p.944). The usage of predictive algorithms, in combination with artificial intelligence and big data could allow for more efficient selling of financial products than banks currently do, spurring risky behaviour on both sides (Wijermars, 2022 p.951).

The most important in this case, as opposed to the adaptive algorithm, is the learning algorithm, the machine learning approach focusses on behavioural patterns to predict future demand and willingness to pay (Seele, 2019 p.7). Self-reinforcing algorithms do not even need programmers to adapt it, making the initial value laden modelling of extreme importance, until this bias problem can be resolved by technical means (Seele, 2019 p.7). The

CPB uses an array of highly developed algorithms to calculate (in cooperation with organisations like the Dutch central bank and the central economic planning bureau), having to consider the governing coalition's budget plan's effect on innovation, efficiency and growth in defence, climate, care, social security, and other posts of spending (Centraal Planbureau, 2022 p.4). The CPB's increasing raw computation power, multitude of algorithms and inclusion of numerous (interacting) variables makes for a trustworthy prediction of macro-economic policymaking and the effects of policy on the budgetary outcome, pointing out that it is technical constraints that limit progress is algorithmic policymaking (Hasselman, 2004 p.3).

6.3 Evaluation Phase.

Third, technical issues are at the root of the evaluation phase. The computer system has been utilised for policymaking since the 1980-1990s, even though the values used to create policy and shape algorithms have changed over time of course (Ingrams, 2019 p.129). AI will be, if it is not already, the largest wealth-generating part of the economy (Pedram, 2021 p.150). One of the issues presented by Pedram (2021 p.156) is that algorithms in the market economy can be subject to cartel forming, which can be inefficient. Nevertheless the advantages of using algorithms in cost reductions, price discrimination and strategic discounting via competition law has thwarted most of the negative effects (Pedram, 2021). The 'what if' tool is one of the real-world tools used here to provide an example to why one can make this inference, as this tool can create more transparency through open-source tensor board web applications that enable users to analyse machine learning models, thereby attempting to approach the counterfactual (Felzmann, 2019 p.11).

To make an instrument suitable for economic evaluations, societal values need to be attached to all possible outcomes of the combinations of the variables in a survey, especially when levels of measurement (scales) are used, due to the crude cut-off between these levels forming a limitation in estimation and a discriminatory effect (Versteegh, 2016 p.343). Abuse of a system is very much about who uses it, as this implies that the system itself is not faulty (Yen, 2021 p.4) argues. The tools themselves cannot be altered and arguing that these are bad without any scientific foundation limits human and societal progress (Yen, 2021 p.4). Remedies, in case of statistical discrimination, for example, may be that to circumvent unseen racial bias one uses a variable for race which might seem inequal but results in a net fairer outcome (Yen, 2021 p.4). A positive outlook on algorithms is achieved by insisting that results of a policy strategy must always be tangible, and that multiple strategies can identify (after which one can ameliorate) faulty algorithms due to bias created by the interplay of the social, environmental, cognitive, and human thought constraints (Yen, 2021 p.7).

Also, for ethical soundness algorithms one needs clear outcomes, with real-time measurements indicating when outcomes are achieved to instate fitting alternations within the framework of measurement rules, which is solvable via technical progress (Christianini, 2019 p.646). In terms of bias, adding subjects to a well-represented strata typically do not alleviate the underrepresented strata problem, as this does not expand meta-analysis per se (Rosch, 2021 p.539). One possible way to resolve this problem is to find correlations between standard sets of demographics, as this does expand meta-analysis possibilities, whilst limiting the opportunities for ex-post data mining of experimental results (Rosch, 2021 p.539). In addition, stratification or block randomised design could test for heterogeneous treatment effects (Rosch, 2021 p.540).

Pre-testing can also be employed using students, a relatively homogenous sample population, as an 86% predictive value, and 67% statistical indifference will ensure that this pre-testing will at least provide one with valuable information (Rosch, 2021 p.542). Pre-testing not only checks for heterogeneous effects but can also generate estimates for sampling variability of treatment effects to facilitate power calculations for future research (Rosch, 2021 p.546). In terms of funding and criteria standardisation, ensuring a fair acceptance of proposals as quality can be objectively tested, further standardises funding provision (Rosch, 2021 p.549). When the technology allows it, the standardisation could be enforced. Developments that could alleviate the technical constraint currently endured might alter the discourse around the trust one can put into a predictive algorithm, fortifying the argument that it is indeed the technological shortcoming that is at the core of why one does not see more predictive economic algorithmic policymaking.

The end-goal for the algorithms to independently gather and analyse data for decision-making, with high accuracy enabling sound decision making (Pedram, 2021 p.157). The CPB wants more action of the government in the handling of external effects of digital failure (due to failing algorithms) that inevitably hurt consumer (Overvest, 2020 p.1). Digital success, which enables the usage of variables like purchasing power, the source of income, household type and income group can then be used to create an accurate picture in predictive economic algorithmic policymaking (Centraal Planbureau, 2021 p.3). Ethical constraints are thus based on alleviation of technical constraints.

7. Conclusion.

The reader has been guided from the societal and academic importance in the introduction to the literature review that displays the plurality of perceptions of flaws in algorithmic policymaking. Then one was presented with the justification of the methods used in the research design. The theoretical inspiration for the research design has proven adequate for a correct analysis of the case and to answer the research question. As seen in the conclusion of the literature review (section 3.6) the theory on algorithms, however recent and respectable, left a gap. This gap was then proposed to be 'what is the main constraint to using predictive economic algorithmic policymaking in the public sector?'.

Then the reader was introduced to the context of what it means to have the Netherlands as the case study. The case selection of the Netherlands was chosen, as the usage, relative transparency and media attention was adequate to form a well-informed answer to the research question. The usage of ministerial reports, CPB documents and local government reports were essential in answering the research question. The usage of examples from not only the public sector, but also stakeholders like big banking, were crucial in corroborating the arguments from the theory around technical solutions for ethical, legislative, lack of organisational readiness, and opacity.

Hereafter, the case analysis connected the theory and the case description, leading to the conclusion that in the Dutch predictive economic algorithmic policymaking process technical constraints are wat limit the implementation of predictive economic policymaking algorithms. The findings of the case analysis follow the structure of the process-tracing method, adhere to the policy design theory, and is structured using the pipeline model proposed by Gulliver (2021 p.269).

When one reads news reports (referring to the 'kindertoeslagenaffaire') about how an algorithm was discriminatory or too unreliable in predicting economic developments, usually with a policing component, a technical explanation (and solution) is not often centre stage. The question why predictive economic algorithms are constrained, leading to these unfavourable outcomes was investigated. It was then concluded that it is essentially technical constraints instead of opacity, legislative, no organisational readiness, or ethical constraints that limit predictive economic algorithmic policymaking in the public sector the Netherlands.

7.1 Discussion.

The status quo should not be taken for granted, nor should it be perpetuated, meaning that the application of algorithms is the future is quite inevitable, but that how one implements them alters their societal value significantly. One could see this debate around the use of algorithms to circle back to a fundamentally economic question, whether one prefers efficiency over equality, and how people perceive this to be fair. It is concluded that the constraints on predictive economic algorithmic policymaking can be experienced via the symptoms, be it perceived ethical or organisational readiness limits or what have you, yet all these issues will most likely be solvable in the future.

This research acknowledges that it has been faced with constraints of time, budget, available personnel resources. The greatest setback endured can be defined as the non-responsiveness of both the governmental institutions and the big banking sector corporations. The argument of premature closure, where one did not investigate all relevant sources is valid, but not reasonable (Neuman, 2014 p.4). The categories (phases) are made mutually exclusive in this work, yet the independent variables could also be in a continuum in future research. The reasons of which have been stated or can be inferred from the literature. Nevertheless, one should grasp the opportunity offered into the world of algorithmic policymaking to further investigate the claims made here.

One could state the non-compliance with the interview allows inference that the opacity of organisations is a response per se. This could be classified as being a matter of opacity for the corporations and a matter of missing capacity for the public institutions. The corporations generally mentioned that they could not find the right department to answer my questions, and that the publication of the thesis and the confidentiality of the information warranted a non-compliance. The public sector answered with the reason that the lack of resources available warranted non-compliance. The European institutions contacted did not respond at all. Yet, the question is what is holding back the implementation of more predictive economic algorithms, and whilst the opacity limits cooperation, the property rights ensure that corporations invest in these algorithms. Therefore, any inferences made that would explain the non-response are not directly applicable to explain the lack of use of the algorithms.

Future research could investigate the responsibility gap that one could argue exists, especially in learning algorithms and how this shapes the debate and future of algorithmic policymaking. In addition, as mentioned by Thessen (2016 p.24) funding of agencies and research into predictive algorithms is key to its existence. Therefore, one could investigate funding streams and essentially ‘follow the money’ to look into the future of predictive economic algorithmic policymaking. Most importantly, future research could try to collect the required data from the corporate sector and governmental institutions to further back up the claims made. When successful, the authors could include other types of organisations like NGO’s, multilateral or supranational organisations and local institutions. In addition, future research could engage in a comparative study in which it compares the Dutch context to that of other countries. In doing so, different types of predictive economic algorithms could be investigated, like policing or healthcare algorithms. Lastly, if one has the mathematical prowess to do so, and if the transparency is adequate, one would be able to dissect algorithms and discover their shortcoming and possibilities on a more micro-level.

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