Between promise and practice:

A case study on the perceived transparency of the algorithm register

by

Tristan Maarten René van Haaren

Tristanvanhaaren@gmail.com

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Supervisors:

I. Tempels Moreno Pessoa, Faculty of Behavioral, Management and Social Sciences

Dr. P.J. Klok, Faculty of Behavioral, Management, and Social Sciences

Preface

With this master's thesis, my student life officially comes to an end. In some ways, that chapter already started closing in September 2023, when I began working for the municipality of Enschede. However, now – having completed this step – it is truly over.

This thesis would not have been possible without the support and guidance of many people. First, I would like to thank Igor Pessoa for his endless patience – something I tested extensively. Time and time again, he reassured me that I didn't have to rush, that I could take my time… and that he actually liked that too. I'm still not sure if he meant it or if it was just a well-executed strategy to keep me from stressing, but either way I really appreciated it. His guidance and our engaging discussions have been truly invaluable.

In the final steps, Pieter Jan Klok provided me with sharp and constructive feedback, which made me rethink some of my writing and helped me strengthen my work.

A special thanks to the municipality of Enschede for giving me the time and space to work on my research, and for facilitating my access to the EnschedePanel – which gave me a survey reach many could only dream of in their research.

To my father: thank you for your unwavering support throughout this entire process. And yes-it's finally finished, so no need to ask again; I really am done this time. It's been a long road, but your persistence (and occasional subtle reminders) helped me carry me through. I also can't end this section without mentioning my mother. She didn't get to see me switch studies-or eventually, finish them with joy-but I know she would be incredibly proud.

Thank you all.

Abstract

This study investigates how residents of Enschede perceive the algorithm register as an intervention to improve transparency about algorithm usage by the local government. Although these systems are often heralded as being able to make governments more efficient and equitable (Pencheva et al., 2018), recent controversies in the Netherlands have, however, highlighted the far-reaching consequences when systems such as these are improperly used or implemented.

In response, several initiatives were launched by the Dutch national government. These projects aim to address issues surrounding transparency and accountability. One of these projects is the Dutch algorithm register, which serves as a central platform for all governmental organizations to publish and share information on the algorithms- and AI-based systems they employ. However, the effectiveness of this register remains questionable.

To assess the impact of the algorithm register, I conducted a case study focusing on the city of Enschede. A mixed-method approach was used, consisting of a survey with qualitative and quantitative questions, and interviews were conducted to provide further contextualization. Furthermore, a goal for this study was to create a sample of residents with diverse socio-economic backgrounds, based on the assumption that 'citizens' are not a homogenous group – meaning that transparency needs may differ.

The survey I created was distributed through Kennispunt Twente, a local research organization that hosts the 'EnschedePanel'. This panel significantly enhanced my reach, leading to a total of 950 initial responses. After cleaning and categorizing the data into relevant subgroups, a final analysis sample of 780 respondents remained. The data was analyzed sing both statistical and thematic methods. Based on the survey findings, I conducted interviews to deepen and contextualize the results. The combined insights from both data sources were then used to answer the main research question:

How do residents of Enschede perceive the algorithm register as an intervention to improve transparency?

Findings from this study indicate that there is a low awareness of the register, with only 12.1% of respondents being familiar with the register. Awareness, however, varies significantly, with higher-educated individuals being more familiar than lower educated-individuals. Age also played a significant role in awareness levels. This study also underscores that transparency requires both accessibility and explainability. While the register does fulfill some requirements for accessibility, this information is not understandable for all citizens. Furthermore, explainability is lacking entirely, a significant portion of respondents want to understand how decisions are made. As such I conclude that transparency needs to go beyond merely sharing information on a platform. It requires clear explanations of data use and key decisions factors – in a format understandable to diverse backgrounds.

Finally, I highlight that there is a gap between policy intention and practical impact. The register, despite aiming to enhance transparency, does not fully meet public needs. Without improvements, as well as the introduction of other more service-oriented government initiatives, transparency measures risk becoming performative rather than functional.

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1. Background

1.1 Introduction

Over the course of the 20th century, a digitalization wave started within the public sector; this wave slowly swelled in size and led to major changes within the public sector – and is still very much ongoing. Starting with ICT systems, which served a supporting role and ending up with algorithms and AI-based systems taking key roles in decision—making.

Initially, this digitalization wave was set in with the idea that algorithms and AI could make decision-making more efficient and equitable (Pencheva et al., 2018). In some ways, these promises have been fulfilled, while in other ways the consequences of these systems have been far-reaching. Within the Dutch public sector context, several problematic systems can be identified. Plenty of examples are available, here I highlight three prominent cases which gained a lot of media traction. First, we find SyRi, a fraud detection systems that was shut down after the Hague district court (2020) ruled it to be *'discriminatory, stigmatizing and in-transparent'*. A second example can be found in the Dutch child tax benefit scandal, where a self-learning system was used to create risk profiles and mark citizens as potential fraudsters. Once marked as potential fraudsters, these citizens were met with harsh and unjust scrutiny, leading to many receiving large fines, loss of homes, separation from children, and in some cases, even loss of life (amnesty international, 2021). Third, we find 'FSV' a system used to detect potential fraud in tax and benefit applications. This fraud detection system marked 240.00 citizens as potential fraudsters without just cause. Once registered in this system, citizens would be unable to apply for certain government services. The journalist Tahrim Ramdjan was put on this 'black-list' at the age of 15 without every finding out why – only receiving a minor apology once the system was discontinued (Ramdjan, 2022).

Cases such as these deserve a mention, as they highlight the fundamental and far-reaching consequences if such systems are wrongly used or implemented. This does not mean it is all dark clouds. I recent years, issues such as algorithmic fairness and transparency have received growing attention in Dutch media, academia and the public sector, signaling a shift toward more responsible implementation.

The Dutch national government started several projects aimed at improving the transparency of algorithmic decision-making. One of these is the algorithm register. This register, which was launched in December of 2022 serves as a central database where government institutions can voluntarily-and later mandatorily-publish information on algorithm and AI-based systems they employ (Digitale overheid, 2023). On this website algorithms are described through various themes which can be found in appendix A.

This algorithm register is the focus of my research. Said register was launched with the goal of '*increasing transparency'* and through that *'improve citizen trust in algorithm usage by governmental organization'* (Digitale overheid, 2023). By conducting a case study focusing on the city of Enschede I evaluate how citizens perceive this algorithm register as an intervention to improve transparency.

1.2 Societal and Scientific Relevance

In recent years several controversies occurred within the Netherlands in relation to the (mis-) use of algorithmic systems by governmental institutions. Each of these controversies had far-reaching consequences. The municipality of Rotterdam used a '*discriminatory, stigmatizing and in-transparent'* system to detect welfare fraud (Hague district court, 2020), the tax authorities used FSV to detect tax fraud and subsequently marked 240.000 citizens as potential fraudsters based on discriminatory factors (Ramdjan, 2022), and in the Dutch child tax benefit scandal a discriminatory algorithm determined who 'deserved' extra harsh scrutiny (Amnesty International, 2021). These are just some of the well-reported controversies, however, as Wolfsen (2024) said '*Every time we (Privacy Authority) flip over a tile, a new discriminating algorithm is found'* suggesting similar instances will be discovered in the future.

In order to combat this, Wolfsen (2024) as well as various scholars have called for more transparency. The Dutch national government hopes to fulfill this need through the algorithm register as well as some other transparency projects. Results from this study can contribute to a more inclusive approach toward algorithmic transparency and ultimately algorithmic governance. It could help policy-makers in mitigating the potential harms that come with algorithm and AI-based decision-making.

Scientifically this study contributes to the existing literature on algorithmic transparency and serves as an evaluation of the algorithm register in its current form. In this study, extra emphasis was given to the inclusion of respondents with diverse socio-economic backgrounds. Previous studies as well as several governmental projects disproportionately include higher-educated individuals – neglecting that these are often not the groups who are hurt by the (mis-)use of algorithm and AI-based systems.

1.3 Research aim and research questions

Through this study, I aim to evaluate how citizens perceive the algorithm register and to find out if and how algorithmic transparency by governmental organizations could be improved. This will be done by answering the research question:

'How do residents of Enschede perceive the algorithm register as an intervention to improve transparency?'

To help in answering this main question four sub-questions can be defined:

SQ1: To what extent are citizens of Enschede familiar with algorithms, and how do they perceive them?

SQ2: To what extent are citizens in Enschede aware of the existence of the algorithm register?

SQ3: What types of information do citizens deem important in improving transparency in relation to algorithm usage?

SQ4: To what degree are the 'types of information' identified in SQ3 present in the algorithm register?

2. Literature review

The literature review is divided into three sections. First, the algorithms & AI section aims to present a brief general history of these concepts, define them and provide a simplified typology. Secondly, algorithms & AI in the public sector, which puts these concepts and their development in a public sector context. Finally, algorithmic transparency, in which the concept of algorithmic transparency is introduced.

2.1 Algorithms & AI

While 'algorithms' and 'Artificial Intelligence (AI)' are interconnected and frequently used interchangeably, they however refer to two different concepts. To improve understanding and enhance public debate they should be separated. This chapter starts by explaining what algorithms are and where they come from, then it moves on to AI and finishes with a simplified typology based on intelligence and functions.

2.1.1 Algorithms

Ask people in your surroundings what they know about algorithms, and you will probably receive a wide range of answers. Said answers will probably range from examples as simple as 'recipes' and as complicated as autonomous AI systems – while others will simply have no clue. This diversity in answers is understandable, knowing the wide array of algorithms in use and the ever-evolving scope within academic literature.

Historically speaking, the term algorithm is derived from the Latin word algorithmus. Which consists of two parts: algorism and arithmos. Here algorism refers to the medieval art of computing using numerical values and arithmos refers to a step-by-step approach first coined in the 9th century by the Persian mathematician Mohammad ibn Musa al Khwarizmi (Dembiński, 1981). As such, in the historical context, algorithms are defined as a step-by-step approach towards solving numerical problems. This definition encompasses the essence of algorithms – however, it is no longer befitting with the modern-day use of algorithms.

Algorithms became a core concept within the digital age. Scientists such as Harold Stone (1971) defined it as *a set of rules that precisely defines a sequence of operations*. A definition slightly more specified, but still too general for today's use. As a set of rules defining a sequence of operations could also be used to refer to a recipe for baking a cake, and while the author of this piece does enjoy baking a lot – and you can always ask me for recipes – these are not the type of algorithms that should be included in this research.

Making another step forward to the modern era, in 2021 the Dutch general audit office conducted research on algorithms within the Dutch public sector. Part of this research was to create a definition workable for policymaking. This ultimately led to the Dutch audit office defining an algorithm as '*A set of rules and instructions that a computer follows automatically when making calculations to solve a problem or answer a question'.* A definition befitting to this research due to its specificity, table 2.1 further explains the definition based on domain, specificity, usage, and level of automation.

	Domain	Hardware	Usage	Level of automation
Dutch General Audit Office (2021)	Situated algorithms within the digital domain	Specifies that algorithms run on computers excluding non-digital algorithms.	The purpose of an algorithm is to solve a problem or answer a question. A clear goal/endpoint	A pre-defined process is followed automatically

Table 2.1: Audit office definition for algorithms

2.1.2 Artificial intelligence (AI)

AI as a field of research is still fully in development, resulting in various definitions for AI going around these definitions vary widely between domains and applications (WRR, 2021). In the broadest definition, AI is seen as an equivalent of algorithms, this is however not desirable. Seeing these concepts as being equivalent completely ignores the distinctions between the two, which in turn can have significant implications for development, regulations, usage, and hampering public debate.

Through the European Union's AI Act, a definition for AI is defined, which will be used in a public sector context for all member states. With this research focusing on the (Dutch) public sector, this definition is highly applicable. The European Union defines AI as *'A machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. ' (Article 3: definitions | EU Artificial Intelligence Act, 2025).* The European Union provides a somewhat broad but future-proof definition of AI, which encompasses its 'learning' capability through words such as 'infers' and 'autonomy'. To further understand this definition, table 2.2 splits out the various parts of the definition.

	Domain	Hardware	Usage	Level of automation
European Union (2025)	AI takes place within the digital domain	‘A machine-based system’	To generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.	Designed to operate with varying levels of autonomy and may show adaptiveness based on the input it receives.

Table 2.2: Definition of artificial intelligence AI-act

2.1.3 Algorithm & AI typology

In essence, algorithms follow a pre-defined list of rules which remain the same on every iteration, while AI is shown to be autonomous with the capability of changing/improving itself. For many, however, these concepts might still be a form of hocus-pocus, as such a simplified typology is created focusing on the degree of intelligence and practical application.

2.1.3.1 Degree of intelligence

Intelligence is seen as '*The ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria'* (Merriam-Webster, 2023). Within academic literature on algorithms and AI a three-way split into rule-based, narrow intelligence and artificial general intelligence (AGI) is most common.

Starting with the first and lowest form of intelligence: the rule-based or expert system. Decision-making here is done based on pre-defined rules and logic, which remains the same on every iteration (Foster, 2023). These algorithms are programmed for a specific task and will only be able to do said specific task – they have no learning capabilities. These types of systems excel in automating repetitive relatively simple tasks and can, for example, be found in calculating and paying out financial benefits and the approval process of various sorts of permits. The main transparency risk lies with commercial developers who refuse to share the 'rules of the algorithm', as these rules are programmed in by humans. The risk of them becoming unexplainable is relatively low compared to their AI-based counterparts. Other issues can be found in their lack of flexibility, requiring every outcome to be programmed in by hand, increasing complexity. And more 'attitude' based risks in which people assume that due to its 'pre-programmed' nature, these algorithms cannot be wrong – or don't require evaluation.

Secondly, 'narrow intelligence' is an umbrella term underneath which a majority of AI systems currently in use can be found (WRR, 2021). 'Narrow' is a key factor here, narrow because these types of systems excel at a specific task often performed within a specific context (WRR, 2021). These types of systems are often seen as highly intelligent, while in practice they show a limited form of environmental manipulation and abstract thinking. Their 'intelligence' stems from their 'learn & improve' capabilities, which allows them to be trained with data and continue learning while active (WRR, 2021). This is also their main difference with algorithms – due to this learning & improving capability, their rules and outcomes don't necessarily remain the same on every iteration. This is eventually also where their main risk stems from, although initial rules are programmed by humans – eventually through learning & improving these rules will change. This can lead to a black box effect in which it is no longer explainable how a decision came to be (WRR, 2021). In the public sector, we often see narrow intelligent systems in predictive policing, fraud detection, advanced chatbots, and translation software.

Finally, Artificial General Intelligence (AGI) is the end goal of scientists in the field of AI (WRR, 2021). AGI refers to a form of AI which matches or surpasses human intelligence across various domains (WRR, 2021). Showing the ability to manipulate the environment across a diverse set of scenarios and the ability to reach human-like problem solving and abstract thinking skills (WRR, 2021). Table 2.3 shows a comparison of these three concepts with examples.

Type	Explanation	Examples:
Rule-based	Decision-making is based on pre-written rules which remain static on every iteration (Foster, 2023).	Decision trees, expert systems, calculating and paying out benefits
Narrow intelligence	A form of artificial intelligence that excels at a specific task often within a specific context (WRR, 2021). These algorithms can 'learn & improve'	Chatbots, Predictive policing, learning fraud detection/fraud predictions
AGI	A form of artificial intelligence that can match and/or surpass human intelligence across various domains (WRR, 2021).	Is still a theoretical field (WRR, 2021)

Table 2.3: Comparing various forms of algorithmic intelligence

2.1.3.2 Practical application

Starting with algorithm-based systems Fry (2018) defines the five main types of algorithms being predictive, classifying, prioritizing associating, and filtering. These five main types combined with an explanation can be found in Table 2.4 this list is not exhaustive and somewhat simplified but for this research, it is enough. It can be said that all rule-based algorithmic systems use at least one of these functions – although more often a combination of them.

	Explanation	Example
Predictive	Uses historical data to predict the future outcomes;	Used in finance, weather forecasting, fraud detection, etc. Predicting the likelihood for someone to commit fraud, or not be able to pay off a loan.
Classifying	Categorizes people, animals, or things into various categories of classes;	Used in your e-mail filter to filter out spam. Used in the medical field in diagnoses.
Prioritizing	Ranks or prioritizes people, animals, or things based on predefined criteria;	Used to prioritize resource allocation. Ranking projects based on priority.
associating	Identifies relationships between different variables;	Websites such as bol.com use these to find which products are often bought together.
Filtering	Filters unwanted elements from data;	Siri uses this to filter out background noise. Social media filtering algorithms are used to filter out inappropriate data.

Table 2.4 Algorithm applications based on Fry (2018).

A similar table can be created for AI-based systems, this is done in table 2.5, which can be found below. It is important to note that AI-based systems make use of one or more algorithms combined with a mathematical model and data to allow for the 'learn & improve' capabilities which make them so useful.

	Explanation	**Example**
Machine learning	Used for predictive analytics. Searches for patterns in large datasets and then predicts the future. Data is used to train and improve the model;	Used in weather predictions Fraud detection, predictive policing, micro-targeting (Cambridge analytics);
Computer vision	Uses various algorithms and models to detect, process, and interpret visual data. Objects are labeled and can then be used to further train the model;	Used in facial recognition, object detection for self-driving cars, and to detect cancer through medical imaging;
Natural language processing	Uses various algorithms and models to process and interpret human text. These systems are usually trained on large datasets to learn language patterns and detect relationships. These types of AI generate new content based on input text;	Government chatbots, automatic document processing, sentiment analysis on social media, ChatGPT, and document analysis;
Speech recognition	Uses various algorithms and models to convert spoken words into written text;	Voice assistants, voice-controlled devices, Siri, transcription software, Voice-to-text services in public services;
Robotics	In robotics, various previous forms of AI return or come together. The main difference is that here they are combined with a physical aspect, being robotics.	Robots in warehouses, autonomous disaster response robots, autonomous surgery robots, automated cleaners/mowers, and defense.

Table 2.5 based on WRR (2021)

2.2 Algorithms & AI within the public sector

The focus in chapter 2.2 shifts towards the historical development of these technologies within a Dutch public sector context. In this chapter, algorithms and AI are placed within a broader bureaucratic context. Showing how the initial introduction of algorithm-based systems led to fundamental changes within our bureaucratic systems.

2.2.1 The digital shift in bureaucracy

While today it is nearly impossible to find a bureaucratic process that is not fully automated or in some way supported through an algorithmic or AI-based system this was not always the case. In contrast, the bureaucratic systems of the early 20th century were highly personal and labor-intensive. For most processes citizens had to meet up with a public servant face-to-face, to explain their situation or plead a case. Decision-making was strongly intertwined with human interaction and judgment. Such a bureaucratic system can be classified as a 'street-level bureaucracy', a term later defined by Lipsky (1980). Street-level bureaucracies are characterized by scarcity and operational discretion, where scarcity refers to the overwhelming workload, requiring prioritization in bureaucratic processes. Operational discretion here specifically refers to the high degree of subjectivity in bureaucratic decision-making when the law is applied to real-life situations (Lipsky., 1980; Hupe., 2015). Over the course of the 20th century, many transformations took place within bureaucracy's, here we, however, focus on the digital shift.

Starting in the 1960s when the very first basic ICT systems were introduced, these initial systems served a supporting role (Bovens et al., 2018). Which in practice meant such systems helped in standardizing and formalizing various processes, for example with printing out decisions. Over time as these systems became more advanced their role steadily shifted, eventually leading to a shift towards a 'screen-level bureaucracy' in many processes. Here rule-based algorithmic systems took a leading role within bureaucratic processes, meaning, that the discretion of public servants was severely limited, their role in many processes being reduced to registration data and approving/disapproving various decisions made by the rule-based algorithm (Bovens et al., 2018).

Over the course of the 90s, the role of public servants within many processes was further reduced. Data registration in many situations could be done by citizens themselves and/or information could be gathered from other governmental databases. This led to a shift from screen to system-level bureaucracy in many processes. Where initially public servants were responsible for applying the law to real-life situations, now developers took up this responsibility while creating and maintaining these systems (Bovens et al., 2018). Looking at table 2.6 we can see the defining characteristics of each of these bureaucracies.

It is important to note that Street and screen-level bureaucratic processes still exist, a majority however shifted to the system level. In addition, research has shown that all across the board public servants are increasingly being steered and disciplined by ICT systems (Peeters., 2020; Peeters & Widlak., 2018).

	Street-level bureaucracy	**Screen-level bureaucracy**	**System-level bureaucracy**
Role of ICT	Supportive	Leading	Decisive
Functions of ICT	Data registration	Case assessment and virtual assembly line	Execution, control, and external communication
Human interference with individual cases	Full	Partial	None
Organizational backbone	Case managers	Production managers	System designers
Organizational boundaries	Strict, regarding other organizations	Strict, both within and between organizations	Fluid, both within and between organizations
Legal regime	Open, ample discretion, single legal framework	Detailed, little discretion, single legal framework	Detailed, no executive discretion, exchange between legal domains

Table 2.6 Levels of Bureaucracy within IT (Bovens and Zourdis, 2002)

2.2.2 The Dawn of the system-level Bureaucracy

Since the start of the 21st century, system-level bureaucracies are now commonplace. During this era, four major developments within bureaucratic processes can be identified. First, automated decision-making has become more commonplace and boundaryless. Second, system developers have more discretionary space than ever to work on these systems. Third, the rise of data professionals and finally the rise of AI (Bovens et al., 2018).

First, the normalization of automated decision-making processes. Algorithm-based systems have taken over the role of public servants and most government services are fully automated – only requiring human interference when pre-determined risk factors are met (Bovens et al., 2018). On paper, this meant an increase in efficiency and a decrease in bias (Bovens et al., 2018). When improperly used or implemented, these systems, however, have the potential for biased or discriminatory decisions and predictions (Eubanks., 2018; O'Neil., 2016).

The second major development entails a shift in discretionary power from individual bureaucrats toward system developers (Bovens et al., 2018). In the past, these bureaucrats had ample discretion over individual cases. However, due to the implementation of ICTs, this discretion shifted towards system developers who determine which data is shared between departments and organizations, which systems are interconnected, what data is used, and how to program in exceptions. (Bovens et al., 2018).

The third major development is the rise of data professionals (Bovens et al., 2018), mostly taking shape through data analysts (WRR., 2016). These data analysts are tasked with 'making sense' of the large datasets generated by governmental organizations, they look for patterns which can then be programmed into various processes (Evers, 2016). For example, in creating profiles containing characteristics of those who are likely to commit tax fraud.

The fourth major development can be found in the slow and steady emergence of narrow intelligent AI systems within the public sector (Bovens et al., 2018; WRR., 2021; Dutch General Audit Office., 2021). These AI-based systems are often being used to automate medium to high-discretionary tasks with the promise of being more efficient and equitable than humans (Pencheva et al., 2018). Risks in political and judicial checks and balances, however, occur when these narrow intelligent systems are implemented in the form of self-learning systems, making it unclear how decisions came to be. This is also known as the 'black-box risk' (Bovens et al., 2018; WRR, 2021). Such systems can be found in predictive policing/analytics and various types of automated surveillance systems (WRR, 2021).

2.2.3 Issues Surrounding Algorithms and AI

Research has shown that the introduction of algorithm and AI-based systems within the public sector led to major changes altering organizational structures, routines and cultures (Meijer et al., 2021). Large processes are increasingly being automated, and at the individual level, researchers found that public servants are increasingly being steered and disciplined in their decision-making (Peeters., 2020; Peeters & Widlak., 2018). Although these developments are often heralded as being more efficient and equitable (Pencheva et al., 2018), critique is also on the rise as such systems have the potential for biased or discriminatory decisions and predictions (Eubanks., 2018; O'Neil., 2016).

Zooming into the Dutch context, we find how several controversies occurred in recent years surrounding such systems. These controversies had their effect, KPMG (2023) found that between 2020 and 2023 trust in algorithms and AI-based systems used in the public sector decreased by an average of 19% per year. As Wolfsen (2024) mentioned, many discriminatory and improper algorithms are still being used. A critical point underlying these issues is a lack of algorithmic transparency (Busuioc., 2020; Meijer and Grimmelikhuijsen., 2020).

2.3 Algorithmic transparency

2.3.1 Introducing Algorithmic Transparency

In the previous chapter, the concept of algorithmic transparency was briefly introduced. As we see a growing use of algorithm and AI-based systems within the public sector, their subsequent (negative) consequences are also becoming more visible. As such the academic community is increasingly calling for more attention to be given to algorithmic transparency. This call resonates across various fields, such as computer science (Miller., 2019), data ethics (Lepri et al., 2019) and public administration (Busuioc., 2020; Grimmelikhuijsen., 2020).

Literature on algorithmic transparency generally considers two core elements: *accessibility* and *explainability* (Giest and Grimmelikhuijsen., 2020), a brief summary of these elements can be found in Table 2.7. These two core elements fit with broader transparency literature. A study that evaluated 25 years of governmental transparency found that most definitions include the availability of information on decision-making processes, budgets, operations, or performance of governmental bodies. Building on this general definition, and by explicitly including accessibility and explainability Grimmelikhuijsen (2022) defines algorithmic transparency as being 'achieved' when '*external actors can access the underlying data and code of an algorithm and the outcome produced by it are explainable in a way a human being can understand'*.

	Description
Accessibility	General information surrounding the algorithmic system such as, Public availability of source code, model and/or data.
Explainability	The outcome of an algorithm can be explained in a way a human can understand how or why an algorithmic decision was reached.

Table 2.7: Comparing accessibility and explainability (Giest and Grimmelikhuijsen., 2020)

Accessibility and explainability are seen as key factors in improving trustworthiness and reducing bias (Miller., 2019; Rudin., 2019; Grimmelikhuijsen., 2022). However, upholding these factors will remain a significant challenge for the foreseeable future (Ananny, 2016; Sandvig et al., 2016; Giest, 2019; Dencik & Kaun, 2020).

2.3.2 Accessibility

Accessibility focuses on general information surrounding a system. It involves factors such as source code, the model, data used or other relevant factors (Grimmelikhuijsen., 2022). Accessibility goes beyond merely making information available to the public, it should take into account various target groups. For example, sharing source code is a form of accessibility, however, most citizens won't understand code if they look at it (Annany and Crawford., 2016), even experts often struggle to understand if code if they look at it (Kroll et al., 2016). Because of technical aspects such as this some scholars argue that it might be better for independent auditors to evaluate source code, model, and data used by an algorithmic system to evaluate them for accuracy and fairness (Tutt., 2017). As such an importation dimension in accessibility is 'accessibility for whom'.

The algorithm register currently being implemented by the Dutch national government is a form of transparency through accessibility. This register, which was first launched in December of 2022 serves as a central database for all governmental institutions to publish and share information on the algorithms they employ, for now voluntarily – later mandatory (Digitale overheid., 2023). Eventually, the register should contain all algorithms that '*impact people and influence policy'* (Hofmans, 2022). The website of the register states that its goal is to '*increase transparency'* and through that '*improve citizen trust in algorithm usage by governmental organizations'* (Digitale overheid., 2023).

Origins of the register can be found at the national and international levels. Nationally, a Green party motion from 2021 can be identified as calling for stricter rules on algorithm usage and an increase in transparency through a national register. Before this, some municipalities such as Amsterdam already had their own register. The Green party motion was filed in a debate on the child tax benefit fraud, and should be seen as an answer to the discriminating algorithms used in that controversy. At the international level, one should look at the AI-act, which will make it mandatory for member state to register their high-risk algorithms in a European database. As a preparation for this European database, member states have begun setting up their own registers, making it easier to transfer to the European database once available.

The Dutch register was created based on knowledge from pilots, experience with other registers and through 'extensive target group evaluations' (Digitale overheid., 2024). Information is however not publicly available and as such cannot be evaluated. While conducting the literature study, there was no public research available which legitimizes the registers approach towards transparency.

Another project fostering accessibility which was gaining traction at the time of writing was the 'Algoritmewijzer', developed by the consultancy firm 'Innovalor' in cooperation with various governmental organizations (Innovalor., 2020). This viewing guide aims to inform citizens of the key characteristics of an algorithm (Innovalor., 2020). Methodologically speaking , however, their research seems somewhat questionable due to the use of guiding questions in their survey and non-diverse samples in their surveys. For the latter, I refer to table 2.8 which shows the demographic build-up of their various user tests. It leans heavily on higher educated individuals, something recurring within this field.

Round	**N=**	**Age**	**Educational background**
1	71	54% (18-34), 31% (55-74), 15% (75+)	7% (Middle educated), 5 93% (higher educated). 66
2	198	6% (18-34), 33% (35-54), 59% (55-74), 2% (75+).	2 % (Lower educated), 4 27% (middle educated), 53 71% (higher educated). 140
3	156	10% (18-34), 38% (35-54), 49% (55-74), 2% (75+).	4% (Lower educated), 6 12% (middle educated), 19 82% (higher educated). 128

Table 2.8 derived from Innovator (2020) Note: several tables don't add up to 100, this is however part of their official publication.

2.3.3 Explainability

Explainability involves the ‘how and why’ of decision-making. Explainability is achieved when a non-expert can understand how a decision was made, allowing them to challenge it if deemed unjust. This seems very close a the more general ‘procedural fairness theory’, a theory which states that decisions that are not well explained or not open to comment are less acceptable – thereby decreasing trust in the decision-maker (Linder, Kanerfald Early., 1990; Tyler., 2006 as cited in Grimmelikhuijsen 2022). Grimmelikhuijsen (2022) highlights three fundamental points in achieving explainability:

1. Clearly identifying which variables were crucial for the outcome, with an explanation (Friedrich and Zanker., 2011; Kizilcec., 2016);
2. Provide clear and understandable reasons for (negative) decisions, these allow citizens to assess the fairness of a decision (De Fine Licht and De Fine Licht., 2020; Tyler., 2006);
3. Provide clear and understandable explanations allowing those affected to contest a decision (Mittelstadt et al., 2016).

Achieving the above factors at a technical level should be relatively straightforward for rule-based algorithms due to their static nature. Algorithms are pre-defined and remain the same on every iteration. For narrow-intelligent systems, this, however, becomes significantly more challenging, especially those with (self-)learning capabilities. Such systems can quickly turn into black boxes in which the decision-making process becomes difficult to understand – even for many experts (Bovens et al., 2018; WRR., 2021).

Within academic literature, various approaches can be identified for improving the explainability of these systems. For starters a transparency-first approach should become essential when designing these systems, making transparent decision-making a key focus point (Rudin., 2019). Specifically for narrow intelligent systems Miller (2019) calls for more attention to be given to explainable AI (XAI) techniques. XAI uses various techniques to improve the explainability of narrow-intelligent systems such as data visualizations, building surrogate models, and post-hoc techniques to name a few.

Having the technical ability to explain a decision is only the start. Next, it is important to think about ‘how’ this can then be communicated to those affected. Empirical evidence on the ‘how’ focusing on the public sector and involving ‘real people’ are relatively scarce, making such information under-researched and often contested (Nieuwenhuizen et al., 2024). Generally, however, we could assume that principles from the earlier mentioned procedural fairness theory could be applied in algorithmic decision-making as well. Meaning that a citizen should have access to information necessary to understand and contest a decision. Such information should be provided in such a way that it can be understood by citizens of various backgrounds.

2.4 Conceptual framework

In this chapter, I present the conceptual framework used to investigate how citizens of Enschede perceive the algorithm register as an intervention to improve transparency. The framework is based on existing literature on algorithmic transparency and incorporates key factors influencing citizen perception.

The central concept investigated in this research is the algorithm register. The register is a governmental intervention designed to increase transparency regarding algorithm and AI usage within the public sector. It serves as a database for governmental organizations to register and share information on the algorithms they employ, with the goal of enhancing transparency and trust.

Algorithmic transparency is my independent variable, it is key in determining how citizens perceive the algorithm register and contains two fundamental elements:

1. **Accessibility:** The availability of information regarding an algorithm, entails information such as source code, model, data, and also more general information describing the functioning of an algorithm. An important dimension for accessibility is also 'accessible to whom', meaning that one should determine a target audience;
2. **Explainability:** The extent to which a decision made by an algorithm can be understood by a non-expert, it allows citizens to understand and contest algorithmic decisions if necessary.

Citizen perception is my dependent variable, it refers to how citizens of Enschede evaluate the register in terms of effectiveness. This perception is shaped by citizens ability to access and understand the information provided in the register. Moderating factors in this research are citizen characteristics, for this we have access to age, gender and educational background. I assume that these citizen characteristics affect how governments should approach their accessibility and explainability related policies.

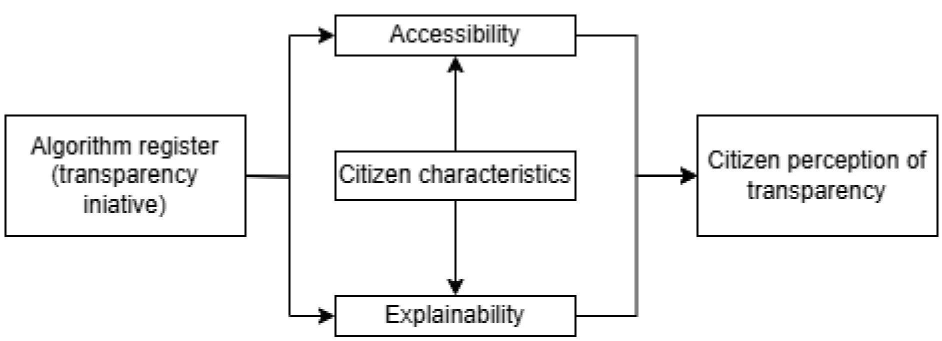

Figure: 2.9: conceptual framework

This conceptual framework provides a structured approach to analyzing the effectiveness of the algorithm register in enhancing transparency. By considering accessibility, explainability and individual citizen characteristics, this study aims to assess whether the register enhances perceived transparency.

3. Methodology

3.1 Introduction

In this chapter, we present the methodological approach followed for answering the main research question and sub-questions. The chapter is divided into the research design, data collection methods, data analysis methods, integration of methods, ethical considerations, and limitations. It finishes with a summary providing an overview of the most important step of the methodological approach.

3.2 CIO-office Enschede

I conducted this research while working for the CIO office (**C**hief **I**nformation **O**ffice), part of the municipal government of Enschede. The CIO office is a strategic policy-making department aimed at improving government services through digitalization. The CIO office provided funding for the data collection phase of this research, allowing me to work with 'Kennispunt Twente', a local research organization, which greatly boosted my reach for the survey.

Agreements were made on my independence as a researcher; this in practice meant that staff from the CIO office helped me by proofreading work and allowing me to use their network. Neither the CIO office nor the municipality had any influence over the contents of this research, its methodology, and subsequent results.

3.3 Research design

This study aims to evaluate how citizens of Enschede perceive the algorithm register as an intervention to improve transparency. It requires us to explore the concept of algorithmic transparency and research how citizens perceive it. For that purpose, we conducted a case study. Merriam-Webster dictionary (2023) defines a case study as *'An intensive analysis of an individual unit (such as a person or community) stressing developmental factors in relation to the environment'.* When conducting a case study, one is required to make deliberate choices for an individual unit with a clear set of boundaries (Denzin & Lincoln, 2017) I essentially build a 'casing' around our unit (C. Ragings, 1997. As cited in Denzin & Lincoln, 2017). I focus on citizens living in Enschede who are at least 18 years old.

Within the specified case the following steps were taken.

1. **Phase 1: Literature review:** Desk research is conducted to provide us with a theoretical framework for evaluating the concept of 'transparency' and improve our understanding of the concept of 'algorithms'.
2. **Phase 2: Mixed-method survey:** a survey is sent out containing closed questions giving us quantitative data and open-ended questions, providing further contextual understanding through qualitative data
3. **Phase 3: qualitative – interview based:** After analyzing the survey results, we conduct interviews to improve our contextual understanding.

3.3 Data collection & analysis methods

3.3.1 Phase 1 – Literature review

Initially, a literature review was conducted aimed at improving our understanding of topics related to algorithms & AI. This led to a theory section divided into three topics building onto each other.

In the first section, we lay the foundations for our understanding of 'algorithms & AI'; we show that although these two are interconnected, they also offer several distinctions. To determine definitions for these concepts, we utilized Dutch and EU policy papers as these are the most relevant for our situations. Aside from these policy papers, we mainly focused on academic articles from 2020 and later to ensure the most up-to-date information. Older academic work was mostly used when it was cited in one of the aforementioned 'up-to-date' works.

After establishing these concepts, we shift our focus towards creating a timeline for the implementation and use of algorithms & AI within the Dutch public sector. Our timeline focuses on the bigger picture; going into too much detail is unnecessary for the scope of this research. This timeline runs from the early 90s until today. I match our search strategy to these periods and focused solely on articles discussing the Dutch context. The aim of this chapter is mainly for us to create an understanding that algorithms & AI are not as new as they are often put out to be.

Finally, we discuss the topic of algorithmic transparency, which is a focus point for this work. We include articles discussing algorithmic transparency and procedural fairness theory. The latter theory is included as it is a long-standing theory for approaching and designing governmental procedures and as the literature review shows it ties in well with certain aspects of algorithmic transparency. Articles we focus on work from 2020 and onwards as these include the AI context, older work was used when it was referenced in the aforementioned 'up to date' articles.

3.3.2 Phase 2 – Data collection & analysis – mixed method survey

For the second phase, a survey was created based on the information collected through the literature review. The survey explores topics such as:

- Citizen's perception and understanding of algorithms;
- Citizen desirability concerning algorithm usage;
- Algorithmic transparency with extra attention to concepts relevant to explainability & accessibility;
- The algorithm register.

The survey helps in creating a baseline understanding of how citizens of Enschede approach these topics. Question a mixed-method approach is taken where we utilize a mix of the following question types:

- 10 questions using a 5-point Likert scale;
- 3 questions using an open-ended format;
- 2 questions using a Yes/No format;
- 1 question involving a ranking format.

While designing the survey, extra attention was given to decreasing the abstractness and difficulty of the topic. This in practice meant that we first designed an academic-level survey, which was then re-formulated to be at a b1 language level. B1 is a language level that can be understood by a majority of citizens including those without a formal education (Ministerie van Algemene Zaken, 2024). It employs short active sentences and words we all use in our daily lives. This was done to ensure that we would be able to collect responses from citizens of diverse socio-economic backgrounds. Policy within the fields of AI & algorithms is written by highly educated individuals, and we can see that research in this field often has an overrepresentation of the same group in surveys/interviews as well. I would assume this stems from factors such as the abstractness and/or difficulty of the topic, the fact that some demographics are in general harder to reach, and finally a certain level of complacency in attempting to reach these groups. When policy is aimed at improving transparency, but said policy is not written with an inclusive approach – the policy in place is flawed. Once the survey was finished, it was then shared with a communication advisor from the municipality who evaluated and help improve it where necessary. Next I did several test runs with citizens from various backgrounds. The finished survey can be found in Appendix B, Table 3.1 illustrates which survey questions were used to answer what sub-question in the results section.

Sub-question	*Relevant survey question*
SQ1: To what extent do citizens of Enschede know and perceive algorithms, and how would they define them based on their understanding?	V1, V2, V5, V14
SQ2: To what extent are citizens in Enschede aware of the existence of the algorithm register?	V10, V12, V15
SQ3: What types of information do citizens deem important in improving transparency in relation to algorithm usage?	V8, V11, V14
SQ4: To what degree are the 'types of information' identified in SQ3 present in the algorithm register?	Using SQ3

Table 3.1

Initially, the survey was spread among citizens living in Enschede who were at least 18 years old and members of the EnschedePanel. The EnschedePanel is an online research instrument containing 1819 citizens. From the get-go, we knew the panel had a slight overpopulation of 45+ citizens. To help balance, the survey was further spread amongst students at the ROC, Saxion, and University of Twente, as well as an ad campaign through social media.

Upon closing the survey 864 panel members had responded, meaning a response rate of 47.5%. A additional 82 people were reached through alternative channels, bringing the total to 946 respondents. This dataset was then uploaded to JASP which is an open source statistical analysis program. In JASP we conducted a data-cleaning procedure in which the first step was to check whether respondents filled in all the questions. This led to us removing 123 respondents from our dataset bringing the total to 823. Next, a second clean-up round was conducted where respondents who gave 'unserious' answers were removed, leading to an additional 18 respondents being removed giving us the final sample of 805 respondents. Three background variables were present in the survey, allowing us to describe the demographic makeup of the sample. These variables are gender, age, and educational level. Starting with gender in table 3.2.

Gender	Frequency	Percentage
Male	523	65.0%
Female	282	35.0%
Total	805	100%

Table 3.2: Gender division within the sample

Next, we find the age for which an overview can be found in Table 3.3. here we see an overrepresentation of the 60+ group with 61.2%. Later in this chapter, we discuss how we accounted for the overrepresentation of various groups.

Age category	Frequency	Percentage
18 – 29	39	4.8%
30 – 44	90	11.2%
45 – 59	183	22.7%
60+	493	61.2%
Total	805	100%

Table 3.3: Age division within the sample

Finally, table 3.4 shows an overview of the educational division within our sample. In the survey respondents were able to choose between 6 educational categories: primary, vmbo/havo, havo/vwo, MBO, HBO, and WO. These were then recoded into ‘lower educated’ consisting of primary school and vmbo/mavo, ‘middle educated’ consisting of havo/vwo and mbo, and finally ‘higher educated’ consisting of HBO and WO. This approach simplifies further analysis, by grouping educational categories that are relatively similar. Here we end up with an overrepresentation of the higher-educated

Age category	Frequency	Percentage
Lower educated	67	8.3%
Middle educated	207	25.7%
Higher educated	531	66.0%
Total	805	100%

Table 3.4: educational division within the sample

Tests were run to determine the significance of each of these demographic factors, here we found that age and education had a significant effect on all questions used in this research. While gender was insignificant in all, as such gender was excluded in further analysis. Next, a solution had to be found for the overrepresentation of the elderly and higher educated. Here it was decided to create 7 sub-groups based on education and age with the requirement of having at least 30 respondents. Excluding the groups with less than 30 respondents had the effect that an additional 25 respondents were excluded leading to a total sample of 780 respondents. Table 3.5 shows a description of this final sample, note that we do show the groups with less than 30 respondents – but these won’t be included in further analysis.

	Lower-educated				*Middle educated*				*Higher educated*			
Age	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+
Respondents	0	0	6	57	7	12	52	132	32	78	121	298

Table 3.5: Creating of demographic subgroups

3.3.3 Phase 3 – Data collection & analysis – interviews

After finishing the second phase we have the bulk of our data available and analyzed, it essentially means that we answered several sub-questions and provided some degree of context through the qualitative questions asked in the survey. To provide context to our findings interviews were conducted. For these interviews a semi-structured script was written where themes from the survey were combined with themes from the theory section.

Now to further contextualize our results interviews were conducted. Before these interviews could be conducted, first an interview script had to be written. A semi-structured approach was chosen where findings from the survey and theory were combined into broader themes, short interviews were conducted based on these themes. As can be seen in appendix C the interview script dealt with such topics as algorithmic familiarity, the algorithm register, perception of transparency, factors of transparency, accessibility and explainability. Results from these interviews were loosely used to help contextualize results from the survey.

With the interview script ready, it was necessary to determine who would be interviewed, as interviewing 194 people – although interesting – is unfortunately beyond my capabilities. As such, selection criteria had to be determined to decide who would be invited. I made use of the format used to create groups for the survey analysis. consequently, gender is excluded Aswell, as it was determined insignificant, as mentioned in section 3.3.2

Age	Amount	Education based division
18 – 29	7	2 lower, 2 middle, 3 higher
30 – 44	7	2 lower, 3 middle, 2 higher
45 – 59	8	3 lower, 2 middle, 3 higher
60+	8	3 lower, 3 middle, 2 higher

Table 3.6: Interview sample

People included in this final list were randomly selected and invited through an e-mail which can be found in Appendix F**,** in this e-mail respondents were again thanked for filling in the survey and leaving behind their contact details. Respondents were invited for 10-15 minute long interviews which could be done online or offline. In the E-mail I already asked respondents for an approval for recording the interview, recording the interview allows for full focus on the topics and ensuring a smooth conversation without unnecessary distractions.

3.5 Ethical considerations

The BMS ethical committee for the humanities & social sciences domain assessed the ethical aspects of this research project. Based on the information provided, the committee did not have any ethical concerns regarding this project. As such, ethical approval was granted for the methodological approach presented in this report this ethical request was filed under request number 240882.

For this project, surveys and interviews were used to gather information. When undertaking this methodological approach, informed consent and anonymization should be key focus points. As such, at the start of the survey, respondents were informed about how their responses would be used in this and potential future research. For the interviews, a similar approach was undertaken where the respondent signed for consent.

Data collected through this project is kept strictly confidential and anonymous. The survey contains some identifying factors such as gender, age, educational background, and neighborhood – these, however, cannot be traced back to the individual level. During the survey, respondents were able to leave behind their contact information – this information was kept in a separate location and destroyed after the interviews were conducted.

4. Results

As discussed in the methodology section, demographically speaking, our sample is not representative of the municipality as a whole. As such, the decision was made to create 7 subgroups based on education and age. For each of the questions, first, a general description of the responses will be provided. Then, for further analysis, the split is applied. At the end of this chapter in section 4.4 a summary will be provided of the results, this summary will be used to answer the four sub-questions. Section 4.1 – 4.3 will be used to discuss themes relevant in answering these sub-questions.

4.1 Familiarity with and perception of algorithms

This sub-section can essentially be split up into two parts: ‘familiarity with algorithms’ and ‘perception of algorithms.

4.1.1 Familiarity with algorithms

Starting with citizen familiarity with algorithms, respondents were asked whether they were familiar with algorithms on a 1-5 scale. In Table 4.1, we find the results for this question. Responses are generally centered around 3, with a slight skew towards a higher rating made visible by the mean of 3.3. There is some variation, but responses are not extremely dispersed, which is shown by the standard deviation of 0.9. Furthermore, we see that only 14.5% of citizens have limited to no knowledge of algorithms, while 41% have a basic understanding and 44.5% have practical or advanced experience with the concept.

V1: How familiar are you with algorithms?	N	%		
1 Not at all familiar: I don’t know what algorithms are	39	4.8	Median	3.0
2 Somewhat familiar: I know the word, but don’t know what it means	78	9.7	Mean	3.3
3 Neutral: I think I know what algorithms are, but I don’t deal with them	330	41	Minimum	1
4 Familiar: I know what algorithms are and I have practical experience	292	36.3	Maximum	5
5 Well-known: I have advanced knowledge and experience	66	8.2	Std. deviation	0.9
Total	**805**	**100%**	Variance	0.9

Table 4.1: Sample description: To what extent are you familiar with algorithms?

Further zooming in on our groups through Table 4.2, the lower-educated 60+ group has the lowest familiarity. While the highest level of familiarity can be found within the higher-educated 18-29 age group. Furthermore, it appears as if both age and education have some form of an effect on familiarity as there appears to be a trend within the data. During the interview phase, it was noticeable that often younger respondents saw algorithms as something they find all across their daily lives – something you cannot go without. AI for them was, however, a new thing, something they were familiar with through services like ChatGPT but not much else. Among the more elderly respondents, we found the opposite: both concepts were seen as new or mixed up within their responses.

	Lower-educated				Middle educated				Higher educated			
Age	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+
Median	.	.	.	2	.	.	3	3	4	4	4	3
Mean	.	.	.	2.2	.	.	3.2	2.9	4.3	3.9	3.7	3.4
Min.	.	.	.	1	.	.	1	1	3	1	1	1
Max.	.	.	.	4	.	.	4	5	5	5	5	5
Std. dev	.	.	.	0.9	.	.	0.7	0.9	0.7	0.9	0.7	0.8
Variance	.	.	.	0.8	.	.	0.6	0.8	0.5	0.7	0.5	0.6
Respondents	0	0	0	61	0	0	54	134	32	78	123	298

Table 4.2: Grouped Description: To what extent are you familiar with algorithms?

4.1.2 Perception of Algorithms

Next, results are shared on how algorithms are perceived by respondents. Respondents were asked how they perceived algorithms on a 1-5 scale, Table 4.3 shows these results. Responses show a positive skew, which is shown through the median of 4.0 being higher than the mean of 3.5. The standard deviation of 1.1 suggests a mix of opinions, as some respondents gave very low ratings, lowering the mean score.

Further inspection shows that only 3.9% of citizens said they were not at all worried about the usage of algorithms. Compared to 58.8% who are very to extremely worried about their usage.

V2	N	%		
1 Not worried at all	31	3.9	Median	4.0
2 Somewhat worried	153	19.0	Mean	3.5
3 Neutral	138	17.1	Minimum	1
4 Very worried	330	41.0	Maximum	5
5 Extremely worried	143	17.8	Std. deviation	1.1
I don't know	10	1.2	Variance	1.2
Total	**795**	**100%**		

Table 4.3: Sample description: Do you worry about the usage of algorithms?

Further zooming in on our groups through Table 4.4, it can be seen that higher-educated 18-29 respondents are the least worried, while the higher-educated 45-59 respondents are the most worried with a slight margin. Across groups, relatively high standard deviations can be seen. This suggests that there is quite a lot of diversity within responses.

	Lower-educated				*Middle educated*				*Higher educated*			
Age	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+
Median	.	.	.	3	.	.	4.0	4	3	4	4	4
Mean	.	.	.	3.3	.	.	3.5	3.4	3	3.3	3.7	3.6
Min.	.	.	.	1	.	.	1	1	1	1	1	1
Max.	.	.	.	5	.	.	5	5	5	5	5	5
Std. dev	.	.	.	1.2	.	.	1.2	1.1	1.2	1.1	1.1	1.0
Variance	.	.	.	1.3	.	.	1.4	1.2	1.5	1.3	1.1	1.1
Respondents	0	0	6	57	7	12	52	132	32	78	121	298

Table 4.4: Grouped Description: Do you worry about the usage of algorithms?

In the survey, several open questions were posed. Through them, additional data was collected, which is relevant in determining algorithmic perception. Specifically in this instance, the negative side of perceptions. The key takeaway from the survey in this regard can be found in:

- **Fear of a lack of tailored solutions** (47 mentions): Citizens mention a fear of rigid systems that will fail to accommodate individual circumstances;
- **Risk for Bias** (32 mentions): Concerns about a biased decision-making process. This can be linked to procedural fairness, which, as the name suggests, focuses on the fairness of the procedure;
- **Privacy violations** (28 mentions): Citizens express fear of a violation of their privacy rights;
- Recent **controversies** (26 mentions) with systems involving algorithms and **general distrust** (14 mentions) in the government contribute to general skepticism.

Furthermore, while conducting the interviews, we found that although citizens often understand that there is a certain necessity to systems such as these, recent controversies have fueled their skepticism over these systems. It has made them more aware of what can go wrong when these systems are implemented improperly.

4.2 The algorithm register

4.2.1 Familiarity with the algorithm register

In Table 4.5, the results are presented for the survey question which asked respondents whether they were familiar with the algorithm register. It can be seen that only 12.1% of respondents were aware of the existence of the register at the time of filling in the register.

V12	*N*	*%*
Yes	97	12.1%
No	708	87.9%
Total	805	100%

Table 4.5: Population description: familiarity with algorithm register

Further zooming in on our groups, in Table 4.6, it can be seen that lower-educated 60+ respondents were the least familiar with the register, while the higher-educated 30-44 respondents were the most familiar. During the interview phase, respondents were again asked about the algorithm register. In the interview phase, respondents were asked whether they had used the register after learning about it in the survey. Here, 8/10 respondents pointed out that although they had checked the website on a handful of occasions, they were not too enthusiastic. They found that the website was too vague/complicated for them.

V12	*Lower-educated*				*Middle educated*				*Higher educated*			
Age	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+
Yes	.	.	.	3.7%	.	.	7.5%	8.2%	10.3%	35.9%	15.4%	8.7%
No	.	.	.	96.3%	.	.	92.5%	91.8%	89.7%	64.1%	84.6%	91.3%
Total	0	0	6	61	7	12	54	134	32	78	123	298

Table 4.6: Percentage of respondents who are aware of the algorithm register

4.2.2 Knowing when an algorithm is used

Something that can be seen as relevant in researching interest in the algorithm register is finding out whether respondents are interested in knowing when an algorithm is used to begin with. In Table 4.7, results are presented that show an overwhelming majority of 80.6% finds this important. This is further reinforced by the median of 4.1 and mean of 4 showing a positive skew. Furthermore, data is tightly clustered around the mean, as indicated by the standard deviation of 0.8.

V10	*N*	*%*		
1 Not at all important	4	0.5	Median	4
2 Not important	22	2.8	Mean	4.1
3 Neutral	127	16.0	Minimum	1
4 Somewhat important	375	47.3	Maximum	5
5 Very important	264	33.3	Std. deviation	0.8
Total	792	100	Variance	0.6

Table 4.7: Population description: how important is it to know which algorithms the municipality uses?

Further exploring this by zooming in on our groups in Table 4.8. We find that mean scores across groups are relatively close together, with all of them showing that respondents find it important to know when an algorithm is used.

	Lower-educated				Middle educated				Higher educated			
Age	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+
Median	.	.	.	4	.	.	4	4	4.0	4	4	4
Mean	.	.	.	4	.	.	4.2	4.1	3.8	3.9	4.1	4.2
Min.	.	.	.	2	.	.	3	1	2	1	1	2
Max.	.	.	.	5	.	.	5	5	5	5	5	5
Std. dev	.	.	.	0.8	.	.	0.8	0.8	0.9	1	0.8	0.7
Variance	.	.	.	0.7	.	.	0.6	0.6	0.8	1	0.7	0.5
Respondents	0	0	5	60	7	12	54	129	32	78	121	294

Table 4.8: Group-based description: How important is it to know which algorithms the municipality employs?

4.2.3 Comparing the algorithm register to other mediums for sharing information

In another survey question, we asked respondents about various platforms for sharing information. The Dutch national government selected the algorithm register as the best platform. There are, however, other routes that could be taken. I asked respondents about the suitability of sharing information through the register, social media, the municipal website, or physical letters. Figure 4.9 provides us with results for the general sample. It should be noted that social media scores the lowest across all groups, while the municipal website scores the highest.

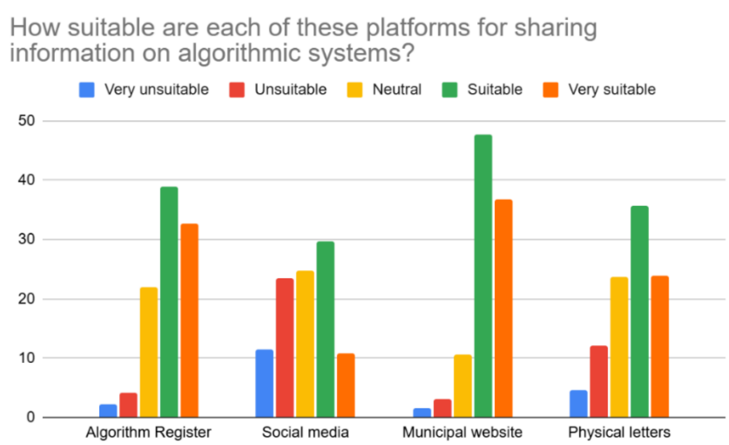

Fig 4.9 How suitable are each of these platforms for sharing information on algorithmic systems

Zooming in on our groups through Table 4.10. This table only shows the mean score for each medium to improve readability. For each group, the highest scoring medium was marked green while the lowest was marked in red. Social media scores the lowest, an explanation for this can be found in the final question of the survey, here respondents were able to leave behind any general thoughts about the survey. Many respondents took this opportunity to explicitly point out that the municipality should not use social media to share official information due to fake news being ever present on these platforms.. In addition, similar sentiment was repeated in the interviews.

The municipal website scores highest across 6/7 groups. Respondents explain this by stating that although the register is an interesting website containing a lot of information, that excessiveness is eventually its downfall. When dealing with the municipality, respondents want to find ‘all relevant information’ on the municipal website. They wish information to be placed on the website of the organizations they are dealing with.

Physical letters also score relatively well. Respondents giving positive scores often voice that providing information through letters might help reach the elderly who are less digitally savvy. Additionally, the issue of fairness was connected with physical letters: 'placing information on algorithms in the decision letters I receive from the municipality help me better understand whether a decision was fair'. Respondents who are less favorable of physical letters fear that this might lead to additional printing of letters, which can be seen as a waste of paper and damaging to the environment.

Group	*Algorithm register*	*Social Media*	*Municipal website*	*Physical letters*
Lower educated 60+	3,4	3,0	3,4	3,9
Middle-educated 45-59	4,0	3,1	4,1	3,8
Middle educated 60+	3,8	3,3	4,2	4,0
Higher educated 18-29	4,5	3,1	4,6	3,4
Higher educated 30-44	4,2	2,7	4,3	2,9
Higher educated 45-59	4,1	2,9	4,3	3,4
Higher educated 60+	3,9	3,1	4,1	3,7

Table 4.10: Grouped description: Favorability in communication channels. Red = least favorable & green = most favorable.

4.3 Factors relevant to algorithmic transparency

4.3.1 Explaining a decision made by an algorithm

Starting with Table 4.11, I explored whether citizens find it important to understand how an algorithmic decision came to be. Here, it can be seen that 85.9% of respondents find this important. This is further shown by the median of 4 and a mean of 4.2, indicating it is positively skewed toward the upper end. Furthermore, the standard deviation of 0.8 suggests a tight clustering around the mean.

V8	N	%		
1 Not at all important	4	0.5	Median	4.0
2 Not important	16	2.0	Mean	4.2
3 Neutral	91	11.6	Minimum	1.0
4 Somewhat important	390	49.7	Maximum	5.0
5 Very important	284	36.2	Std. deviation	0.8
Total	**785**	**100**	Variance	0.6

Table 4.11: population description: How important is it to know how an algorithmic decision came to be?

Further zooming in on our groups in Table 4.12, it can be seen that the mean lies relatively close together across groups. This indicates that it is seen as important across all groups. This could be expected beforehand due to the low standard deviation.

V8	*Lower-educated*				*Middle educated*				*Higher educated*			
Age	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+	18-29	30-44	45-59	60+
Median	.	.	.	4	.	.	4.0	4.0	4.0	4.0	4	4
Mean	.	.	.	3.9	.	.	4.2	4.1	4.2	4.2	4.4	4.2
Min.	.	.	.	1	.	.	2.0	1	2	1	2	1
Max.	.	.	.	5	.	.	5.0	5	5	5	5	5
Std. dev	.	.	.	0.9	.	.	0.8	0.8	0.8	0.8	0.7	0.7
Variance	.	.	.	0.8	.	.	0.7	0.6	0.7	0.6	0.5	0.5
Respondents	0	0	6	57	7	11	54	129	32	75	120	294

Table 4.12: Group-based description: How important is it to know how an algorithmic decision came to be?

4.3.2 What to communicate

Next, respondents were given a ranking question where they could show which type of information they found most important. Due to software limitations, a group-based analysis is not possible here. Results show that respondents find it most important to know how an algorithm came to its decision. This was closely followed by its goal, while which information was used was third. Then a leap is taken, and the more technical 'what rules' follows. The table ends with appeals and benefits being seen as the least important.

V11	*Average rank*	*Rank based on average*
How the algorithm came to its decision	2.683	1
The goal of the algorithm	2.721	2
Information used by the algorithm	3.016	3
Out of which rules the algorithm consists	3.707	4
How and where objection to a decision can be made	4.249	5
Benefits of using said algorithm	4.624	6

Table 4.13: Sample description ranking answers

The 'what' to communicate aspect can be further explored through the data collected via the open questions posed in the survey. The coding scheme for this can be found in Appendix E. Relevant to this question are accessibility and explainability factors.

On the topic of accessibility, we found that citizens have a strong desire for transparency and accountability regarding the use of algorithmic systems. Key concerns in this regard include:

- **Human involvement** (54 mentions): A significant part of responses referred to the importance of knowing whether a human is involved in or overseeing the algorithmic decisions.
- **Algorithmic goals** (46 mentions): Understanding the purpose and objectives of the algorithm is seen as important by many.
- **Algorithmic presence** (32 mentions): Respondents wish to know whether an algorithm or AI-based system is used within a process.
- **Responsibility** (5 mentions): Although mentioned significantly less than the other factors, it is still relevant as it further shows that people find it important to know where responsibility lies with the municipality or another organization.

Other respondents mentioned technical details such as the source code (10 mentions) or adherence to rules and regulations (2 mentions). Although these factors are interesting, they are more technical in nature and are more relevant for a sub-group of citizens with a deeper understanding who wish for more information.

On the topic of explainability, we found that citizens often wish to understand how algorithms function and how decisions are made when these are directly relevant to them. Key concerns in this regard include:

- **Data transparency (**54 mentions): Citizens mainly wish to know which data specifically led to the decision. Allowing citizens to understand and appeal to the process if necessary.
- **Decision process (**38 mentions): Citizens mainly wish to know which procedural steps led to the decision which was made, and the decision-making process needs to be understandable.
- **Procedural fairness (**37 mentions): This is seen as an umbrella term for catching various mentions relevant to understanding and being able to appeal to a procedure. It questions if the procedure followed a fair and orderly manner.
- **Significant variable (**19 mentions): Citizens wish to explicitly know which specific factors were most influential in a decision-making process.

4.4 Summarizing findings

4.4.1 SQ1: To what extent are citizens of Enschede familiar with algorithms, and how do they perceive them?

Starting with the aspect of familiarity, Table 4.1 presents responses from a 1-5 scale survey question on familiarity. We can see that respondents (according to them) have a decent level of familiarity with algorithms, which is shown by the mean score of 3.2. In this survey question we asked respondents to rank their level of familiarity on a 1-5 scale, where 3 equals: I think I know what algorithms are, but I don't deal with them. However, further zooming in on this score through Table 4.2 reveals additional important information. Through this table we can see that both education and age seems to have an effect on familiarity.

For example, within our higher-educated category, the 18-29 scores the highest in familiarity with a mean score of 4.3, while the 60+ group scores the lowest with a mean score of 3.4. If we compare between educational groups, we see that middle-educated and lower-educated individuals score significantly lower in their understanding. The key takeaway is that familiarity with the concept of algorithms differs between educational and age groups. Education has a positive influence on familiarity; as education level goes up, familiarity follows. While age has a negative influence on familiarity.

Regarding perception, Table 4.3 shows that 58.8% of respondents are worried about the usage of algorithms. Further zooming in on the various groups in Table 4.4, we find that all groups are worried to a degree about the usage of algorithms. With higher educated 18-29 citizens being the least worried and higher educated 45-59 citizens being the most worried. Across groups, however, we find relatively high standard deviation scores, suggesting a high degree of diversity within responses.

Further exploring this topic, we found 4 key factors affecting citizens' perception. Although not explicitly mentioned every time, it could be argued that the basis for this worry lies within controversies and general government distrust. Specifically, controversies such as the recent child tax benefit scandal or SyRi have led to a newfound interest among citizens in algorithmic systems usage by the government. Due to these controversies, citizens have become fearful of a lack of tailored approaches, a risk of bias, and a violation of privacy rights. Citizens understand that these systems are necessary for various processes, but recent controversies have highlighted that government organizations are often less structured and risk-averse in the creation of these systems than they should be.

4.4.2 SQ2: To what extent are citizens of Enschede familiar with the algorithm register?

Starting with Table 4.5, 12.1% of respondents were aware of the existence of the algorithm register. By further zooming through Table 4.6, we see a difference in familiarity with the register between educational and age groups. We find the highest average score in the higher-educated category, something which is also influenced by the 35.9% outlier in the higher-educated category. Overall, it can be concluded that respondents are unfamiliar with the register. When asked about this during the interview phase, respondents often pointed out that when they, for example, deal with the municipality, they wish to find all relevant information on the municipality website. Going to a separate website for this did not make them enthusiastic. Respondents would also often refer to the website as being too vague and overcomplicated.

This low level of familiarity with the register, however, remains interesting as Table 4.7 showed that respondents found it quite important to know which algorithms a municipality uses. This is portrayed by the mean score of 4.1. Again, further zooming in on the various groups, we found a quite uniform score where across all groups, citizens were quite interested to know which algorithms a municipality uses.

4.4.3 SQ3: What types of information do citizens deem important in improving transparency in relation to algorithm usage?

Based on the theory, we see that algorithmic transparency consists of explainability and accessibility. Both factors are important in improving transparency with regard to algorithmic systems. Starting with an open-ended question, which was coded in Appendix E, we identified which factors of accessibility and explainability respondents found most important.

Regarding accessibility, the key for respondents was to know if and when a human was involved in the algorithm process, understand the purpose and objectives of the algorithm, know when and where algorithms are used, and where the responsibility lies for the algorithmic system. More technical details such as source code were also mentioned, but this aspect is often more interesting for a very specific part of the demographic who have the required technical understanding.

On the topic of explainability, respondents mentioned various information types. This is important for respondents in the context of a decision made about them, as such this information is specified. It is not about having a register with general information. Respondents mentioned the importance of data transparency, specifically focusing on which data is used within a decision-making process. Other returning themes refer to understanding which procedural steps were taken, general comments in relation to procedural fairness, and the importance of knowing which variable/factor was most significant within a decision-making process.

The importance of explainability in general is further reinforced through Table 4.11, which shows that an overwhelming majority of respondents find it important to understand how a decision came to be, with 85.9% of responses. Zooming in on the various groups through Table 4.12, we see that this sentiment is similar across groups.

A general finding for this sub-question is that both explainability and accessibility are relevant factors for algorithmic transparency. Where accessibility for our respondents mainly focuses on general non-technical information. While explainability focuses on understanding how a decision came to be.

4.4.4 SQ4: To what degree are the ‘types of information’ identified in SQ3 present in the algorithm register?

Through sub-question three, we concluded that both explainability and accessibility are relevant factors for algorithmic transparency. Where accessibility should mainly focus on general non-technical information understandable for various types of citizens. While explainability is more focused on the individual level, explainability should take focus when a decision is made for or about a citizen. It essentially means that a citizen should always have enough information to understand how a decision came to be, which allows the citizen to evaluate whether a decision was made legitimately.

On the topic of accessibility, sub-question three highlighted the importance of knowing whether a human is involved in an algorithmic process, understanding the purpose and objectives of the algorithm, knowing where responsibility lies, and finally, knowing when and where an algorithm is being used. I believe the latter ‘when and where’ is an important factor to keep in mind when looking at accessibility. Because, the information highlighted in sub-question three is present within the algorithm register. However, it requires a citizen to actively seek out the information he/she requires and know which algorithm is being used to allow him/her to look for it. It is not standard practice to point out if and where algorithmic systems are being used, nor which system. As such, the algorithm register does fulfill some of those accessibility needs for those who proactively seek it out. It intertwines to a degree with our finding that respondents preferred the website of the municipality as a platform for providing information over the register.

Factors of explainability are in their entirety not present, which is understandable as these factors focus more on the individual level. In sub-question three, I highlighted the importance of data transparency and focused on ‘which data was used in the decision-making process’, an overview of the procedural steps, aspects of procedural fairness theory, and the importance of knowing the most significant variable. The sentiment of finding it important to understand how a decision came to be was voiced across the various groups. Based on the survey data and theory, we can also conclude that in providing explanations, it is important to be understandable for various educational and age groups. Hence, an approach where language is set at the most accessible level could be useful.

5. Conclusion and discussion

5.1 Conclusion

In this study, we explored how residents of Enschede perceive the algorithm register as an intervention to improve transparency concerning the usage of algorithms. The sub-questions answered in section 4.4 are fundamental in answering the main research question:

'How do residents of Enschede perceive the algorithm register as an intervention to improve transparency?'

Residents of Enschede generally view the algorithm register as a positive step towards increasing transparency, but its current impact is limited. Awareness of the register is low: only 12.1% of survey respondents were familiar with it. Moreover, awareness varies significantly across demographic groups, ranging from just 3.7% to 35.9%. Higher-educated individuals are more likely to be familiar with the register, while awareness is notably lower among elderly or lower-educated respondents. These findings highlight the need for a more proactive and tailored communication strategy – proactive to raise overall awareness, and tailored to effectively reach underrepresented groups.

Concerns about algorithmic decision-making are widespread. Only 3.9% of respondents reported having no concerns at all, while a significant majority expressed varying levels of worry. Many linked their skepticism to a broader distrust in government, often referencing recent controversies such as the child tax benefits scandal. Despite these concerns, respondents generally acknowledged the necessity of algorithms within various governmental processes. However, they expressed concerns regarding a lack of personalization, the potential for bias and the risk of infringing on individual rights. These concerns underscore the importance of meaningful transparency initiatives.

To be effective, such initiatives must consider both accessibility and explainability. This dual requirement, emphasized in the theoretical literature, is strongly supported by my findings. The register currently focuses on accessibility by listing which algorithms are used and providing users with general information. It however does little to make these algorithms understandable to citizens – allow them to understand how processes work. The gap in explainability is substantial: 85.9% of respondents indicated they want to understand how algorithmic decisions were made. Meeting this needs requires more than merely giving access to information. It requires sharing key decision factors, understanding which data is used and most of all organizing it in such a way that citizens can assess whether a procedure was fair.

Overall, there appears to be a disconnect between the theoretical policy goals of transparency initiatives, and their practical implementation. While the register is a step in the right direction, it is not yet structured in a way that meets the public needs. Without proactive efforts to enhance usability of the register and integrate transparency initiatives into government services. Algorithmic transparency initiatives run the risk of becoming performative rather than functional.

5.2 Discussion

Findings presented in this study provide a nuanced understanding of how residents of Enschede perceive the algorithm register as an intervention to improve transparency. While its goal was to enhance transparency, its practical impact remains limited due to low awareness, accessibility and explainability challenges, and a lack of tailored communication strategies.

National research by KPMG (2023) indicates that trust in algorithmic systems used within governments is steadily decreasing, largely due to recent controversies surrounding the use of such systems. Scholars have also raised concerns related to fairness, privacy and bias in algorithmic decision-making (Busuioc., 2020; Grimmelikhuijsen., 2020). The findings of this study reinforces these trust related issues, as we found that only 3.9% of respondents expressed no concerns over algorithm usage. These worries also differ greatly between demographic groups. Interestingly enough, respondents pointed out that they understand that algorithms are necessary in certain processes, they remain concerned due to potential for algorithmic bias, fear for a violation of human rights, a lack of tailored approaches and recent controversies.

To combat this distrust, scholars are calling for more algorithmic transparency (Miller., 2019; Lepri et al., 2019; Busuioc., 2020; Grimmelikhuijsen., 2020). Work by Giest and Grimmelikhuijsen (2020) highlighted the importance of both accessibility and explainability. This study's findings further reinforce the importance of these concepts in improving transparency. An addition from this study however focuses on 'transparency for who' as we found that transparency initiatives often cater to individuals who already have a higher level of understanding of algorithmic decision-making, while lower-educated and elderly individuals are often left uninformed. Catch-all solutions should carefully consider various demographic groups, or run the risk of creating inequality in access to information.

A key finding in this study is that respondents preferred the municipal website over the nationally oriented register. This challenges the national government's assumption that a centralized register is the most effective tool for informing the public (Ministerie van Algemene Zaken., 2023). I assume this conclusion mostly applies to local government organizations, this branch of government has close ties to its citizens – more so than for example the tax authority. The results from this research suggest that municipalities may benefit from adopting a localized approach to transparency, and integrating transparency efforts into their own website or services.

Furthermore, elderly and lower-educated individuals, expressed the need for non-digital communication, such as physical letters. These findings suggest that municipalities should reconsider how transparency initiatives are designed and whether the register should serve as a supplementary rather than primary tool for algorithmic transparency. The findings of this thesis highlight the gap between algorithmic transparency theory and its practical implementation. While the algorithm register represents an important step toward increasing transparency, its current design does not align with how citizens seek and process information. Transparency efforts must go beyond making information available—they must ensure accessibility, clarity, and integration into citizens' direct interactions with government services. A more proactive and tailored approach is necessary to ensure that transparency initiatives benefit all demographic groups rather than reinforcing existing inequalities. Without such refinements, transparency efforts risk failing to achieve their intended purpose.

5.3 Research limitations

This study comes with several methodological limitations, despite efforts to reduce these they still remain relevant. First, as discussed in the methodology section, the sample is not fully representative for the city of Enschede. While creating separate groups of at least 30 respondents did help mitigate some of this overrepresentation concerns, the absence of certain demographic groups could not be fully resolved.

Second, in my coding and thematic analysis I worked on my own. This means that this analysis might have been affected by my personal bias, although I carefully considered relevant theory, attempted to uphold neutrality and searched out further contextualization through my interviews – bias may still have affected my outcomes.

Third, my affiliation with the municipality, while not influencing the content or conclusions of this research, presents a potential limitation. Despite making every effort to uphold strict research independence, unconscious bias may have played a role in data interpretation.

Finally, a practical limitation arose from software constraints. The organization I worked with for data collection required me to use municipal IT systems to save and process the data. The municipality however did not provide access to advanced statistical programs such as R or SPSS. As a workaround, an open-source variant with limited functionality such as the inability to recode variables or conduct advanced statistical tests may have restricted the depths of analysis.

5.4 Recommendations

5.4.1 For future study

Based on the findings within this thesis, various recommendations can be made for future studies. Starting with inclusivity in transparency initiatives. Lower- and middle- educated individuals are disproportionately affected when algorithmic systems go haywire, while transparency initiatives often seem to cater to higher-educated individuals who are less affected. As such, I recommend a large-scale qualitative research project, assessing various communication styles and tailoring these to different literacy levels. Inspiration can be taken from national government projects on 'direct duidelijk' or b1 level communication.

Next, a recurring observation – both in literature, this research, and in conversations with senior policy advisors at the municipality, as well as in public debate. It is noticeable there is a certain degree of conceptual confusion surrounding algorithms and AI. Many important stakeholders struggle to fully grasp these concepts leading to them being frequently used interchangeably. Despite representing significantly different technologies and applications. This may become problematic, as it disregards important nuances in functionality, governance implications, and potential risks. Future research could explore how public officials, and citizens conceptualize and differentiate between these concepts, special attention should be given to how these understandings influence decision-making, trust, and policy development. Such research may help in improving digital literacy, as well as foster more effective communication on the use of automated systems within the public sector.

Finally, in this study we found that specific demographic groups are lacking in their awareness and understanding of algorithmic systems. To further understand how specific demographic groups can be better reached, a policy analysis could be conducted on education and awareness campaigns implemented by governmental organizations.

5.4.2 For policymakers

Several recommendation for policymakers can be made based on the findings presented in this research. I wish to highlight four of these:

First, policymakers should focus on increasing public awareness of the register through targeted communication. Through this research we found that only 12.1% of respondents were aware of the existence of the register, with large disparities between demographic groups. To increase awareness tailored campaigns need to be developed, which specifically target less-aware groups such as elderly or lower-educated individuals.

Second, in this research we found that respondents preferred the municipal website over the register. We assume this finding is related to the nature of local governments as being close to citizens. I recommend to include key components of the register into the municipal website, in addition to clearly communicating about this information.

Third, the register aims to provide transparency to citizens by focusing on accessibility, but it fails in supporting understanding of algorithmic decision-making. Two approaches can be taken to improving said explainability. The first focuses on the register itself, the second will be discussed in the next policy-maker recommendation. Improving explainability in the register requires more attention towards understandable summaries, visual explanations and concrete use cases. Policy-makers should ensure that citizens can understand which data is used, how decisions are made, and how fairness is assessed.

Fourth, embed transparency into government services, not just registers. Transparency efforts in their current form can be perceived as passive and performative rather than functional. I recommend to incorporate algorithmic transparency into everyday interactions. When someone receives a decision made with an automated system, it should be clear to said citizen that an automated system was used. Furthermore, the decision needs to be explained in an understandable way – allowing the receiver to challenge the decision if it was made improperly.

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A. Overview algorithm register

General information

Variable	Explanation
Name	The name used to identify the algorithm;
Organizations	The full name of the organization in which the algorithm is used;
Short description	A short description on how the algorithm is used;
(self-) learning?	Non-self-learning: human decides which rules to follow Self-learning: The algorithm 'learns' and improves itself;
Policy terrain	The policy terrain in which the algorithm is used;
Status	Defined as: in development, being used, no longer used;
Starting date	Month in which the algorithm became operational;
Contact information	Contact information of the organizations using the algorithm;

Responsible usage

Variable	Explanation
Goal and impact	The goal for which the algorithm was developed and the degree of impact the algorithm has on people or companies;
Considerations	An evaluation of the pros and cons and an explanation of why usage of this algorithm is reasonably justified;
Human interference	A description of how results from this algorithm are used by humans, how they are evaluated, and how they can be changed if necessary;
Risk management	An overview of the identified risks and how these can be mitigated;
Legal basis	The legal base for the process in which the algorithm is employed;
Impact test	To define impact, which tests were used? Examples are: The data protection impact assessment (DPIA) or Human rights and algorithms impact assessment (IAMA);

Technical operation

Variable	Explanation
Type of data	An overview of the type of data used by the algorithm or was used to create the algorithm.
Supplier	The name of the (external) supplier of the algorithm.

B. Survey question

Introduction:

Fijn dat u wilt meedoen aan deze vragenlijst over algoritmen! De gemeente Enschede is benieuwd naar uw mening over algoritmen en het gebruik daarvan door de gemeente. We stellen u eerst enkele algemene vragen. Daarna krijgt u uitleg over de begrippen en volgen nog een aantal vragen.

Uw gegevens worden anoniem behandeld. Uw antwoorden zijn dus niet naar u te herleiden, tenzij u uw gegevens deelt in de open antwoorden Vult u bij een open antwoord persoons- of contactgegevens in, dan geeft u ons toestemming om deze met de gemeente Enschede te delen

ALGORITMEN ALGEMEEN

V1 **Hoe bekend bent u met algoritmen?**

- Zeer onbekend: ik weet niet wat algoritmen zijn
- Onbekend: ik heb er wel eens van gehoord, maar weet er verder weinig van
- Neutraal: ik weet ongeveer wat algoritmen zijn maar heb er geen ervaring mee
- Bekend: Ik weet goed wat algoritmen zijn en heb er enige praktische ervaring mee
- Zeer bekend: Ik heb uitgebreide kennis van en ervaring met algoritmen

Wat is een algoritme?
Een algoritme is een soort instructieboekje voor de computer. Het vertelt de computer precies wat hij moet doen om een bepaalde taak uit te voeren. Hierdoor kan de computer een taak zelf uitvoeren. De definitie van een algoritme is een verzameling van regels en instructies die een computer automatisch volgt bij het maken van berekeningen om een probleem op te lossen of een vraag te beantwoorden.

Deze worden bijvoorbeeld gebruikt om:

- Te bepalen of iemand in aanmerking komt voor een parkeervergunning aan de hand van ingevulde informatie;
- Te bepalen of en hoeveel huurtoeslag iemand ontvangt aan de hand van financiële informatie;
- Automatische chatrobots op een website die vragen kunnen beantwoorden of helpen met aanvragen.

TOEPASSING ALGORITMEN

U heeft net gelezen wat algoritmen precies zijn. De volgende vragen gaan over uw mening over algoritmen en het gebruik van algoritmen.

V2 **In welke mate maakt u zich in het algemeen zorgen over het gebruik van algoritmen?**

- o Helemaal geen zorgen
- o Weinig zorgen
- o Neutraal
- o Enige zorgen
- o Veel zorgen
- o Weet ik niet

V3 **In hoeverre maakt u zich zorgen over dat gemeenten niet open zijn over de algoritmen die zij gebruiken?**

- o Helemaal niet belangrijk
- o Niet belangrijk
- o Neutraal
- o Belangrijk
- o Heel belangrijk
- o Weet ik niet

V4 **Denkt u dat de gemeente Enschede al gebruik maakt van algoritmen?**

- o Ja
- o Nee
- o Weet ik niet
- o Wil ik niet zeggen

V5 **Waarom denkt u dit?**

V6 **Wat zou u ervan vinden als de gemeente Enschede algoritmen gebruikt in de volgende situaties? (matrix)**

Sterk op tegen Op tegen Neutraal Voor Helemaal voor

Bepalen of iemand een parkeervergunning krijgt

Berekenen of iemand huurtoeslag krijgt en hoeveel

Parkeercontroles automatisch uitvoeren, bijvoorbeeld met slimme auto's die kentekens kunnen lezen

Het maken van beleid, bijvoorbeeld door op basis van historische gegevens te bepalen waar in de stad extra controle door handhaving nodig is

De persoonlijke gegevens van burgers uit bestanden halen, zodat de bestanden openbaar gemaakt kunnen worden.

Inschatten wat de kans is dat iemand fraude pleegt, bijvoorbeeld iemand die werkt in de bijstand

INFORMEREN ALGORITME GEBRUIK

De volgende vragen gaan over de openheid van de gemeente Enschede over het gebruik van algoritmen.

V7 **In hoeverre vindt u dat de gemeente Enschede open is over het gebruik van algoritmen?**

- o Helemaal niet belangrijk
- o Niet belangrijk
- o Neutraal
- o Belangrijk
- o Heel belangrijk
- o Weet ik niet

V8 **Hoe belangrijk vindt u het om te weten hoe een algoritme binnen de gemeente Enschede tot een beslissing is gekomen?**

- o Helemaal niet belangrijk
- o Niet belangrijk
- o Neutraal
- o Belangrijk
- o Heel belangrijk
- o Weet ik niet

V9 **Hoe belangrijk vindt u het om te weten hoe een medewerker van de gemeente Enschede tot een beslissing is gekomen?**

- o Helemaal niet belangrijk
- o Niet belangrijk
- o Neutraal
- o Belangrijk
- o Heel belangrijk
- o Weet ik niet

V10 **Hoe belangrijk vindt u het dat u informatie krijgt over welke algoritmen de gemeente gebruikt?**

- Helemaal niet belangrijk
- Niet belangrijk
- Neutraal
- Belangrijk
- Heel belangrijk
- Weet ik niet

V11 **Wat vindt u belangrijk om te weten van een algoritme dat door de gemeente Enschede wordt gebruikt? Plaats onderstaande antwoorden van meest belangrijk tot minst belangrijk**

- Doel van het gebruik
- Informatie waar een algoritme mee werkt
- Voordelen van het gebruik van algoritmen
- Uit welke regels een algoritme bestaat
- Hoe en waar ik bezwaar kan maken tegen het gebruik van algoritmen
- Hoe een beslissing genomen wordt door een algoritme

ALGORITMEREGISTER

V12 Bent u bekend met het algoritmeregister?

- Ja
- Nee
- Weet ik niet
- Wil ik niet zeggen

Vanuit de Nederlandse overheid is het 'algoritmeregister' opgezet. Dit is een website waarop u informatie kan vinden over alle algoritmen die ingezet worden door verschillende overheidsorganisaties. Op dit moment is het register nog niet verplicht, dus hij is op dit moment niet volledig. Maar in de toekomst kan u hier een overzicht vinden van de verschillende algoritmen die door gemeente Enschede en andere overheidsorganisaties gebruikt worden.

Van deze algoritmen kunt u dan bijvoorbeeld lezen wat het doel is, hoe zij gebruikt worden, wat voor impact zij kunnen hebben op u en welk type informatie zij gebruiken.

Als u meer wilt weten over het algoritmeregister, kunt u daarover lezen op de website van het algoritmeregister.

U heeft zojuist een toelichting over het algoritmeregister gelezen. Nu volgen er enkele vragen over het algoritmeregister.

V13 **In hoeverre bent u het eens met de volgende stellingen?**
Helemaal eens eens neutraal oneens helemaal oneens
Het is goed dat het algoritmeregister bestaat
Het algoritmeregister versterkt een gevoel van openheid

V14 **Wat vindt u belangrijk om te weten over een algoritme dat door de gemeente Enschede of een ander onderdeel van de overheid gebruikt wordt?**

- Open vraag

V15 **Welke van onderstaande kanalen vindt u geschikt voor de gemeente Enschede om meer open te kunnen zijn over algoritmen die zij gebruikt? Schaal ieder kanaal van zeer ongeschikt tot zeer geschikt.**

- Algoritmeregister gebruiken
- Informatie delen via sociale media
- Het delen van informatie via de website van de gemeente
- Inwoners informeren door brieven

V16 **Wilt u de vorige vraag toelichten? Zijn er wellicht andere kanalen die u geschikt vindt voor de gemeente om meer open te zijn over algoritmen die zij gebruikt? (niet verplicht)**

V17 **Wat is uw hoogst afgerond opleiding?**

- Lagere school/ basisonderwijs/ geen onderwijs
- Vmbo/ mavo
- Havo/ vwo
- Middelbaar beroepsonderwijs (mbo)
- Middelbaar beroepsonderwijs (hbo)
- Wetenschappelijk onderwijs (universiteit)
- Wil ik niet zeggen

V18 **Geslacht**

- Man
- Vrouw
- Overig
- Wil ik niet zeggen

V19 **Leeftijdscategorie**

- Tot 30
- 30 – 44
- 45 – 59
- 60+
- Wil ik niet zeggen

V20 **In welke wijk woont u?**

C. Interview Script

Category	Guideline
Introduction	Hello! First of all, I want to thank you for taking the time to fill in our survey and speficially for leaving behind your email adress for further research. As I've already mentioned in my email to you, we are researching algorithmic transparency where our specific point of focus is how citizens of Enschede perceive this and how they would wish to be informed. This interview is about your personal perceptions and experiences, as such it is important that you freely share your thoughts. There are no wrong answers here. We will start this interview with several background questions, after which we slowly move into more topic specific questions. Everything we discuss during this interview will be kept strictly confidential and information which can trace back to you as a person will be anonymized. To ensure we can focus on our conversation, without missing any information I would like to record this session, is that okay for you? I will start the recording now.
Background info Casual way of exploring background Education factor Out of interest: why did they want to be contacted for further research. Establishing the respondent's level of 'experience' with local government	To begin with, I would like to ask you some questions regarding your background. 1. Can you tell me a bit about yourself? are you currently working, studying, retired or something else? 2. What is your highest level of education? 3. What made you fill in your e-mail address for a follow-up interview? 4. Do you often interact with local government services, either online or offline?
Interview portion Familiarity Further questions available to provide more context. Familiarity, and feels like a good way to get talking	From here on we will specifically focus on algorithms and transparency in relation to using these. 1. Based on your understanding, what are algorithms? a. How did you come to that understanding? b. Could you further elaborate on that? c. If AI/algorithms are mentioned separately --> how do you deviate between the two? 2. What do you think of organizations using algorithms? a. If answer refers to private org: what about public org? b. If positive: do you know where your positive view stems from? c. If negative: do you know where your negative view stems from?

Register, transparency and 'importance' of register	3. In your opinion, how important is it to have an overview of all the algorithms used by a municipality, and what are the reasons behind your view?
Register, transparency, factors of transparency	4. What type of information would you expect to find in such a register for it to enhance your feeling of transparency?
Register, factors of transparency	5. Do you think the algorithm register should include information on how algorithms are tested for fairness or bias? Why do you feel that way?
Register, transparency, data transparency	6. In your opinion, how important is it for the register to include details about the types of data it uses, and why?
Menselijke maat	7. How important is it for you to understand how the algorithms handle individual who don't fit typical profiles, and why?
Accessibility	8. How important is it for you to know what and how algorithms/AI systems are used by the municipality? Why do you feel that this is important?
Explainability	9. How important is it for you to understand how decisions are made using algorithms in use by the municipality? Why do you feel that this is important?
Closing remarks	That concludes the final question from my side. Is there anything else you would like to add or are there any closing remarks from your side? Thank you for taking the time to fill in the survey and allowing us to invite you for this interview.

D. Survey results overview

V1 | Question: How familiar are you with algorithms? | Total N = 946

Answer	N	Percentage
Not at all familiar: I don't know what algorithms are	61	6
Somewhat familiar: I know the word but don't know what it means	107	11
Neutral: I think I know what algorithms are, but I don't deal with them	380	40
Familiar: I know what algorithms are and I have practical experience	326	34
Well-known: I have advanced knowledge and experience	72	8
Total:	**946**	**100**

V2 | Question: to what extent do you worry about the use of algorithms | Total N = 928

Answer	N	Percentage
Not at all worried	40	4
Slightly worried	174	19
Neutral	167	18
Very worried	376	41
Extremely worried	155	17
I don't know	16	2
Total	**928**	**100**

V3 | Question: To what extent do you worry about the municipality not being open about the algorithms they use | Total N = 921

Answer	N	Percentage
Not at all worried	30	3
Slightly worried	147	16
Neutral	178	19
Very worried	340	37
Extremely worried	194	21
I don't know	32	3
Total	**921**	**100**

V4 | Question: Do you think the municipality already uses algorithms? | Total N = 915

Answer	N	Percentage
Yes	712	78
No	7	1
I don't know	195	21
I don't want to say	1	0
Total	**915**	**100**

V5 | Building on question V4, why do you believe this? --> open question

V6 | Question: what is your opinion about using algorithms in these situations? | Total N = 878

6.1 Determining whether someone gets a parking permit

Answer	N	Percentage
Strongly against	54	6
Against	162	18
Neutral	258	29
In favor	281	32
Strongly in favor	95	11
I don't know	28	3
Total	**878**	**100**

6.2 calculating whether someone gets rent benefit and how much

Answer	N	Percentage
Strongly against	83	9
Against	211	24
Neutral	183	21
In favor	280	32
Strongly in favor	91	10
I don't know	30	3
Total	**878**	**100**

6.3 automatic parking controls

Answer	N	Percentage
Strongly against	85	10
Against	137	16
Neutral	198	23
In favor	299	34
Strongly in favor	144	16
I don't know	15	2
Total	**878**	**100**

6.4 Policymaking

Answer	N	Percentage
Strongly against	66	8
Against	156	18
Neutral	209	24
In favor	318	36
Strongly in favor	111	13
I don't know	18	2
Total	**878**	**100**

6.5 Taking the personal data out of documents, so these documents can be made public

Answer	N	Percentage
Strongly against	230	26
Against	283	32
Neutral	161	18
In favor	119	14
Strongly in favor	47	5
I don't know	38	4
Total	**878**	**100**

6.6 Risk for Fraud Calculations

Answer	N	Percentage
Strongly against	213	24
Against	242	28
Neutral	165	19
In favor	150	17
Strongly in favor	81	9
I don't know	27	3
Total	**878**	**100**

V7 | Question: To what extent is the municipality of Enschede open about algorithm usage according to you | Total N = 873

Answer	N	Percentage
Not at all transparent	68	8
Barely transparent	182	21
Neutral	205	23
Slightly transparent	44	5
Fully transparent	16	2
I don't know	358	41
Total	**873**	**100**

V8 | Question: How important is it for you to understand how an algorithm came to a decision| Total N = 871

Answer	N	Percentage
Not at all important	4	0
Not important	20	2
Neutral	101	12
important	421	48
Very important	300	34
Don't know	25	3
Total	**871**	**100**

V9 | Question: How important is it for you to know how a public servant from the municipality came to a decision? | Total N = 869

Answer	N	Percentage
Not at all important	2	0
Not important	14	2
Neutral	59	7
important	413	48
Very important	372	43
Don't know	9	1
Total	**869**	**100**

V10 | Question: How important is it for you to know what algorithms the municipality uses? | Total N = 867

Answer	N	Percentage
Not at all important	4	0
Not important	24	3
Neutral	135	16
important	410	47
Very important	278	32
Don't know	16	2
Total	**867**	**100**

V11 | Question: Ranking from top to bottom, what are the most important things you want to know about an algorithm? | Total N = 852

Answer	.	Rank based on average
How the algorithm came to its decision	2.683	1
The goal of the algorithm	2.721	2
Information used by the algorithm	3.016	3
Out of which rules the algorithm consists	3.707	4
How and where objection to a decision can be made	4.249	5
Benefits of using said algorithm	4.624	6

V12 | Question: have you ever heard of the algorithm register? | Total N = 852

Answer	N	Percentage
Yes	103	12
No	713	84
Don't know	34	4
Don't want to answer	2	0
Total	**867**	**100**

V13| Question: to what extent do you agree with the following statements? | Total N = 844

13.1 It is good that the algorithm register exists?

Answer	N	Percentage
Completely agree	340	40
Somewhat agreeable	309	37
Neutral	135	16
Disagree	22	3
Completely disagree	10	1
Don't know	28	3
Totals	**844**	**100**

13.2 The algorithm register increases my transparency perception

Answer	N	Percentage
Completely agree	157	19
Somewhat agreeable	344	41
Neutral	200	24
Disagree	79	9
Completely disagree	32	4
Don't know	21	4
Totals	**844**	**100**

V14: What is important for you to know about an algorithm being used by the municipality or another governmental organization? --> Open question

V15 Which of the channels below are suitable for communicating about algorithms? | Total N = 824

15.1 Algorithm register

Answer	N	Percentage
Very unsuitable	17	2
Unsuitable	32	4
Neutral	173	21
Suitable	300	36
Very suitable	253	31
Don't know	49	6
Totals	**824**	**100**

15.2 Sharing information on social media

Answer	N	Percentage
Very unsuitable	93	11
Unsuitable	187	23
Neutral	197	24
Suitable	235	29
Very suitable	84	10
Don't know	28	3
Totals	**824**	**100**

15.3 Sharing information on the website

Answer	N	Percentage
Very unsuitable	11	1
Unsuitable	27	3
Neutral	84	10
Suitable	386	47
Very suitable	296	36
Don't know	20	2
Totals	**824**	**100**

15.4 Informing citizens through letters

Answer	N	Percentage
Very unsuitable	38	5
Unsuitable	93	11
Neutral	188	23
Suitable	289	35
Very suitable	193	23
Don't know	23	3
Totals	824	100

V16: Any additional comments on the previous question, are there other ways you would wish to be informed or any comments about the suggestions mentioned? --> Open question

V17: What is the highest level of education you achieved? | Total N = 873

Answer	N	Percentage
lower education/ primary school/ no education	5	0,6%
Vmbo / mavo	62	7,7
Havo / vwo	49	6,1
mbo	159	19,7
HBO	327	40,5
Universiteit	205	25,4
Total	**807**	**100**

Excluding those who answered: do not know (-16)

V18: What is your gender? | Total N = 946

Answer	N	Percentage
Male	591	62,5
Female	350	37,0
Other / don't want to say	5	0,5
Total	**946**	**100**

V19: What is your age category? | Total N = 946

Answer	N	Percentage
18 to 29	42	4
30 - 44	99	10
45 - 58	228	24
60+	574	61
Don't want to say	3	0
Total	**946**	**100**

E. Coding scheme open-ended questions

Theme	**Subcategory**	**Description**	#
Accessibility factors	Human check	Does the algorithm involve a human check	54
	The goal of the algorithm	What are the goals that are achieved with the algorithm	46
	Algorithm presence	Are algorithms or AI present	32
	Why is an algorithm used	Arguments for why an algorithm is used	22
	Source code	A group of instructions a programmer writes using computer programming languages	10
	Responsibility	Where does the responsibility for the algorithm lie within the organization	5
	Rules and regulations	Which rules and regulations does the algorithm fall under	2
	Developer	Who developed the algorithm	2
Explainability factors	Which data led to the decision	When an algorithm makes a decision about an individual. Which data led to said decision.	54
	Decision process	Which steps led to the decision made by the algorithm	38
	Procedural fairness	Factors relevant to knowing how a procedure went.	37
	Significant variable	Which variables were the most significant in decision-making?	19
Algorithmic aversion	Lack of tailored	Fear of a strict process allowing no leeway for non-standard individuals	47
	Risk for bias	Biased decision-making rules	32
	Controversy	Recent controversies in relation to algorithms negatively impacting citizen perception	26
	Privacy Rights	Fear of privacy violations through: illegal data, data being interconnected without approval, and other relevant	28
	Biased data	Fear for biased discriminatory datasets	20
	General distrust	General distrust through factors outside of the municipalities reach	14
	Lack of human contact	Citizens fear that there will no longer be a possibility for human contact	14
General factors	Expertise	Training of public servants	21
	Independent auditor	Evaluation should lie with an external organization	12

F. Interview invitation

Beste [Naam]

Recent heeft u een enquête ingevuld van Kennispunt Twente over het gebruik van algoritmen door de gemeente Enschede. Aan het einde van deze enquête heeft u uw contactgegeven achtergelaten en aangegeven open te staan voor vervolgonderzoek, vandaar deze mail.

Graag wil ik u uitnodigen voor een kort interview van ongeveer 20 minuten. Tijdens dit interview gaan we in gesprek over enkele onderwerpen uit de enquête. Dit gesprek is voor ons erg waardevol, omdat we zo de resultaten beter kunnen begrijpen en zo beter beleid kunnen schrijven.

Hieronder vindt u enkele momenten waarop ik beschikbaar ben voor dit interview. Zou u mij 2-3 momenten kunnen sturen die u uitkomen?

Voor het interview kunnen we fysiek afspreken op het stadhuis, of we kunnen online via bijvoorbeeld teams bellen.

- Dinsdag 29 november 12:00 – 18:00
- Woensdag 30 november 12:00 – 18:00
- Donderdag 31 november 12:00 – 18:00
- Woensdag 6 november 09:00 – 18:00
- Vrijdag 8 november 09:00 – 16:00
- Dinsdag 12 november 09:00 – 18:00
- Woensdag 13 november 09:00 – 18:00

Alvast bedankt,

Met vriendelijke groet,

Tristan van Haaren