Hybrid Data Competencies

Identifying required competencies for data-driven decision-making in local governments

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Abstract

New technologies such as Big Data Analytics and the Internet of Things hold the promise of providing new insights that can potentially improve decision-making of local governments. However, in practice there seem to be few examples of this actually happening. Academic literature suggests an impediment to its widespread adoption revolves around a lack of existence of appropriate human competencies in local governments. However, what these competencies exactly are has not been identified so far. This study fills this gap by identifying the competencies that are required in the process of data-driven decision-making (DDDM) in local governments. It does so by first developing a preliminary theoretical model, which is used as the basis for studying how DDDM processes take place in practice in a 'typical' local government in the Netherlands. A combination of twelve expert interviews and twenty-two Behavioral Event Interviews (BEIs) provide the empirical data of this study. Based on the analysis of this, this study finds that the DDDM process as observed in the case is hybrid. It is a combination of the rationalities of 'traditional' decision-making and of 'pure' data-driven decision-making. Building on this finding, the competencies identified as required in this process are also hybrid. They are a combination of traditional and new competencies that should be connected in different phases in the process of DDDM by local governments. This will help them exploit the possibilities data offers in a responsible way. This is important in today's society in which the influence of new technologies will only increase.

List of abbreviations

AI	Artificial Intelligence
BDA	Big Data Analytics
CBS	Central Bureau of Statistics
DDDM	Data-driven decision-making
IoT	Internet of Things
NIBUD	National Institute for Budget advising
RE	Respondent Expert
RG	Respondent Gouda
SCP	Netherlands Institute for Social Research
VUCA	Volatile, Uncertain, Complex, and Ambiguous

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1. Introduction

In today's digitalizing and datafying society (Kitchin, 2014; Mayer-Schönberger & Cukier, 2013; Van Dijck, 2014), new technological developments such as Big Data Analytics (BDA) and the Internet of Things (IoT) are accompanied by ambitions of better governance. Following the private sector, the public sector has begun to derive insight from fast growing amounts of data sources, to help support decision-making (Choi, Lee, & Irani, 2018). The promise is that this enables not only analysis of what has happened in the past, but also to predict what will possibly happen in the future. This potentially makes these technologies invaluable for public decision-making (Van der Voort, Klievink, Arnaboldi, & Meijer, 2019). Governments thus hope that improved insights based on data can lead to different, faster, more supported, more precise and cheaper decisions than 'traditional' decisions based on experience and intuition (Berner, Graupner, & Maedche, 2014; McAfee & Jolfsson, 2017; OECD, 2017). This decision-making based on the analysis of data rather than on intuition is referred to as 'data-driven' decision-making (DDDM) (Provost & Fawcett, 2013, p. 53).

1.1 Data-driven decision-making in local governments

Although DDDM is regarded as a promising development for all kinds of governmental organizations, especially local governments perceive it as an opportunity to improve decision-making. According to Meijer (2015), that is because specifically at the level of cities, the influence of data and new technologies can be of great importance. All aspects of the city and urban life can be captured in data, potentially transforming cities into a 'smart city' (Meijer & Bolívar, 2016). Smart city technologies include smart grids, sensor networks, smart parking, smart lighting, city dashboards and real-time information apps (Coletta & Kitchin, 2017, p. 2). Local governments can use these technologies with the aim of improving decisions and thereby policy and services (Meijer, 2015, p. 10).

However, the abundance of data has thus far not led to the improvements that one would have expected (Höchtl, Parycek, & Schöllhammer, 2016, p. 150). Although the talk of data-driven decision-making is now prevalent in many local governments, there are still relatively few examples of data actually being used to shape public policy (Poel, Meyer, & Schroeder, 2018). According to de Bruijn and van der Voort (2016, p. 61), data often does not reach or has an insufficient influence on decision-making or is insufficiently used by public decision-makers (De Bruijn & Van der Voort, 2016, p. 61). Local government use of new technologies in decision-making therefore still seems to be at it's infancy (Desouza & Jacob, 2017).

1.2 Competencies as a challenge to data-driven decision-making

The question is: why is this so? It seems that the mere fact that data and the tools to analyze it are available in itself does not create public value (Klievink, Romijn, Cunningham, & de Bruijn, 2017, p. 279). Literature suggests a reason for this is that besides having the data and the tools to analyze it, governments also need to make sure they have the appropriate human competencies. This currently doesn't seem to be the case (Brown, Chui, & Manyika, 2011; Desouza & Jacob, 2017; Kim, Trimi, & Chung, 2014; Malomo & Sena, 2017). Therefore, an impediment to the widespread usage of data in decision-making in local governments seems to revolves around a lack of existence of appropriate data analytics and resulting competencies (Choi et al., 2018). This only becomes more problematic when the importance of data increases (De Bruijn & Van der Voort, 2016).

Although many studies stress the importance of developing the 'right' competencies in governments in order to exploit new technologies (Brown et al., 2011; Desouza & Jacob, 2017; Kim et al., 2014; Malomo & Sena, 2017), none of them explain what these 'right' competencies actually entail. They don't define them more specifically than 'human', 'technology' and 'data' competencies (Kim et al., 2014) or "skills that allow for the analysis and modeling of complex phenomena" (Malomo & Sena, 2017, p. 17). This means there are currently no studies that have identified and specified the competencies that are required in the process of DDDM in local governments.

1.3 Research question

This study aims to fill this literature gap by conducting an explorative, qualitative study, addressing the following research question: *which competencies are required in the process of data-driven decision-making in local governments?* In order to identify the required competencies, the concept of competencies should first be defined. This is important as there are many definitions of this concept (Winterton, Delamare-Le Deist, & Stringfellow, 2005). Furthermore - as will become clear from this discussion of the concept of competency - this study follows a 'multimethod' approach to identifying competencies (Du Chatenier, Verstegen, Biemans, Mulder, & Omta, 2010; Sandberg, 2000; Winterton et al., 2005). The basic idea of this approach is that in order to identify competencies, the specific work activities or processes in which they are required need to be defined first. In this study, this is the process of DDDM in local governments. The second theoretical sub-question will be used to theoretically define this process, by explaining how DDDM differs from 'traditional' decision-making. Lastly, the relationship between this DDDM and required competencies will be specified by explaining which phases constitute the process of DDDM in local governments and what this means for the competencies required therein. This results in the following theoretical sub-questions:

1. *What are competencies?*
2. *What does the process of data-driven decision-making look like and how does it differ from 'traditional' decision-making?*
3. *What is the relationship between data-driven decision-making and required competencies?*

The result of answering these three theoretical sub-questions is the development of a preliminary theoretical model of required competencies in the process of DDDM in local governments. I develop this model by combining the Knowledge Pyramid of Ackoff (1989) with the phase model of Teisman (2000). The reason I develop this model is that thus far, no model of DDDM as it takes place in local governments in practice has been developed. The model forms the basis for studying the competencies that are required in this process. I empirically identify these competencies using the following empirical sub-questions:

4. *To what extent does the theoretically defined data-driven decision-making process actually take place in practice?*
5. *Which competencies are required in the data-driven decision-making process as it actually takes place in practice?*

1.4 Study design

The case focused on in this study is the local government of Gouda in the Netherlands. Gouda can be considered a 'typical' case, as it is a medium-sized, urban local government that has recently started to experiment with DDDM. In the Netherlands, large, urban local governments are front-runners in DDDM (Evers, Haagoort, & Wesseling, 2017). They often have the time and money to invest in data labs (VNG Realisatie, 2019). However, these frontrunners are usually the exception in terms of development. As discussed before, most local governments are still at the early stages of adoption of data-driven decision-making (Desouza & Jacob, 2017; Malomo & Sena, 2017; Poel et al., 2018). Gouda can therefore considered to be in a 'normal' or 'average' position when it comes to data-driven decision-making in local governments, and is thus a 'typical case' (Ritchie & Lewis, 2003).

In this study, I do not aim to find out what competencies civil servants 'should' possess in DDDM based on the possibilities new technologies offer in theory. As explained, studies taking this approach thus far (Brown et al., 2011; Desouza & Jacob, 2017; Kim et al., 2014; Malomo & Sena, 2017) have not been able to sufficiently specify required competencies. I therefore take a different approach. I ground this study in the reality of DDDM rather than in an abstract model of what it should be and which competencies it should need (Cheng, Dainty, & Moore, 2005). The empirical data are obtained using the competency study method of Spencer & Spencer (1993). This method fits the idea of identifying competencies based on actual practices. Moreover, this method is considered the most scientifically rigorous approach for identifying competencies (Getha-Taylor, 2008).

1.5 Relevance

The specific research topic and research methods employed in this study contribute to public administration literature and practice in several important ways. First, this study specifically distances itself from other, more abstract studies on required competencies in DDDM, by grounding it in the reality of this process instead of in theoretical presumptions. This provides new insights into how the process of DDDM actually takes place in practice in an average local government. Second, in this study I develop a preliminary theoretical model of required competencies in the process of DDDM in local governments. Such a model has not been developed in public administration literature thus far. It is therefore not only theoretically significant, but it also provides a heuristic that can be used by practitioners - other (local) governmental organizations - to identify the competencies that are required in DDDM processes as they take place in their organization. Third, this study is one of the first academic studies that identifies which competencies are required in the process of DDDM in local governments. It thereby contributes to filling this existing gap in academic literature. Fourth, the empirical verification of the competencies required in DDDM can inform current human resource management practices of local governments, including hiring, training, and rewarding of local governmental employees (Getha-Taylor, 2008, p. 105).

2. Theoretical framework

In this chapter, the three theoretical sub-questions as posed in the introduction will be answered. First, I will elaborate on competency theory. I will position myself towards theoretical approaches to studying competencies and theories on the definition of the term competency. Furthermore, I will describe adjacent theoretical frameworks of competencies that I use as guiding concepts in identifying and defining competencies in this study. Second, I will elaborate upon the process for which the competencies are required: data-driven decision-making in local governments. I will do so by explaining new technologies that enable DDDM and by comparing this to 'traditional' decision-making. Third, using these insights, I will combine the competency and DDDM theories to develop a preliminary theoretical model of required competencies in DDDM in local governments. For this, I built on the knowledge pyramid of Ackoff (1989) and the phase model of Teisman (2000).

2.1 Competency

This section takes up the first theoretical question: what are competencies?

2.1.1 Defining competency

According to Winterton (2005, p. 12), "there is such confusion and debate concerning the concept of 'competency' that it is impossible to identify or impute a coherent theory or to arrive at a definition capable of accommodating and reconciling all the different ways that the term is used." Based on this statement, in this section I do not aim to provide a comprehensive overview of all the possible definitions of competencies and to approaches to study it. I will simply explain which definition of competency I follow and why I do so.

For identifying competency, I follow the work of Getha-Taylor (2008) on collaborative competencies in governmental organizations. Her study is one of the most cited studies on competencies that is specifically tailored to governmental organizations. I use the same definitions of competency as her, and the same method to empirically study competencies (which will be explained in the third chapter: methods).

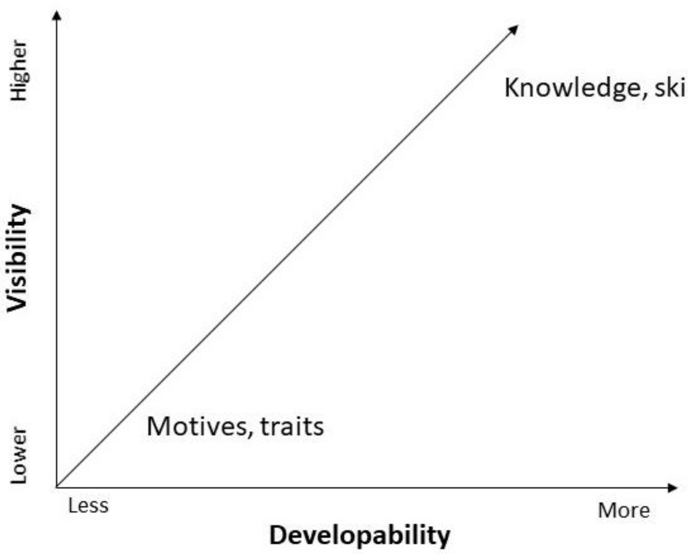
According to Getha-Taylor (2008, p. 105) "the empirical study of competencies originated with David McClelland's pioneering article in American Psychologist in 1973. This article began a movement that argued that exams and IQ tests, then the standards of hiring, were useless in predicting job success. Competencies were suggested as another means to predict success in the workplace." Mcclelland's (1973) work took hold among organizational psychologists, who have been finetuning the competency identification method ever since (Getha-Taylor, 2008). Building on the work of McClelland, Boyatzis (1982, p. 21) first defined the term competency as "an underlying characteristic of an individual which is causally related to effective or superior performance in a job." While other definitions exist, they essentially build on or borrow from Boyatzis (Thompson, Stuart, & Lindsay, 1996). This definition of competency expands beyond the 'traditional' HR focus on knowledge and skills, to include motives and traits that influence performance (Getha-Taylor, 2008; Groeneveld, Steijn, & Van der Parre, 2009). In this sense, the term competency is a generic umbrella term for knowledge, skills, trait and motive competencies (Caldwell, 2008). Below, the difference between these various types of competencies and the relationship between them will be outlined.

Knowledge is the result of an interaction between intelligence (capacity to learn) and situation (opportunity to learn). Knowledge includes underpinning theory and concepts, as well as tacit knowledge gained as a result of the experience of performing certain tasks (Winterton et al., 2005). *Skill* usually refers to a level of performance, in the sense of accuracy and speed in performing particular tasks ('skilled performance'). Skills develop over time with practice and are goal-directed in response to some demand in the external environment (Winterton et al., 2005, p. 12). *Motives* are the things a person consistently thinks about or wants, which causes action. Motives drive, direct and select behavior toward certain actions or goals and away from others. *Traits* are physical characteristics and consistent responses to situations (Spencer & Spencer, 1993, pp. 9-11).

2.1.2 Developability of competencies

According to Spencer & Spencer (1993), all of the terms above together form competency. *Knowledge* and *skill* competencies tend to be visible and relatively surface characteristics of people and therefore easier to develop. *Motives* and *traits* competencies are more hidden and more central to a person's personality, and therefore more difficult to assess and develop (Spencer & Spencer, 1993). Figure 1 represents the relationship between the visibility of a competency and its developability (the extent to which it is easy or hard to develop).

Figure 1: Relationship between visibility of a competency and it's developability, based on Spencer & Spencer (1993).



Because of this gradation of developability of competencies, competencies can serve as the foundation for hiring, training, and developing employees (Getha-Taylor, 2008). Based on Figure 1, it can be concluded that if certain work activities or processes require certain motive or trait competencies, these will be harder to develop. It is thus better to hire employees that already possess these competencies to perform this work process. If a work process requires knowledge or skill competencies, these can be developed amongst employees.

2.1.4 Approach to identifying competencies

Now that the term competency is defined, it is important to position this study towards approaches to identifying competencies in practice. According to Winterton (2005), the identification of competency is generally centered on job analysis. Within this tradition, a well-known distinction of competency identification approaches is made by Sandberg (2000): worker-oriented; work-oriented; and multimethod-oriented.

Within the worker-oriented approach, competency is primarily seen as constituted by attributes possessed by individual workers. The definition of Boyatzis (1982) fits within this approach. The component attributes are identified through investigation of job incumbents and supervisors, usually quantified and then correlated to job performance. In this approach, competencies are thus not identified in relation to specific work activities or processes, but defined in generic, context-independent terms. The advantage of this approach is that competencies can be assessed and linked to performance, which enabled pinpointing the competencies that should be developed in order to improve performance. The downside is that these competencies are often regarded as too generic and too context-independent.

The second, work-oriented approach "takes work as the starting point, identifies work activities that are central to a particular job role and then identifies the personal attributes required to achieve appropriate outcomes. This is the approach most often adopted in considering strategic or distinctive firm competences underpinning competitive advantage." (Winterton et. al, 2005, p. 22). The result of this approach are competencies defined in very specific, context-dependent terms. The downside of this approach is that it is hard to assess these competencies on an individual level and to link them to performance.

The last approach is the multi-method approach. The approach consists of identifying the activities central for accomplishing specific work, transforming those activities into personal attributes, and identifying competencies (Du Chatenier, Verstegen, Biemans, Mulder, & Omta, 2010, p. 272). This approach thereby resolves the disadvantages of the previous two approaches. It prevents formulating too generic and context-independent competencies by identifying them based on specific work activities or processes. However, it *defines* competencies on an individual level, which enables assessment and development of these competencies. Because of this, "Sandberg argues that 'multimethod-oriented' approaches, which involves aligning personal attributes with work activities, are more adequate for a comprehensive analysis" (Winterton et al., 2005, p. 20).

Because of its comprehensiveness, I follow the latter approach. I first identify the specific work process for which I aim to identify competencies: the process of DDDM in local governments. I then identify the competencies that are required in this process. To do so, I use the competency method of Spencer & Spencer (1993). The core idea of this method is to first 'openly' approach the empirical material to identify competencies, to then link them to what is already known about competencies. For this latter purpose, I use pre-existing competency definitions to give meaning to these inductively identified competencies. The advantage of this is that pre-existing competencies are usually already categorized as knowledge, skills, traits or motives. This enables making statements about the extent to which the identified competencies can be developed, by putting them on the scale presented in Figure 1. This identification process will be further described in the methods chapter below. Now, I move on to describing pre-existing competencies from adjacent studies, that will be used in this study.

2.1.5 Adjacent competency frameworks

Below, I outline two adjacent studies that use generic competency definitions in their frameworks. These studies provide guiding definitions of competencies that are potentially required in the process of DDDM in local governments. These are the '21st century skills' framework (Voogt & Pareja Roblin, 2010, 2012) and the 'competencies of the 21st century public manager' framework (Van der Wal, 2017).

The 21st century skills framework is influential in education and educational research. 21st century skills studies focus on the skills that students in all levels of education need to develop in preparation for their work in today's digitalizing and datafying society (Voogt & Pareja Roblin, 2012). In an extensive literature review, Voogt and Pareja Roblin (2012) analyzed eight widely used frameworks that addressed the rationale, goals, implementation, and assessment of 21st century competences. They state that ultimately the frameworks seem to converge on a common set of 21st century skills: digital literacy, creativity, problem solving, collaborating, communication, citizenship, critical thinking and productivity. All of these are skill competencies (see Table 1).

Although touching upon important new competencies, 21st century skills studies focus specifically on students and their preparation for the job market both for the public and private sector. They are therefore not tailored to civil servants and the specific context of public decision-making. However, public and private organizations and employees are widely believed to differ (Boyne, 2002). This suggests that the specific work context of civil servants should be taken into account. For example, in using data in decision-making, public employees have to ensure they contribute to public value (Bannister & Connolly, 2014), not just to making profit. Also, politics are especially close to local civil servants (Lambooy, 1989), which could impact the competencies they need in data-driven decision-making. This framework thereby does not take the specific context of decision-making in local governments into account.

The focus on the context of public decision-making is provided by Van der Wal (2017). Van der Wal (2017) provides a tentative overview of the main required competencies that characterize 21st century public manager (see Table 1). This is a lesser-known framework, yet specifically tailored to decision-making in public organizations. According to Van der Wal (2017), in the 21st century, networked information society, decision-making is characterized by volatility, uncertainty, complexity, and ambiguousness (VUCA) (Dickinson, 2018). Following Rhodes (2016), Van der Wal (2017) states that in this complex decision-making environment, some traditional competencies remain important, whereas others will become less important and will be replaced when external and internal pressures so dictate. The 21st century public manager thus will have to combine traditional (but still important) and new (increasingly important), sometimes competing competencies depending on the audience, issue and context at hand, in order to be successful and effective. In describing these traditional and new competencies, Van der Wal (2017) makes a distinction between knowledge and skill competencies and motive and trait competencies (see Table 1). In line with the literature on competency developability as discussed above, Van der Wal (2017) states that the first category of competencies (e.g. teamwork, engaging stakeholders) will be relatively easy to develop. The second category of competencies (e.g. innovativeness, entrepreneurialism) will be more difficult to develop.

However, this study of Van der Wal (2017) focuses specifically on public managers and not on civil servants in general. Furthermore, these competencies are focused on general decision-making in the 21st century, not on data-driven decision-making. It is thus again a useful framework as it identifies potentially relevant competencies because of its focus on required competencies in VUCA decision-making environments, but it is not specifically tailored to DDDM in local governments.

To conclude, these two competency frameworks provide definitions of competencies that are potentially relevant in DDDM because of their general focus on work in the 21st century digitalizing and datafying society. However, they are not specifically tailored to civil servants in general, nor to the process of DDDM in local governments. The pre-defined competencies listed in Table 1 are thus used as guiding concepts to give meaning to the competencies that are inductively identified in this study. Table 1 is therefore not used as a framework that will deductively be tested.

Table 1: Overview of 21st century skills, adapted from Voogt & Pareja Roblin (2012) and overview of traditional and new competencies of 21st century public managers, adapted from Van der Wal (2017).

	21st century skills	
Knowledge, skills	Data literacy Creativity Problem solving Collaborating Communication Citizenship	
	Competencies of the 21st century public manager	
	'Traditional' but still necessary	*'New' and increasingly necessary*
Knowledge, skills	Political astuteness Counselling Diplomacy Bargaining Domain expertise	Networking Teamwork Engaging stakeholders Collaborating Customer-orientation IT-saviness (particularly social media literacy and data analytical skills) Design thinking Storytelling (branding, framing) Navigating
Motives, traits	Judgement Prudence Selflessness Humaneness Neutrality	Innovativeness Responsiveness Agility Ingenuity Courage Entrepreneurialism

2.2 The difference between DDDM and traditional decision-making

Now that it is clear what the concept of competency entails, the second theoretical sub-question that will be addressed is: what does the process of data-driven decision-making look like and how does it differ from 'traditional' decision-making?

Using data in decision-making is not new. Governments have been using data in decision-making for decades (Heinrich, 2007; Rieder & Simon, 2016). What is new is the flux of new technological developments, such as the possibility of linking multiple, often real-time, sources trough 'Big Data analytics' (BDA) and the Internet of Things (IoT) (Vetzo, Gerards, & Nehmelman, 2018). In the next section, first, these new technologies and their potential risks are discussed. Second, the difference between policymaking and decision-making will be discussed, followed by how these new technologies impact decision-making.

2.2.1 New technologies for decision-making

The new technological possibilities of BDA and IoT show a high degree of coherence (Vetzo et al., 2018). When it comes to Big Data, there is no agreed academic or industry definition (Floridi, 2014). The most commonly referred to definition includes the so called 'three Vs': Volume, Velocity and Variety (Berner et al., 2014; Kitchin, 2014). There is a multitude (volume) of various data (variety) that can also be processed real-time (velocity) into usable information (Van der Voort & Crompvoets, 2016, p. 4). Big Data is thus more regarded as a combination of characteristics and developments that are present to varying degrees in different datasets, than as a well-defined technology (Vetzo et al., 2018, p. 17). The three V's are what makes Big Data different from 'traditional' data that have been around for a long time, such as periodic population counts (Vetzo et al., 2018). Its value comes from the patterns that can be derived by making connections between pieces of data, about an individual, about individuals in relation to others, about groups of people, or simply about the structure of information itself (boyd & Crawford, 2011). However, Big Data is often considered a poor term. Big Data is less about data that is big than it is about a capacity to search, aggregate, and cross-reference (large) data sets (boyd & Crawford, 2012, p. 663). Indeed, the concept of DDDM includes systematically basing decision-making on data, in which the most important driver is the increasingly automated collection and analysis of data. However, this can also include smaller data files. That is why it is incorrect to use the term 'big data' when studying the process of DDDM in local governments (Wesseling et al., 2018, p. 18). This study will therefore not use the term 'Big Data', but 'data'.

What do these new technologies that enable DDDM entail? First, the Internet of Things (IoT) is the development in which more and more 'everyday' devices or appliances are connected to the internet (Vetzo et al., 2018). Opposed to data that are directly provided by citizens themselves - for example by filling out forms to apply for official documents or governmental subsidies (Leenes, 2016) - in IoT data are obtained indirectly, through for example cameras, or sensors in buildings, cars, and streetlights, that are connected to the internet and automatically transmitted online (Mergel, Rethemeyer, & Isett, 2016). These types of real-time data can be used to form indicators, which are recurrent quantified measures that can be tracked over time to provide information about stasis and change with respect to a particular phenomenon. These trends can be revealed by charting them as graphs or maps, but also by inserting the IoT data into models of various kinds to try to explain present patterns or to simulate and predict what might happen under different circumstances (Kitchin, Lauriault, & McArdle, 2015, pp. 8, 9).

The importance of revealing trends through graphs and figures shows that in using new technologies, visualization is very important. Visualizations (such as graphs, diagrams, and maps) have long been used to summarize and communicate data (Kitchin et al., 2015, p. 10). A 'new' visualization tool that is often used is dashboarding (Wesseling et al., 2018). Dashboards provide a means of collecting and displaying a number of indicators through a common graphic interface, often without users needing to learn how to handle data or use specialist visualization software. Traditionally, dashboards displayed fixed graphics, but more recently they have become more interactive in nature with users being able to interact with the data, changing the mode of display and selecting and querying data (Kitchin et al., 2015).

2.2.2 Responsibility

Using these new technologies in decision-making does not come without risks. Data can be good or bad, better or worse, messy, incomplete, inconsistent and insufficient (Kitchin, 2014; Kitchin et al., 2015). That is because involvement of human actors is indispensable for the proper functioning of data analysis (Vetzo et al., 2018, p. 24). That is not surprising, as technical systems are the solidification of thousands of design decisions (Van den Hoven, 2013, p. 107). Furthermore, human involvement is necessary to interpret the results obtained from data analysis and to assess their relevance and validity (Vetzo et al., 2018, p. 24). In DDDM, many decisions are thus made by humans, making it a far from a value neutral undertaking (Janssen & Kuk, 2016; Van den Hoven, 2013). If outcomes of data analyses are used in a negligent or uncritical way, this can lead to 'unethical' errors in public decision-making (Vetzo et al., 2018).

To address this issue, Van den Hoven (2013, p. 105) states that in any type of innovation that involves technology, there is virtue in making particular values at play explicit, evaluate how their implementation works out in practice, and adjust our thinking accordingly. He therefore advocates 'responsible innovation'. This is defined as innovation which – when implemented – "expands the set of relevant feasible options regarding solving a set of moral problems" (Van den Hoven, 2013, p. 111). In practice it means that responsible innovation should contribute to better solutions of societal challenges. This is done by actively mapping ethical and societal aspects and incorporating them in the design process of an innovation from the onset, for example by determining what the potential impact for stakeholders involved will be. Furthermore, it involves engaging stakeholders in the development process by regularly asking them for feedback and adjusting innovations based on this (NWO-MVI, 2016). According to the most widely definition of stakeholders (Scholl, 2005, p. 743), "a stakeholder in an organization is (by its definition) any group or individual who can affect or is affected by the achievement of the organization's objective" (Freeman, 1984, p. 5). For local governments stakeholders are then any citizen, citizen group, private or public organization that is affected by the local governments objective (De Bruijn, 2003).

In this study, I argue that DDDM should be executed in this responsible manner. If DDDM is to live up to its expectations of *better* decision-making, this *better* should also include responsibility.

2.2.3 The difference between DDDM and 'traditional' decision-making

How do the new technologies - according to academic literature - change decision-making? First, the frequency at which information is obtained changes. Data usage in traditional decision-making often relied on specific periods of collection of data. A serious limitation of this is the risk of outdatedness. Census data, for example, often runs the risk of being out of date at the time they are used in the process of formulating and implementing new policies (Höchtl et al., 2016). The new technological developments as described above enable linking vast amounts of different, real-time data sources. This holds the promise of predicting the present and even the future, which enables extracting trends where none could previously be found (Van der Voort et al., 2019, p. 28). To illustrate this, under the influence of these new technologies, census data could completely change. Through the combination of several databases, census data could be produced on an almost daily, rolling basis instead of being updated only once or twice a decade (Höchtl et al., 2016).

Second, the way in which information is derived from data fundamentally changes. Datasets were originally analyzed with the aim of verifying specific hypotheses or questions formulated beforehand (queries). Interlinked data analysis, on the other hand, is specifically data-driven (Vetzo et al., 2018). The purpose of this is to find relevant patterns and connections in datasets by combining data sources (Janssen & Van den Hoven, 2015, p. 363). In the analysis, large amounts of connections are tested with the aim of distilling relevant information from the data. The knowledge gathered from data analysis is no longer exclusively within the bandwidth of hypotheses drawn up by people, but it is primarily based on what the data itself 'says'. One of the promises of new technologies is therefore that there is less need to look for causal relations between phenomena. The data tells you that something is correlated and that should be 'enough' (De Bruijn & Van der Voort, 2016). From an epistemological point of view, data-driven approaches thus follow the logic of the new experimentalism, in which knowledge is derived from experimental observations, not theory (Van der Aalst, Bichler, & Heinzl, 2017).

Third, the ways in which information is obtained and used in decision-making fundamentally changes. As explained, in data-driven decision-making, decisions are based on the analysis of data rather than purely on intuition (Provost & Fawcett, 2013). According to Rabari and Storper (2015, p. 31), this intuition is traditionally derived by local governments by mixing information from their direct experience with the environment with information derived from their membership in wider social networks that were not necessarily local. Today, ever-larger doses of information are derived from information technologies as opposed to traditional social networks (Rabari & Storper, 2015, p. 31). In DDDM, the analysis of this data is the primary source of the decision to be made, not the experience, intuition and expertise of civil servants (Provost & Fawcett, 2013).

In sum, from the discussion above it becomes clear that in DDDM, (1) the data are used to provide insight into the past, present and future, (2) the data are the starting point of the decision-making process, and (3) the data are the primary source of information to base decisions on. This is different from traditional decision-making in which experience and expertise of civil servants is combined with other sources of information and used to analyze the past, starting from specific questions and problems. Table 2 provides an overview of this difference.

Table 2: Difference between traditional decision-making and data-driven decision-making.

Traditional decision-making	**Data-driven decision-making**
Insight into the past	Insight into the past, present and future
Problem as starting point	Data as starting point
Expertise and experience primary sources of final decision	Data primary source of final decision

2.3 Preliminary model of required competencies in DDDM

The theoretical definition of DDDM as described above enabled distinguishing it from traditional decision-making. However, it is not clear yet what the *process* of DDDM itself looks like. It is necessary to systematically study what DDDM looks like in practice, as this allows employing the multimethod-approach of competency identification. According to this method, the activities actually taking place in the process of DDDM first have to be identified, to then identify which competencies this requires. I therefore formulate a preliminary theoretical framework that enables systematically distinguishing which activities typically constitute the process of public DDDM. Based on this, I can identify the competencies that are required in these activities. In developing this preliminary model, I answer the last theoretical sub-question: what is the relationship between data-driven decision-making and required competencies?

I develop a preliminary theoretical model because there are no studies that have developed a comprehensive model of the process of DDDM in local governments yet. Van der Voort et al. (2019) developed a useful heuristic that enables analysis of how data impacts decision-making of governments, through several theoretical lenses. However, this model doesn't provide insight into the specific activities or steps that form the process of decision-making.

A model that does described steps is developed by Höchtl et al. (2016, p. 148). They discuss the process of decision-making using the policy cycle theory, yet in the light of technology. Hötchl et al. (2016) argue that the distinctive feature of new technologies is the possibility of real-time processing, which enables continuous evaluation in the policy cycle. Thus, Hötchl et al. (2016) propose a revised 'E-policy cycle' in which evaluation does not happen at the end of the process but continuously throughout the process. This opens up the possibility of permanent reiteration, reassessment, and consideration. However, this model assumes the availability of high quality, real-time information for all stages of the policy cycle. As explained, in reality, data is often messy, incorrect and inconsistent. Not surprisingly, for local governments this ideal of real-time evaluation is still far away (Evers et al., 2017; Wesseling et al., 2018). I therefore conclude that the E-policy cycle as a theoretical model is an interesting, yet futuristic model that does not represent the current practice of local governments.

Because of the lack of useful models that can form the basis of the analysis of DDDM in local governments, I will develop such a model in this study. I will do this by combining the well-known Knowledge Pyramid of Ackoff (1989) with the phase model of policymaking of Teisman (2000).

2.3.1 Policymaking and decision-making

Before this model can be developed, it is important to first distinguish between policymaking and decision-making. There are no clear-cut definitions of both concepts and the relationship between them. I follow Lowi (1970), who argues it is essential to distinguish between policymaking and decision-making, because treating policy as though it were synonymous with decision blurs the distinction between the macro and micro level of reality (Lowi, 1970, p. 317). Below, I outline some definitions of policymaking (macro level) and decision-making (micro level) and position myself towards them.

Policymaking

Since the 1950's, there has been an influential strand of research in public administration that describes policymaking as a clear-cut process that can be analyzed (Parsons, 1995, p. 11). The idea of modeling the policy process in terms of stages was first put forward by Lasswell (1956). His model has been successful as a basic framework for the field of policy studies and became the starting point of a variety of typologies of the policy process. Today, the differentiation between agenda-setting, policy formulation, decision-making, implementation, and evaluation (eventually leading to termination) has become the conventional way to describe the chronology of a policy process (Jann & Wegrich, 2007, p. 43). In these policy process models, the focus is on decisions taken by a focal actor (usually a public organization), targeting a specific problem. Attention is paid to this focal actor and the way in which this central actor organizes its own policy processes (Teisman, 2000, p. 952). It therefore provides insight into how a single actor defines policy in terms of problems and solutions, policy adoption, implementation and evaluation.

This rationalistic policy process approach has been criticized by authors that do not agree that policymaking can be described in neat stages. One such influential criticism is that of Lindblom (1980), who states that policymaking is a complex process without a definite beginning or end – "somehow a complex set of forces that together produce effects called 'policies'" (Lindblom, 1980, p 5). According to Teisman (2000, p. 940), because of this criticism, "scholars using the rationalistic policy process approach are aware that empiricism deviates from this, but feel it is worthwhile to reconstruct policymaking as though it was taking place in phases. The phase metaphor allows scientists to develop different theories regarding the various stages" Rationalistic models are therefore useful for systematically describing a policy process under the assumption that this is a simplified representation of reality. I do not follow this rationalistic approach in this narrow sense, but use an alternative approach to policy- and decision-making, which I will explain below.

Decision-making

In the definition of the policy process as a clear-cut process, decision-making is depicted as a single stage within the process. According to Birkland (2011) "the decision-making process begins after an issue or problem is placed on the agenda and makes its way through the legislative process until it comes close to the decision agenda. The decision agenda is that relatively small collection of things about which an organization must make decisions" (Birkland, 2011, p. 253). This idea of decision-making as a single stage has long been disputed by Etzioni (1967). According to him, in the concept of social decision-making, vague commitments of normative and political nature are translated into specific commitments to one or more specific courses of action (Etzioni, 1967, p. 385). These decisions are made by weighing alternatives that are formulated based on information. He argues that rational models such as the policy cycle in which decision-making is depicted as a clear-cut process in which an actor carefully weights its alternatives and chooses amongst them is unrealistic and undesirable. In reality, there is no such thing as clear values and sufficient information in order to make a rational consideration between alternatives. He argues that decision-making is a process of several decisions, referring to it as 'mixed scanning'. He differentiates fundamental decisions from incremental ones: "fundamental decisions are made by exploring the main alternatives the actor sees in view of his conception of his goals, but – unlike what rationalism would indicate – details and specifications are omitted so as that an overview is feasible. Incremental decisions are made but within the context of fundamental decisions (fundamental reviews)" (Etzioni, 1967, pp. 389, 390).

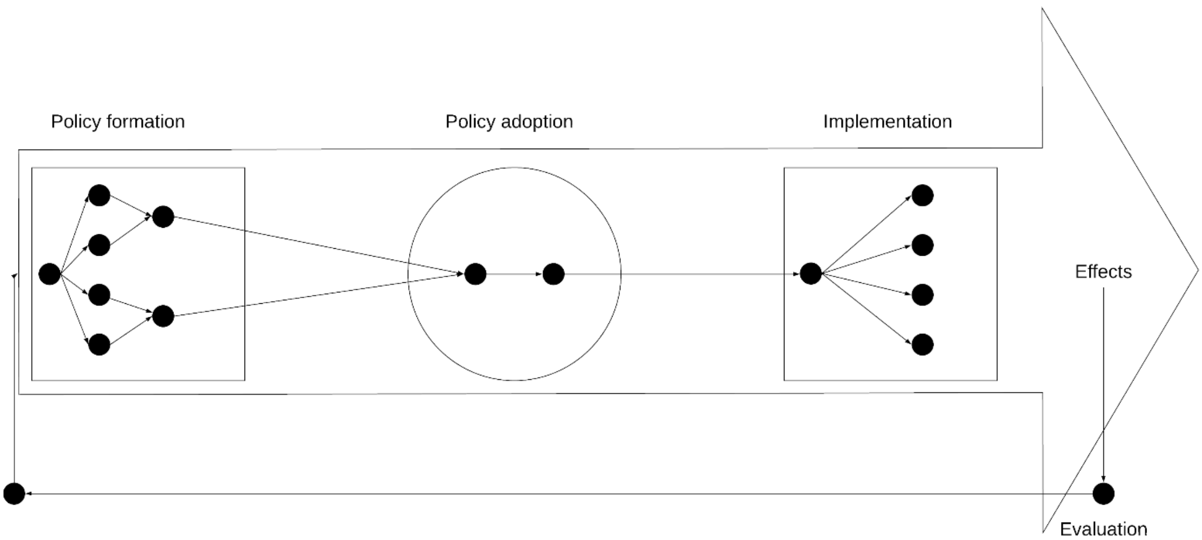
Combining policy and decision-making

I combine the policy process approach with the approach to decision-making of Etzioni (1967) in my approach to decision-making. I argue that decision-making is indeed part of the policy process, however it does not happen only at one stage, but happens several times throughout the whole process. In the following, based on this idea, I develop a preliminary model for required competencies in the process of DDDM processes.

2.3.2 The phase model

The first model I use for the development of the preliminary theoretical model is the so called 'phase model' of Teisman (2000). In line with the rationalistic models as described above, this is a model depicting the policy process of a single focal actor as a clear-cut chain of phases (see Figure 2): policy formation, policy adoption, implementation, and evaluation (Teisman, 2000, p. 940). Even though this model depicts the policy process in a rational way, it does follow the logic of the mixed scanning decision-making approach of Etzioni (1967). Figure 2 shows that within the overarching policy process (depicted by the large arrow), several decisions take place. The black dots in the different stages represent these decisions. The small arrows show that these different decisions can lead to different decision pathways and potentially different outcomes of the policymaking process.

Figure 2: The phase model, adapted from Teisman (2000). Note: the grey arrow depicts the policymaking process, the black dots represents the decisions made within this process.



For the development of the preliminary theoretical model, I follow the assumption that various decisions are made in a policymaking process of an actor, in this case a local government. However, I do not focus on the different stages of the phase model (policy formation, adoption etc.). In other words, I do not focus on the macro level of policymaking. Instead I zoom in on the micro level of decision-making itself.

As explained, according to Etzioni (1967), decisions are made based on a weighing of alternatives that are in turn formulated based on information. However, how exactly this information is obtained is not specified by Etzioni (1967) or by Teisman (2000). It is not clear whether information is obtained through civil servants' intuition, experience and expertise, or through other types of sources. That is why, based on the discussion of DDDM above, for the purpose of developing a DDDM model for local governments, I assume that all of these decisions are made based upon information that is derived from data analysis. These decisions are thus data-driven. In order to make this assumption explicit in the model, I will combine the Teisman (2000) model with the Knowledge Pyramid model of Ackoff (1989).

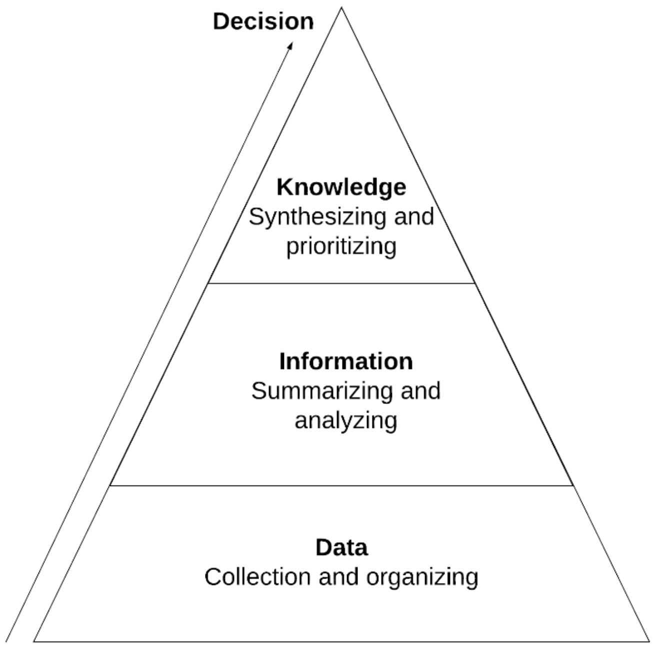
2.3.3 The Knowledge Pyramid

The 'Knowledge Pyramid' is a well-known framework in the domain of information science and knowledge management (Jennex, 2009). It is first developed by Ackoff (1989) in the field of organization and management theory (Mandinach, Honey, & Light, 2006). I build on a simplified model of the Ackoff (1989) pyramid as developed by Light, Wexler and Heinze (2004). According to them, most theories following the logic of the knowledge pyramid draw distinctions among data, information, and knowledge. Similarly, Light et al. (20004) discern three "phases" of a continuum that begins with 'raw' data and ends with meaningful knowledge that is used to make decisions (Mandinach, 2012; Mandinach et al., 2006). This is depicted in Figure 3. The inference from this figure is that data begets information begets knowledge. Furthermore, there is more data than information and more information than knowledge (Jennex, 2009).

How does the process from data to decision take place? According to Light et al. (2004), it starts with 'raw' data. However, I agree with the literature stating that the concept of 'raw' data is considered to be an oxymoron (Van Dijck, 2014). As explained, data can be good or bad, messy, inconsistent etc. and are therefore never just 'hard' numbers. I do agree however, that data do not have meaning in and of itself (Light et al., 2004). Whether or not data become information depends on the understanding of the person looking at the data, their interpretation. That is exactly what happens in the second phase, information, in which data that is given meaning by connecting it to a context. Information is therefore defined as "data used to comprehend and organize an environment, unveiling an understanding of relations between data and context" (Light et al., 2004, p. 3). Alone, however, information does not carry any implications for future action. That is why the last phase of the model is knowledge, which is defined as "the collection of information deemed useful, and eventually used to guide action" (Light et al., 2004, p. 4).

The eventual core idea of the model is that six broad actions are used to transform data into knowledge (Ackoff, 1989). According to Mandinach et al. (2006), these actions seem to align with each of the points along the continuum. At the data level, the two relevant actions are "collect" and "organize". The actions at the information level are "analyze" and "summarize". At the knowledge level, "synthesize" and "prioritize" are the actions seen as relevant (Mandinach et al., 2006). This process of transforming data into knowledge that is eventually used to base a decision upon, is depicted by the arrow on the left side of the pyramid in Figure 3.

Figure 3: Simplified Knowledge Pyramid model of Ackoff (1989), adapted from Light et al. (2004).



2.3.4 Integration of the models

As explained, I combine the phase model of Teisman (2000) with the Knoweldge Pyramid of Ackoff (1989) to form a preliminary theoretical model of required competencies for the process of DDDM in local governments. Figure 4 presents this model. Building on the model of Teisman (2000), the large arrow represents the overall policy process as it is organized by a local government. As Figure 2 shows, the Teisman (2000) model makes a distinction between the policy process at large (depicted by the arrow), and different decisions taken within this process (depicted by the black dots). In this study, I argue that the different decisions taken within the policy process are data-driven in accordance with the Knowledge Pyramid of Ackoff (1989). Figure 4 depicts this by putting the knowledge pyramid several times in the policymaking process. The knowledge pyramid triangles represent the black dots in Figure 2. The assumption is that data-driven decisions (micro level) are made several times throughout the overall policymaking process (macro level).

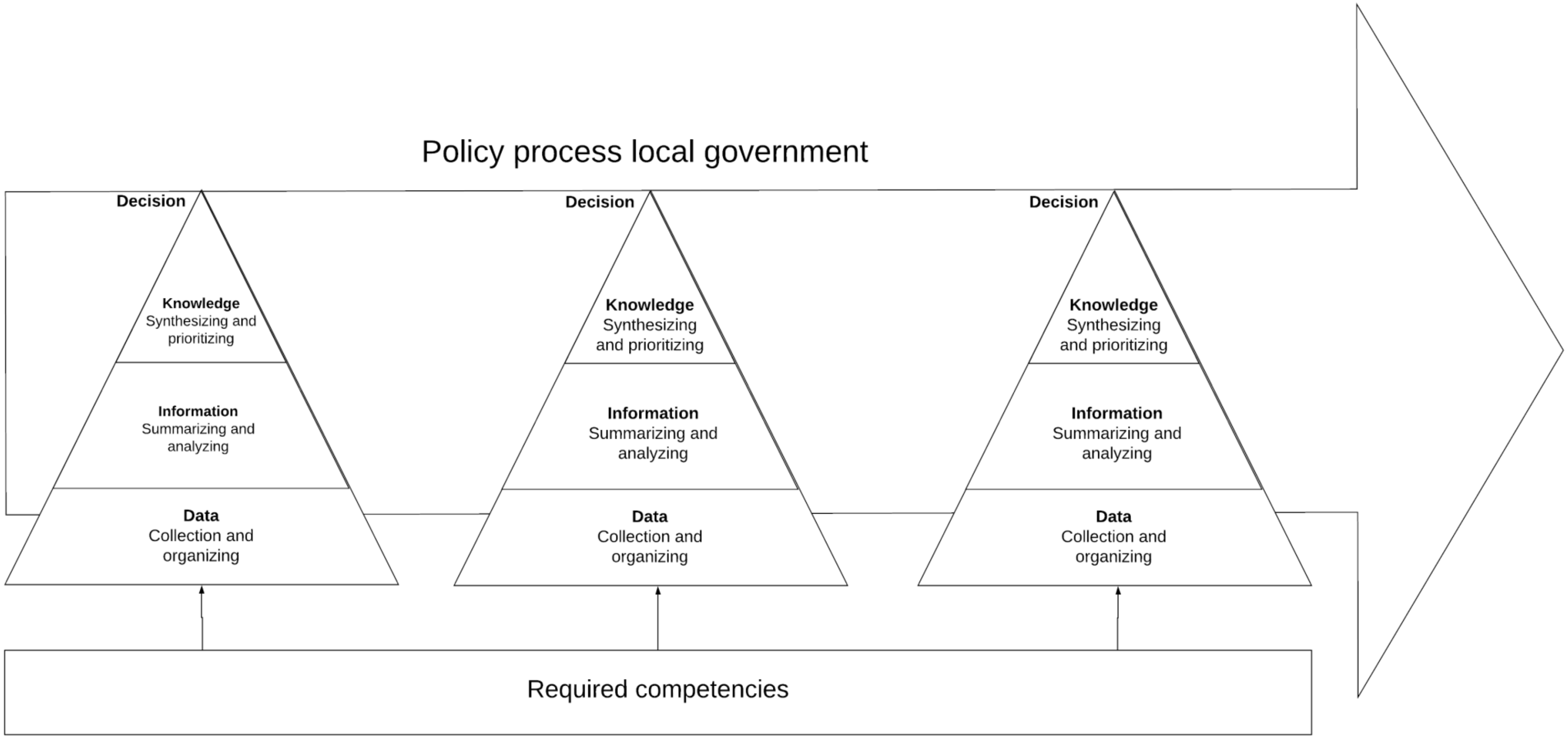
How will this model be used to empirically identify competencies? In Figure 4, the box below the Knowledge Pyramids with the word 'competencies' in it represents the assumption that competencies are required in these decision-making processes. Based on empirical data, I identify these competencies. In doing so, I start from two general assumptions. The first assumption is that different competencies are important in different phases, as these require different activities. For example, the data phase requires data collection and organizing, whilst the knowledge phase requires synthesizing and prioritizing. Building on the multi-method approach to identifying competencies (Du Chatenier et al., 2010; Winterton et al., 2005), I assume that these different activities within the different phases can require different competencies. I thereby assume that competencies are required within the different phases of the knowledge pyramid, not between the phases.

The second assumption is that because I focus on required competencies on the level of different phases, I am also able to study to what extent these competencies should be possessed by everyone involved in these phases, or only by at least someone. This assumption steams from the fact that it is not realistic to expect from one person to possess all competencies that are required in a phase. That is because competencies required in work activities are often conflicting or even contradictory

(Bekkers, 2018, p. 44). By studying the required competencies on the level of a phase in the DDDM process, the possibility exists of compensation for the lack of competency of individuals by calling upon those of others (Kauffeld, 2006, p. 3). I assume that because of this possibility of compensation, by default a competency does not have to be possessed by everyone involved as long as it is present in the phase in the DDDM process.

There is an important cautionary note to the preliminary theoretical model. Figure 4 represents both the process of policymaking and decision-making as clear-cut, linear processes. As explained, this is subject to critique. I therefore argue that this preliminary theoretical model does not aim to perfectly represent reality, but that it provides a heuristic that enables distinguishing between individual stages in the DDDM process (Höchtl et al., 2016; Jann & Wegrich, 2007), and therefore the different competencies required in these phases. I use this model in this way: first to identify which activities take place within the process of DDDM in a local government in the Netherlands, and second, based on the above, to identify the competencies that are required in these phases. In doing so, I aim to answer the two empirical sub-questions as posed in the introduction. In the following chapter, the methodological approach of obtaining the empirical material will be outlined.

Figure 4: Preliminary theoretical model of required competencies in the process of data-driven decision-making in local governments.



3 Methods

This chapters describes the research methods employed in this study. First, the overarching research strategy will be explained. Second, the competency study method of Spencer & Spencer (1993) that is roughly followed in this study for data collection and analysis will be outlined.

3.1 Research strategy

This study aims to answer the research question: which competencies are required in the process of data-driven decision-making in local governments? As explained, this is done by first developing a preliminary theoretical model (see the theoretical chapter), which is used as the basis for studying which competencies are required in the process of data-driven decision-making in local governments.

To identify the competencies required in the DDDM process, I execute an exploratory, qualitative case study. This allows for an in-depth view of what the process of DDDM looks like in practice in a local government. Because single case studies are limited in terms of external validity (Blatter & Haverland, 2012; Yin, 2013), the purpose of this approach is learning rather than establishing hard facts (Yin, 2009).

The data collection and analysis of this study will be executed by roughly following the competency study method as developed by Spencer & Spencer (1993). It fits well within the practice-based approach of this study, as according to Spencer and Spencer (1993, p. 215), "the basic principle of the competency approach is that what people think or say about their [competencies] is not credible. Only what they actually do, in the most critical incidents they have faced, is to be believed." The competency method of Spencer & Spencer (1993) and the corresponding techniques of data collection and analysis, allow the identification of competencies based on what civil servants do in practice. This competency method is therefore used as a guideline for the data collection and analysis of this study.

3.2 Competency study

According to Getha-Taylor (2008, p. 109) "There are three primary ways to distill differentiating competencies. The first method, the classic study design, uses criterion samples to distinguish average from superior per- formers. The second method is an abbreviated study, which relies on expert panels to determine competencies of interest. The final method is used when there are not enough jobholders in a particular job to offer comparisons. This final method focuses on single case studies of incumbents to offer insights on future needs (Spencer & Spencer, 1993, p. 93)" In this study, I follow this latter design. That is because as explained in the introduction, although the talk of DDDM is now prevalent in many public sectors, there are still relatively few examples of data actually being used in decision-making in local governments. This means that there are currently very few civil servants that have actually executed or are executing DDDM in their day-to-day work. I focus on the local government of Gouda and the select group of civil servants that already have experience in data-driven decision-making. Below, this case will be introduced, followed by the design of the competency study method.

3.2.1 Empirical case: the local government of Gouda

The case focused on in this study is the local government of Gouda. Gouda is a city and local government in the province of South-Holland in the Netherlands with 73,181 inhabitants (CBS, 2019). The local government as an organization has approximately 500 employees. It is roughly structured in accordance with the so-called integral ´direction´ model of local governmental organizations (Aardema & Korsten, 2009). This means there are three different directors that supervise so called ´domains´. The largest domains are the social domain and the environmental and spatial planning domain. The third, smaller domain is the safety domain. In a narrow sense, the social domain relates to everything that local governments do in the field of labor, care and youth (Pommer & Boelhouwer, 2016). The environmental and planning domain includes spatial planning, infrastructure, environment and public housing (Derksen & Ephraim, 2011). The safety domain concerns everything that has to do with maintaining public order in the local government. In these three different domains, policymaking and execution are brought together. The local government furthermore has several 'staff' departments, such as a finance, legal, HR and information and automatization department.

3.2.2 Sampling

As will be discussed below, this study uses two groups of respondents: civil servants of Gouda and experts in the field of data-driven decision-making and of competencies of civil servants.

The first group consists of twenty-two civil servants of Gouda (see Table 3). As just explained, in this study civil servants that have experience with DDDM are studied. More specifically, civil servants were selected based on the criterion that they have finished one whole data-driven decision-making process. This is purposive sampling, which means that the sample units were chosen because they have particular features or characteristics which will enable detailed exploration and understanding of the central theme of this study (Ritchie & Lewis, 2003). In the group of civil servants, a mix was sought of different domains of expertise and different roles within the organization, to cover the full spectrum of civil servants within a local government as much as possible. Besides policymakers of the three domains of Gouda, some civil servants that are working in the Information and Automatization department but specifically focus on one of the three domains were interviewed as well. Lastly, two civil servants of the Customer Contact Centre were interviewed. These people are closest to the 'execution' of policy. One of them works for the environment and spatial planning domain, and the other for the social domain.

The civil servants were sampled with the help of two information managers working in Gouda, who knew which people had experience in DDDM. To double check whether the respondents truly had experience, they were asked in the beginning of the interview to shortly describe a DDDM process. All of the civil servants that were put forward by the information managers were able to do so. They therefore met the selection criterion and were included in the sample.

Table 3: Overview of the respondents of Gouda.

Nr.	Domain
RG1[1]	Social
RG2	Enviroment and Spatial planning
RG3	Enviroment and Spatial planning
RG4	Enviroment and Spatial planning
RG5	Enviroment and Spatial planning
RG6	Safety
RG7	Social
RG8	Information and Automatization
RG9	Enviroment and Spatial planning
RG10	Enviroment and Spatial planning
RG11	Enviroment and Spatial planning
RG12	Enviroment and Spatial planning
RG13	Social
RG14	Social
RG15	Social
RG16	Customer Contact Center
RG17	Social
RG18	Customer Contact Center
RG19	Information and Automatization
RG20	Enviroment and Spatial planning
RG21	Information and Automatization
RG22	Information and Automatization

The second group consists of twelve experts (see Table 4). Experts are useful because they can paint a quick picture of required competencies (Getha-Taylor, 2008; Spencer & Spencer, 1993). In line with the recommendations of Spencer & Spencer (1993), experts were asked to identify competencies they consider necessary in the process of DDDM in local governments. They were thus not interviewed using the BEI method (which will be explained further on).

In this study, experts were 'purposively' sampled as well. A mix was sought of experts from different organizations (universities, ministries, local governments, consulting companies) and experts that have different expertise, such as knowledge about data-driven decision-making, or knowledge of competencies of civil servants. This mix was made in order to establish a broad view on the required competencies in the process of DDDM. The expert interviews provided an additional source of data, which was used to triangulate the competencies identified in the BEIs. This will be explained below.

[1] Respondents of the local government of Gouda are referred to as 'RG' and experts are referred to as 'RE'.

Table 4: Overview of the expert respondents.

Nr.	Organization	Position
RE1[2]	Utrecht University	PhD-student algorithmic accountability
RE2	Ministry of Interior Affairs and Kingdom Relations	Policy advisor E-government
RE3	The Greenland	Consultant
RE4	The Greenland	Consultant
RE4	Ynformed	Director and consultant
RE5	VNG Realisatie	Program manager
RE6	Local government of Amsterdam	Director social domain
RE7	Ynformed	Director and consultant
RE8	Leiden University	Professor roles, values and competences of public managers in a changing work environment
RE9	The Netherlands Enterprise Company	Strategic advisor organizational development
RE10	The Netherlands Enterprise Company	Policy advisor data-driven transformation
RE11	Utrecht University	Professor public collaboration, innovation and leadership
RE12	Twente University	Professor philosophy of technology

3.3.4 Data collection

After the two groups of respondents were selected, the data was collected. This was done by interviewing both groups of respondents. The interviews were executed over the same time period, so the description below does not imply the order of the interviews.

Behavioral Event Interviews

The interviews with the respondents of Gouda were Behavioral Event Interviews (BEIs) (Spencer & Spencer (1993). BEIs are required to identify the full spectrum of competencies necessary to perform a job successfully, which is why this method is now considered standard procedure for all competency studies (Getha-Taylor, 2008, pp. 105, 108). The reason for choosing BEI over traditional interview methods is that people often do not know what their competencies, strengths, weaknesses and even their job likes and dislikes really are. The basic principle of the competency approach is therefore that what people think or say about their motives or skills is not credible enough. That is why the purpose of the BEI method is to get behind what people say they do to find out what they actually do (Spencer,1993, p. 115). The BEI contains five steps (with the focus on step 3):

1. Introduction and explanation: Introducing yourself and explaining the purpose and format of the interview.
2. Job responsibilities: Getting the interviewee to describe his or her most important job tasks and responsibilities.
3. Behavioral events: Asking the interviewee to describe, in detail, some of the most important situations he or she has experienced in the job – some ‘high points’ or major successes and some ‘low points’ or key failures.
4. Characteristics needed to do the job: Asking the interviewee to describe what he or she thinks it takes for someone to do the job effectively.

[2] Experts are referred to as ‘RE’ and respondents of the local government of Gouda are referred to as ‘RG’.

5. Conclusion and summary: Thanking the interviewee for his/her time and summarizing key incidents and findings from the interview.

BEIs were conducted with twenty-two civil servants. The interviews lasted between forty-five and ninety minutes and were recorded by the interviewer. In the BEIs, respondents did not only describe what they did when conducting the process of DDDM, they also described which competencies they perceived as important in this process. They did so because they were informed about the goal of this study: to identify competencies required in the process of DDDM. They often brought up these competencies themselves. Table 5 shows the questionnaire that was used in the interviews.

Table 5: BEI questionnaire as conducted in the local government of Gouda, adapted from Getha-Taylor (2008).

Behavioral Event Interview Method (BEI)	**Questions**
Introduction and explanation	The purpose of this interview is to find out what people here at the local government of Gouda need to be able to work responsibly execute data-driven decision-making. The best way to do this is to ask experts like you, who actually execute data-driven decision-making, how you do it. I would like to know the most important/critical moments that you have encountered while using data in decision-making. I will ask you to describe (1) a few successful experiences and (2) a few difficult situations.
Work activities	- What are your most important tasks or responsibilities? - What did you do before you started working here? - How much of your time do you spend approximately per week working with data (in percentages)?
Behavior	- Please recall a specific experience you've had in using data in decision-making that went particularly well for you (a high point). I'm interested in learning from your best experience. Please walk me through it from beginning to end. - Please recall an experience you've had in using data in decision-making in which you felt you weren't as effective as you could be, when things didn't go well, or when you were particularly frustrated (a low point). I'm interested in learning from your toughest experience. Please walk me through it from beginning to end.
Responsibility	- In these situations, have you considered the risks of using data? Can you explain this? - Have you considered the potential impact on stakeholders and other groups?
Characteristics needed to do the job	- At which point in the aforementioned situations would you have liked to do something differently? Why? - On which characteristics/qualities would you hire people to do your job?
Conclusion and summary	The data from this interview will be transcribed and processed completely anonymous. Thank you for your time and help.

Expert interviews

In line with the recommendations of Spencer & Spencer (1993), the interviews with the experts were semi-structured interviews. The experts were asked the following two open questions:

1. What is - according to you - the difference between 'traditional' decision-making and data-driven decision-making?
2. Which competences are – according to you - required in this 'new' process of data-driven decision-making?

These two questions were the basis of the interview. Follow-up questions were added during the interview by the interviewer. Following this structure, the experts identified the competencies they considered necessary in the process of DDDM in local governments. They did so by describing these competencies in general or linking them to specific DDDM processes they had experienced. The interviews lasted between forty minutes and eighty minutes and were recorded by the interviewer.

3.3.5 Analysis

The thirty-four recorded interviews were transcribed. These transcripts formed the empirical data of this study. The next step was to qualitatively code this empirical data, using a mixture of deductive and inductive analysis (Spencer & Spencer, 1993) in Nvivo 12 (Boeije, 2014). As explained above, the identification of competencies was executed using the multimethod approach. Below, the three-step analysis process that was executed is described in detail.

The first step of the analysis consisted of identifying the activities that constitutes the process of DDDM in practice in Gouda. This was done by analyzing the BEI transcripts based on the preliminary theoretical model as depicted in Figure 4. This started by zooming out on the policymaking process and analyzing to what extent respondents of Gouda described several different DDDM processes within a larger policymaking process. This was followed by zooming in on these DDDM processes. This was done to identify to what extent these DDDM processes as described by the respondents of Gouda in the BEIs actually corresponded with the phases of data, information, knowledge and decision as depicted in figure 4.

The second step consisted of identifying the required competencies in these phases of the DDDM processes. To do so, the BEIS and expert interviews were coded. In the expert interviews, the experts listed competencies they considered to be required in the process of DDDM. As previously described, experts often did not describe these competencies within specific phases of the DDDM processes, but in general. These general competencies were first inductively coded. Afterwards, the description of the codes was deductively matched to existing competency definitions as depicted in Table 1. Some of the inductively identified competencies as described by experts corresponded directly with one of the definitions of competencies in Table 1. Examples of this are ‘critical thinking’ and ‘teamwork’. However, some others did not correspond to existing definitions. In these cases, the description of the competencies was inductively matched to existing definitions. For example, several experts specifically mentioned the competency ‘asking the ‘right’ questions'. By this they meant being able to formulate questions that can be answered using data. This was deductively re-coded to ‘data literacy’. In this step it was also identified whether a competency should be possessed by everyone involved or by at least someone involved. Concluding that a competency should be possessed by everyone involved was only done if several respondents specifically stated this was the case with specific reasons why. That is because, as described in the theoretical chapter, the assumption is that by default, competencies only need to be possessed by at least someone involved in the DDDM process, as compensation of competencies is possible on the level of the process.

The BEIs were coded roughly using the same steps. However, in the BEIs it was possible to identify the competencies within the different phases of the DDDM process as identified in the first step of the analysis. In the BEIs, respondents did not only describe what they did when conducting the process of data-driven decision-making, they also described which competencies they perceived as important in this process. Although not part of the BEI method in the strictest sense of Spencer & Spencer (1993), this proved to be highly valuable information as it enabled the same inductive coding process as the one used for the expert interviews. First, competencies that were specifically discussed by respondents were identified. Second, competencies that were not specifically discussed by respondents, but indirectly described through the actions they described were identified. This latter is in line with the ‘standard’ BEI analysis method of Spencer & Spencer (1993). For example, the action ‘checking how data was registered and why it was registered like that’ was coded as ‘critical thinking’. Third, these competency definitions were inductively matched to one of the existing definitions in Table 1. This enabled determining the type of competency (knowledge, skill, motive or trait). Fourth, for these competencies it was again identified whether they should be possessed by everyone involved or at least by someone involved.

In the third and last step, the most important required competencies were selected. The reason for this is that according to literature on competency profile development, researchers should try to limit the total number of competencies to a reasonable number. It is considered better to have fewer and more detailed competencies than a large number of brief descriptors (Ruggerberg et al., 2011, p. 247). To make a selection of the most important competencies, I used two different criteria. The first criterion was that a competency had to be discussed by both experts and civil servants. In other words, only triangulated competencies were selected. Triangulated means that different sources (in this case the BEIS and the expert interviews) are used to verify data (Yin, 2011, p. 80). Second, I used the criterion of frequency. The threshold was used that at least half of both the experts (at least six) and civil servants (at least eleven) had to discuss a competency for it to be included as ‘required’. This resulted in the identification of eight competencies that met both these criteria. Because the competencies were coded in the BEIs within the different phases of the DDDM process (see final coding tree in the appendix), it was clear in which phases these eight competencies are required.

To summarize, the analysis process consisted of the following steps:

1. Identification of the activities that constitute the phases of the process of DDDM in practice in Gouda by analyzing the BEIs using the preliminary theoretical model as depicted in Figure 4.
2. Identifying the required competencies in the different phases of the DDDM processes by analyzing the BEIs and expert interviews.
3. Identifying the most important required competencies using the criteria of triangulation and frequency of discussion by respondents.

The result of this analysis will be discussed in the next chapter.

4 Results

In this section, the results of this study will be presented. First, the process of data-driven decision-making as it takes place in practice in Gouda is described based on the analysis of the BEIs and the preliminary theoretical model. In doing so, the empirical first sub-question is addressed: to what extent does this 'new' data-driven decision-making process actually take place in practice? Second, the competencies that I identified in the BEIs and expert interviews as required in the phases of this process are described. In doing so, I answer the second empirical sub-question: which competencies are required in the data-driven decision-making process as it actually takes place in practice?

4.1 Hybrid data-driven decision-making

In the BEIs, the twenty-two respondents discussed eighty-one different DDDM processes. In line with the assumption of the model depicted in Figure 4, these decisions ranged from more incremental to more fundamental data-driven ones. An example of a more incremental decision is the decision to replace a certain lighting pole based on data analysis. An example of a more fundamental decision based on data is the decision to change the amount of a subsidy the local government grants to all day-care organizations in Gouda.

However, based on these decision-making processes as described by the respondents, I inductively identified a deviation from the model as depicted in Figure 4. The process usually is not 'purely' data-driven, but is rather a combination of traditional- and data-driven decision-making. This will lead me to conclude that in practice, I observed a hybrid form of DDDM in the local government of Gouda. I will further explain this below.

In the theoretical section it was concluded that in DDDM, (1) the data are used to provide insight into the past, present and the future, (2) the data are the starting point of the decision-making process and (3) the data are the primary source of information to base decisions on. The DDDM processes as observed in Gouda only partially met this definition. First, in many decision-making processes, the data were not the primary source to base the decisions upon. Civil servants used other sources and combined this with the data analyses before making a decision. Examples of other 'harder' sources are reports of for example national research institutes such as the Central Bureau of Statistics (CBS), the Netherlands Institute for Social Research (SCP) and the National Institute for Budget Advising (NIBUD) (RG13, 14). Other frequently used sources are 'softer' information, such as case stories, expert opinions and political whishes (RG7, 9, 10, 14, 15). This makes the process as it currently takes place not fully data-driven, as RG19 explains*: "If we were going to work one hundred percent data-driven, the data would determine things."*

Second, most of the situations that were discussed by the respondents started from a specific question or problem and not from the data. As RG15 explains:

> *"[First] there is a question from the management or the aldermen, we need this or want that. Then you formulate your research question as concrete as possible […] [after determining] this is the assignment we are going to do, then you dive into the data."*

More examples of questions of the local council are 'how much money is spent on which types of childcare in the local government?' (RG14) and 'how can informal care assistance be improved in the local government?' (RG14). An example of a problem is a case in which foundations of houses were damaged in a neighborhood after sewage maintenance. The local government used data to prevent foundation damage in other neighborhoods by informing citizens about the state of the foundation of their own houses (RG2 to 5, RG20). As explained by RG15, these questions or problems sometimes come from inside the administration, and other times from the local council. They are almost always the starting point of the decision-making process, which is followed by collecting data.

However, data are used to not only provide insight into the past, but also the present and future. In the environmental and spatial planning domain, data is often used to perform predictive analysis of required maintenance of all kinds of objects in public space. In the social domain on the other hand, data is mainly used to provide insight into the past and present, for example by showing how many people used or use a certain social service or receive(d) certain social benefits (RG1, RG13 to 15). Only in a few cases data is used to predict the future, such as to gain insight into who might go into debt in the future (RG13). RG13 explains that this latter predictive analysis is actually not so easy to execute in practice (it therefore hasn't been executed yet):

> *"Linking data can be done because there are now systems for that, but what will you do then? If you have that information? How are you going to approach those people, how much is such an approach going to cost? You can get that information, but how to proceed further. What is your role as a municipality in this, how far do you go and how much capacity will you put on it?"*

This statement shows that it is not easy to use predictive analysis in decision-making without a pre-formulated question, because that leads to a lot of un-answered questions about what to do with these new insights.

From this can be concluded that in practice, a hybrid form of decision-making was observed in the local government of Gouda (see table 6). Data are used in the process of decision-making in ways beyond 'traditional' data analysis: predicting the past, present and future. However, the decision-making process itself is still very much structured like the 'traditional' way: starting from a specific problem or question and final decisions based on multiple sources, not only the data. RE10 summarizes this well: *"Right now the [traditional and new] worlds are intermingling."* RG19 explains this further by stating*: "I think we are moving towards a kind of intermediate form of data-driven working. You have much more data at your disposal, but the structure of the organization remains kind of the same."* This conclusion will be explained more detailed in the description of the different phases of the DDDM process as observed in Gouda, that follows in the next section.

Table 6: Difference between traditional decision-making, 'pure' data-driven decision-making and hybrid data-driven decision-making.

Traditional decision-making	**Pure data-driven decision-making**	**Hybrid data-driven decision-making**
Insight into the past	Insight into the past, present and future	Insight into the past, present and future
Problem as starting point	Data as starting point	Problem as starting point
Expertise and experience primary sources of final decision	Data primary source of final decision	Combination of data and expertise and experience sources of final decision

4.2 Four phases of data-driven decision-making

After the previous section showed how DDDM takes place in practice in comparison to the 'pure' theoretical definition, in this section I will zoom in on this process. Figure 4 forms the basis of this analysis. Below, I explain the process of DDDM as it takes place in Gouda, in accordance with the four phases of the DDDM process as depicted in this preliminary model. I do so based on the empirics derived from the BEIs with the civil servants of Gouda. This description lays the groundwork for the description of the identified required competencies that follows afterwards.

4.2.1 Data

Above, it was described that the data is almost never the starting point of the DDDM process, but usually a problem or a question. In practice, the DDDM process thus starts after a question or problem has been formulated. After this, the first phase in hybrid DDDM consists of collecting and organizing data. RG21 describes how this collection can take place in practice:

> *"You have to go and see where you can get the data you need. And then you end up with these very long Excel overviews with all [of your] indicators and the sources and the contacts and then your data in it per period."*

The respondents described a wide variety of data they collect. In the environmental and spatial planning domain, this is mainly measurements or sensor data, for example data about water quality or the state of roads or building. In the social domain, this is mainly citizen registration data, for example registration of which health-care or subsidies citizens receive. This data can both be registered by the local government itself or by stakeholder organizations such as healthcare institutions, social teams or housing corporations. Both domains also use data of complaints of citizens, which is registered in the local government Customer Contact Service (RG16, 18). In the environmental and spatial planning domain, these are for example complaints about defect lighting or flooded streets (RG5, 18). In the social domain, these are for example complaints of citizens that have issues with receiving social benefits (RG16).

In several of the situations that were discussed by the respondents, data collection was outsourced to third parties (RG2, to 6, 9 to 15, 17, 19 to 22). For example, in the environmental and spatial planning domain: *"We often hire an engineering company if we for example need to perform maintenance on a bridge. They do the calculations to see if we need to reinforce or replace the concrete or the deck."* (RG10). In the social domain data collection is less deliberately outsourced, however civil servants are often dependent upon data of third parties, such as healthcare institutions and the social team (RG7, 13, 14, 15).

In most of the situations, several different datasets were collected. The next step is therefore to organize the data by bringing it together in databases. Some civil servants do this themselves, others use the information and automatization department or third parties.

4.2.2 Information

The information phase consists of transforming data into information through analysis and summarizing. According to the respondents, in this phase the first step is performing analysis on a single dataset or on several linked datasets. Often, this is followed by visualization, as RG9 explains*: "I analyze the data and then I make nice graphs."* In the environmental and spatial planning domain, this often entails plotting data on maps, made accessible through geographical information system (GIS) viewers (RG2 to 5, 10, 12, 18). In the social domain this often entails dashboarding (which can also include maps) (RG1, 6, 10, 19, 20, 21). Dashboards provide visual insight into trends and allows for comparison and benchmarking. RG6 explains what such a dashboard looks like in the safety domain: *"You see a picture of Gouda where you can see all [crime] incidents, you can select seven or thirty or ninety day periods, you can zoom in […] and under 'analysis' you see graphs."*

As explained, information is data that is given meaning when connected to a context. RG3 explains why contextualization is very important: *"Only the data tells you nothing, you must also be able to explain the story behind it."* To obtain this story, 'hard' data is supplemented by 'soft' data such as case stories, expertise and experience, that helps gaining insight into the meaning of the data. RG10 explains this for data used in decisions about spatial planning:

> *"Often there are other things going on in a neighborhood such as nuisance, or sometimes politicians want something a bit different. So my role is to bring that data - that is one of the sources for making choices, a very important one – [and other sources] together. To make sure that we are not blindly following the data but also look at how that relates to other, perhaps somewhat softer areas of interest."*

Analysis and summarization are frequently outsourced to third parties as well. They are often performed by engineering or data science companies (RG11, RG14, RG16, R19, RG21). Sometimes, these companies collect the data themselves, other times they use data that is collected by the local government. Reasons for outsourcing are mainly expertise and resources of these companies that the local government itself does not have. However, in some cases civil servants opt for outsourcing because it allows for comparison with other municipalities that use the same external companies for data collection and/or analysis. RG14 explains this choice for a decision about new subsidies for pre-schools in Gouda: *"To calculate kind of objectively what [the amount of the new subsidy] should be, we hired an external consulting company […] because they do that kind of research in many local governments, we could also compare, benchmark."* Based on the comparison with other local governments, the civil servant was able to make a better decision about a reasonable subsidy for pre-school organizations in Gouda. In the section about identified competencies, the significance of this outsourcing to third parties for required competencies will be explained.

An important limitation in the information phase is comparability of the data. Very often, data is obtained from systems in which registration takes place for certain purposes. This data can of course only be used for other purposes if this is in accordance with the General Data Protection Regulation (GDPR). However, even if this is the case, it is often still problematic. For example, in the social domain, data is registered during meetings with clients, such as type of care they receive and why, or their career history (RG7, RG13). The main purpose of registration of this data is for the local government to know which citizens they are dealing with in care and subsidy provision and why, not to link it to other types of data (RG19). Several respondents mentioned that it is therefore nearly impossible to link this type of data with for example financial data that is collected with the main purpose of budgeting (RG1, 7, 10, 11 13, 14). This shows that data that is registered for different purposes in different systems is often not comparable. RG11 explains this for data in the environmental and spatial planning domain:

> *"Inspections [in public space] are carried out with a certain preconceived notion. You cannot use that same data for a completely different purpose without a disclaimer. If you just assume that you can just use that data [without modification], you're going to be disappointed because they may be incomplete."*

The limitations of the data are again important for the required competencies, as will be discussed later on.

4.2.3 Knowledge

As explained in the theoretical chapter, information alone does not carry any implications for future action. According to Figure 4, the next phase in DDDM is therefore knowledge. This refers to the collection of information deemed useful (synthesizing), and eventually used to guide action. Based on the empirical data, there appear to be three different ways of prioritizing information to guide action.

First, information is often prioritized based on the specific problem or question that is addressed (RG1, 9, 10, 14, 19, 21). RG14 explains this: *"There is a difference between the very basic numbers and actually providing insights, that you actually get answers to questions you have."* This statement shows that information is often prioritized based on whether it provides answers to formulated questions.

Second, information is often tailored to specific audiences (RG1, 2 to 5, 9, 19 to 22). RG1 explains: *"The council needs information, management needs another type of information, departments themselves need different information, so everyone needs information at their own level."* This statement indicates there is a horizontal difference in information needs between for example different departments, but also a vertical difference between for example executers, policymakers, public managers and the local council. Information is then prioritized based on the specific audience it is meant for. Other respondents also mentioned prioritizing information based on citizen groups or specific citizens (RG2 to 5, 20). RG20 describes this for a subsidence project in a neighborhood. In this project, citizens received maps that showed whether their house was subsiding or stable. RG20 explains why prioritizing this information was useful: *"[Citizens] received very specific, personal information. We have managed to translate a very big, abstract problem that is going on nationwide to 'what is the situation for my house?'"*

Third, information can be prioritized based on availability (RG 1, 21, 22). RG1 describes this for management information reports that are made for directors in the social domain: *"Often we resort to 'we have this [information] do you need that?', that is sometimes easier than asking 'what do you need?' and then trying to find out what information you have to provide them with.*" For the same management reports, RG22 explains this happens not only because of convenience, but also out of necessity: *"[The information need] can be decided upon somewhere by someone, but to what extent it is realistic and what it means for the process through which the corresponding data is collected is often forgotten."* RG22 means that often people request information that can simply not be collected (yet) the way they would like to receive it. This means information providers often have to resort to providing information that might not be exactly what people asked for, but that they consider to be close enough to the requested information.

4.2.4 Decision

According to Figure 4, in the fourth phase, the acquired knowledge is used to decide which actionable steps will be executed. RG10 explains this for the environmental and spatial planning domain: *"The decisions we make are based on the measurements that we execute […] based on what comes out of those calculations, we choose."*

In the social domain the decision-making itself is mainly done by public managers or politicians. The knowledge is presented to them and they base their decision on this (RG7, 13, 14, 15). RG13 explains: *"[I] present the options as clearly as possible […] but ultimately the choice is a political one. You can provide directions to it, but a different political party could make a different decision."* In the environmental and spatial planning domain, decision-making is also done by politicians, but a bit more frequently also by civil servants themselves (RG4, 9, 10, 11, 20). In the statement below, RG10 explains that sometimes he makes decisions himself, and other times he makes them together with politicians:

> *"I instruct myself to execute certain maintenance of roads and sewages […] but [the department] also has [to make decisions] about climate adaptation, which is a council program […] I am working on drawing up the strategy for this together with the council."*

As already explained, when it comes to the decisions themselves, in pure DDDM the knowledge should be decisive for the decision to be made. In rare situations, this is actually the case. RG13 explains one of these 'purely' data-driven decisions in the social domain:

> *"It was really the underlying dataset […] that offered the most insight and the most substantiation to ultimately offer support for the decision. It gives you an objectification of all those signals from lobby-like groups. We had an existing policy and the analysis showed [something different] than the assumption this policy was based on] […] an individual can of course deviate from this, but that actually gave the support for a fairly radical change."*

However, as already explained above, the empirical data shows that in practice, decisions are often not primarily based on data. Other types of sources such as experience, expertise and political whishes are important as well (RG1, 9, 10, 12, 13, 14, 17). The latter is a confirmation of the statement posed in the theoretical chapter that in local governments, politics are very close to the administration. When it comes to political wishes, respondents mentioned several situations in which knowledge was contradicted by political aspirations (RG1, RG7, RG15, RG21). As RG1 explains: *"Sometimes [managers and politicians] are selective in using the outcome [of a certain analysis] if the results had been very good."* In some cases this actually leads to a different decision that would be expected based on solely the knowledge. RG15 explains this:

> *"In politics it is often a matter of gut feeling or wanting to score in a certain neighborhood. The real problem might be taking place in another neighborhood [according to the data], but perhaps more voters are in this neighborhood."*

4.2.5 Implication of the empirical description of the phases

The discussion of the different phases above shows that civil servants largely follow the phases of the DDDM process as depicted in Figure 4. The discussion further specified how these phases were actually executed and thereby provided more empirical support for the claim that DDDM, as it takes place in Gouda, is a hybrid process. It showed that in the data, information and knowledge phase, problems and questions are used to guide collection of data, transformation of this into information and prioritization of this information into knowledge. Furthermore, it showed that politicians are often the ones making the final decisions. This supports the conclusion that DDDM in practice is a combination of traditional decision-making and pure data-driven decision-making.

The descriptions of the phases as outlined above provide the basis for the competencies that are required in these phases. These competencies will be explained in the next section.

4.3 Required competencies

As described in the methods section, the competencies were identified in a three-step analysis process. First, in all of the phases required competencies were inductively identified. Second, I deductively matched these competencies to existing competency definitions as depicted in Table 1. This was done to give meaning to the inductive analysis. Third, I selected the most important competencies from this analysis. Furthermore, in the theoretical chapter I explained two assumptions about the relationship between the phases of the DDDM process and the competencies that are required in this process. The first assumption was that the required competencies differ per phase. The empirics shows that this is indeed the case, which will be explained below. The second assumption was that some competencies should be possessed by everyone involved, whilst others should be possessed by at least someone involved. This is based on the idea that it is impossible to expect that one civil servant possesses all competencies required in the process of DDDM. Civil servants can supplement each other in the different competencies they possess. The empirics provided support for this assumption as well. It showed that three competencies should be possessed by everyone involved (data, literacy, critical thinking and teamwork), and five competencies should be possessed by at least someone involved in the process (domain expertise, engaging stakeholders, data analytical skills, political astuteness).

Below, the identified eight competencies are discussed based upon these two assumptions. First, I discuss the competencies that are important in all phases of the DDDM process and should be possessed by everyone involved, followed by the competencies that are important in all phases but should be possessed by at least someone involved, and lastly, the competencies that are important in some phases and should be possessed at least by someone involved.

4.3.1 Data literacy

The first identified competency is data literacy. It is important in all phases of the DDDM process and should be possessed by everyone involved. All of the respondents - both experts and respondents of the local government - mentioned some form of this competency explicitly or implicitly[3]. RE1 explains this competency:

> *"I think that for a civil servant [data literacy] is really about that rudimentary understanding data. If you consider literacy as being able to read and write, as a kind of metaphor, the [civil servant] is capable of reading, and the data specialist can read and write and make beautiful poetry. That is kind of a step further."*

The importance of rudimentary understanding of data is acknowledged by two civil servants of Gouda (RG4, 12) who stated they had some trouble in their data-driven projects because they did not fully understand the technologies they were using: *"[The data part] was not entirely my thing, so I found it quite complicated to understand what it exactly meant"* (RG4). Similarly, RG12 states that although not posing a true limitation, not understanding the data and data analysis (not being sufficiently data literate) was a frustrating experience:

> *"I was in charge of a [data-driven] project that I didn't fully understand. I found that very difficult. I understood the content, but I didn't understand the technical side which is just as important […] it would be useful if I knew how [the data analysis] worked. Then I could have assessed [if something I asked the data scientists] was complicated or impossible or easy. That would have been an advantage."*

The statement shows that this civil servant would have liked to understand the technical side of the project as this would have allowed him/her to assess whether a technical request was difficult or easy to solve. Several respondents highlight that in order to understand this, one has to understand the 'data pipeline' (RG2,3, 5 to 10, 12, 14, 16, 18, 19). As RG5 explains, this is a continuing 'mill', starting from data registration and flowing all the way up in the organization. According to RG19, this is a process you have to understand if you are part of a DDDM process. RG22 explains why it is important to understand the data pipeline when describing a management information project:

> *"We must make an official notification of a data breach at the service point. They then take action. In that entire process around such a notification, data can be eliminated in all those*

[3] When stating that respondents mentioned a competency 'explicitly', I mean they specifically stated in their interview that they think this competency is of importance. When stating respondents mentioned a competency 'implicitly', I mean I derived this competency from a description of a certain action as discussed by civil servants in their BEIs. For examples of this, see the explanation of 'analysis' (3.3.5) in the methods chapter.

process steps. Someone can just decide 'no this is not a data breach' and then it does not go on to the next step. But is that in accordance with the definition we have of a data breach? Can this person just say this [is not a data breach]? And how is that then registered? […] You have to be aware of when that process is wrong."

This statement not only shows the importance of understanding the 'data pipeline' in order to be able to read and understand data, it also shows it is important to understand that data is not neutral. RE1 explains: *"That rudimentary idea of data is not neutral, someone chooses to collect data […] of data not as a given but as a taken. That really lies at the heart of data literacy."* I will come back to this point when describing the competency of critical thinking.

Furthermore*,* data literacy entails not only understanding what data is and that it is not neutral, but also knowing how to use data to inform practice. RE3 explains this: *"It is important that [civil servants] learn to recognize when data is relevant for what they are doing […] that when they get a question they think: hey, I could also solve that with data."* RE5 explains this further: *"You must be able to translate a policy issue into information […] I think that is a core competence, that you can reason from policy questions to indicators [and the other way around]."* This is confirmed by many respondents of the local government (RG2, 3, 5, 6, 7, 9, 10, 12, 13, 15, 17, 20, 21, 22). In all of the situations they discussed, it was essential that they understood to what extent data could help them addressing their question or problem, and to what extent it could not. To this latter point several experts (RE1 to 4, 6) add that it is important to carefully consider to what extent using data actually contributes to public value creation.

Lastly, some experts (RE2, 5, 6, 8, 12) state that data literacy is not just literacy in terms of understanding what data is and understanding that data is not neutral, but also the broader implications of datafication as a societal trend. RE5 explains:

> *"You really have to understand what is possible with data [in broader sense]: how do all those data companies [like Uber and Booking] work? Why does it work so well? And you must be able to translate that into your own policy environment […] A civil servant is naturally trained to take a broad view and you really need to understand this, just as you learn about what individualization and historical political trends mean […] If you do not understand that, it is very difficult to make good policy. That goes much further than only data analysis."*

RE2 confirms this by stating:

> *"If you are a civil servant advising on the digitizing society, you have to understand that society […] I think it can no longer be explained if you don't understand anything about IT infrastructure and data architecture."*

These statements and the fact that data literacy as a competency was discussed by every single respondent indicates that data literacy is a competency that should be possessed by all civil servants involved in the DDDM process.

In sum, data literacy entails having some rudimentary understanding of what data is and that it is not neutral, understanding how one can use data in decision-making and understanding what datafication of society entails. Data literacy should be possessed by everyone involved in the DDDM process in all phases of it. It is important to note that data literacy is a different competency than data analytical skills. I will further discuss this below.

4.3.2 Critical thinking

A competency that is strongly related to data literacy is critical thinking. All of the experts and nineteen of the respondents of the local government (RG 1 to 15, 17, 18, 20 to 22) implicitly or explicitly indicated that critical thinking is an important competency in DDDM. It is a competency that should be possessed by everyone involved in the process, in all phases of it.

Critical thinking is important for acting upon the understanding that data is not neutral. Respondents of Gouda mentioned two things they did when executing critical thinking in DDDM. First, several respondents (RG4, 8, 10, 11, 18, 20) indicated that before they start data collection, they consider the risks this poses for the subjects of the data, not only because it is legally required, but also because they are convinced themselves that it is very important. RG20 explains:

> *"What is really important when you start working with data is that you have to carefully consider what the result of what you're doing could be, and the effects it has on the people that it concerns. Data is always about parties or people, and they are going to have an opinion about it, certainly about the negative effects."*

Second, on a more practical level, many respondents mentioned they actively checked the data, its registration and the analysis during the DDDM process (RG1 to 4, 7, 9, 10, 11, 15, 17, 20, 21, 22). They evaluate the following questions: where does this data come from? How was it registered and why? What are the definitions used? Does the data represent in reality? What are potential biases? If any of this is unclear, several respondents actually contacted the people that executed the registration to ask for clarification (RG1, 4, 7, 9, 10, 11, 15).

In the environmental and spatial planning domain, some respondents (RG9, 10, 17) physically go outside to see whether the data are 'correct', especially when they suspect something is wrong. RG10 explains doing this when planning maintenance work on medieval culverts. In this project, the data, information and knowledge phase were outsourced to an engineering company. This meant the civil servant only had to make the final decision about executing the maintenance. Interestingly, according to the model of the engineering company, the culverts should have collapsed already, and if not were about to collapse at any moment. However, when the civil servant checked the culverts, there seemed to be nothing wrong. It turned out that the model of the engineering company made assumptions based on modern-day construction techniques, but the culverts were constructed using medieval techniques that didn't fit this model. RG10 consulted another engineering company specialized in medieval construction techniques. This company concluded that the culverts only needed some reinforcement but other than that were in good shape. RG10 states learning an important lesson from this experience: *"You cannot trust the data blindly because the calculations can completely [destroy reality], that is something I learned here […] on the one hand you are working with a scientific approach and on the other hand you have the actual practice."*

Critical thinking thus requires careful risk analysis before starting a DDDM process, and careful checking throughout the process. However, some respondents also discussed situations that cannot be captured in these two components of critical thinking. They were confronted with specific ethical dilemmas that required contextual knowledge and judgment in order to arrive to a conclusion of how to solve the dilemma (RG1 to 5, 7, 20, 21, 22). One such illustrative example took place in the environmental and spatial planning domain and was discussed by several respondents (RG2 to 5, 20). After a sewage maintenance project had caused damage to foundations of houses due to subsidence, the team responsible for this came up with the idea to provide citizens with information about the state of the foundation of their houses to prevent this from happening again. Satellite information which measured heights of roofs of houses over time was bought from an external company. Based on this, the local government made maps in the colors green (not subsiding), orange (slightly subsiding), or red (severe subsiding). At first, the team wanted to make these maps publicly available, based on the idea that citizens could then together execute maintenance work of their foundations, as they would know about the state of their neighbors, block and street. However, several people involved in the project considered this to be unethical as (1) it could create market disruptions and (2) it could confront citizens with un-called for information that required them to act. After a lot of deliberation, the decision was made to not make the information publicly available but send people individual maps showing only their own house. In addition, citizens were given the choice to receive this information or not. Whether this is the 'right' thing to do of course is subject to debate, but the point is that the civil servants involved carefully considered the effects of their data-driven project. RG20 summarizes how they did this: *"We struggled with what [information] to give and not give, so we had to take a critical look at it and think about it. [We didn't] do that on [our] own, we looked at it with a group."* This shows that critical thinking mainly requires contextual knowledge and careful group deliberation in order to arrive to a decision. Two experts confirm this by stating that critical evaluation of ethical dilemmas requires dynamic criteria depending on the situation and its context (RE1, 12).

Furthermore, some experts (RE1, 2, 12) state that civil servants need to be able to explain why certain risks and decisions were taken. This is very important for responsible DDDM, as explained in the theoretical section. It was concluded that this can be executed by actively mapping ethical and societal aspects and incorporating them in the design process of an innovation from the onset, for example by determining what the potential impact for stakeholders involved will be. This, in combination with the fact that the respondents of Gouda strongly emphasized the importance of addressing ethical dilemmas *together*, underscores the importance of critical thinking for everyone involved in the process.

In sum, critical thinking entails being able to analyze risks and checking how the data is used, and being able to tackle ethical dilemmas by using contextual knowledge and judgement in order to arrive to a conclusion of how to solve it. In addition, one has to be able to explain why certain risks and decisions were taken. Critical thinking should be possessed by everyone involved in the DDDM process, throughout the whole process.

4.3.3 Teamwork

The third identified competency is teamwork. Fourteen respondents of Gouda (RG1 to 4, 6, 7, 9, 12, 15, 17, 19 to 22) and seven experts (RE2, 3, 4, 6, 7, 9, 10) discussed the importance of teamwork. It is a competency that should be possessed by everyone involved throughout the whole DDDM process, which I will explain below.

Many of the respondents stressed the importance of *multidisciplinary* teams (RG1, 3, 7, 9, 15, 12, 17, 19 to 22; RE2, 3, 4, 6, 7, 9, 10). This is in line with the discussion of the phases of the DDDM process as discussed above, in which it was highlighted several times that data expertise needs to be combined with domain expertise. Several respondents stated that these are both highly specialized disciplines. This means you cannot simply turn a domain specialist into a data scientist and the other way around (RG7, 12; RE2, 3, 4, 5, 7). It is thus essential to combine data and domain expertise in multidisciplinary teams. RE5 explains:

> *"You have to work integrally, [domain experts] can't sit on the other side of the building and expect to get answers to their questions, they have to join a team of for example a domain expert, someone from IT and a data analyst."*

A statement of RG12 about the start of a project in the environmental and planning domain confirms this:

> *"What I really liked is that we worked in an interdisciplinary team […] with all of [the people involved] we started thinking and brainstorming. [The data analysts] said: what do you want to be able to see as a result? And then I started thinking: what is important to me? What do I want to see? And then someone from the IT department [of Gouda] brought in the practical perspective: it has to be in line with [the systems] we already have, think of this and think of that."*

This statement shows that people from different disciplines (a domain expert, a data analyst and an IT specialist) brought in different perspectives that complemented each other.

A point that underscores this is the fact that two respondents (RG6, 21) specifically indicated that because they did not have a project team to work together with throughout the DDDM process, they did not succeed as much as they would have liked in it. RG6 explains this for developing a dashboard in the safety domain: "*I should have set up and appointed a kind of project team. [Making explicit that] we do this together, fixed moments where we discuss where we stand, who can do what, what agreements we mak*e" This indicates that interdisciplinary teamwork stretches across the whole hybrid DDDM process, therefore making the teamworking competency important throughout the whole process. Needless to say, teamwork is not executed alone, making this also a competency that should be possessed by every person involved.

It is important to note that interdisciplinary teams often do not only consist of people from the local government itself, but also of people from 'third' parties. As explained in 4.2, data collection and analysis are often outsourced to external consulting companies in the data, information and knowledge phase. Many respondents therefore discussed the importance of working together with private parties (RG6, 10, 11, 12, 14, 17; RE3 to 7, 9, 10). In working with these parties, several respondents addressed that it is important to be cautious. The previous example of the culverts showed the importance of double checking the work executed by third parties, as this might not be correct, as RG10 explains: *"That is also an aspect of collaborating [with third parties], that you don't blindly agree with what [the third party] says, while at the same time taking it serious."* Furthermore, several respondents discussed the importance of independence in engaging third parties. RG15 explains: *"Commercial parties who can [perform certain analyses] are very expensive. And then they can [perform an analysis] but then we can't do it."* Because of this, many civil servants of Gouda explicitly state it is important to make sure that the data, analysis or final product that is delivered by a third party fits within the local governmental organization and its systems (RG3, 4, 12, 17; RE2 to 5).

To summarize, teamwork entails being able to work in an interdisciplinary team consisting of people both from one´s own organization and from third parties to which part of the DDDM process is outsourced. This is a competency that should be possessed by everyone involved, and is important in all phases of the DDDM process.

4.3.4 Domain expertise

The fourth identified competency is domain expertise. It was discussed (implicitly and explicitly) by thirteen respondents of Gouda (RG4, 6, 7, 9 to 14, 17, 19 to 22) and seven respondents (RE1 to 4, 6, 7, 11). This is not surprising considering the conclusion that, in practice, DDDM is actually more problem- or question-driven than data-driven. According to the respondents, domain expertise entails both specialist knowledge of the content of the issues at stake and expertise of the local municipal context in broader sense. As explained in the discussing of teamwork above, this domain expertise needs to be combined with data expertise in multidisciplinary teams. According to the respondents, it doesn't matter who possesses this expertise, but it has to be constantly present throughout the DDDM process. This will be explained below.

In the data phase, domain knowledge is required to understand what the ´raw´ data means, as RE7 explains:

> *"You need someone who understands a lot of the content […] [and] can say 'column F contains all those values but that is impossible'. A data analyst sees coherence between variable A and B, while a domain expert says 'yes those are actually two things that belong together logically, there is nothing surprising about that'."*

In the knowledge phase, domain expertise is needed to put the analysis into context and in the knowledge phase to judge prioritization of the information. This is illustrated by RG20 who explains that domain expertise was necessary to interpret the maps they provided in the subsidence case discussed above:

> *"We could communicate to people that we want to do maintenance in their neighborhood, however their building is red [on the map]. That may just be that you have received new roof tiles and they are a bit thinner and therefore your building has subsided, that is possible. For some people it also went up because they got solar panels on the roof, very logical explanations."*

This statement shows that specific knowledge of why buildings subside or rise was necessary in order to explain the visualizations that were made in the information phase.

Third, in the knowledge phase, domain expertise is required to make decisions about prioritization of information. RG2 explains this for a project in the environmental and spatial planning domain in which a map was developed in GIS. In the statement below, the respondent explains that domain expertise was essential to finding out which information should be prioritized in this map:

> *"In the first test results [of a map], it was very difficult [for the domain expert] to find out: what is it exactly that I'm seeing and what do I not like about it? Some things [this person] didn't like depend on a button or function, on the system, some on the data. So [you need this domain expertise] to assess why it is not [the information] they expected, and what you need to do to improve it."* (RG2)

Lastly, domain expertise is required for making a proper decision, as RE4 explains: *"What you [as a domain expert] see and what you feel is good. And you have to act on it […] if you think it's not good then there is probably a better solution or a simpler solution."* This shows the importance of understanding the context in which the decision is going to be made and the content it concerns.

In summary, it is important to have at least someone involved throughout the whole DDDM who understands the content of the issues at stake and can thereby provide context to the data and its analysis in the data, information, knowledge and decision phase. This is the competency domain expertise.

4.3.5 Engaging stakeholders

The fifth identified competency is engaging stakeholders. The importance of this competency is confirmed by thirteen respondents of Gouda (RG2, 3, 4, 6, 7, 10 to 13, 15, 16, 18, 20) and eight experts and (RE1 to 4, 7 to 10) who implicitly or explicitly mentioned this competency. This competency - according to the empirical data of this study - seems to be mainly important in two phases in the DDDM process: the data phase and the decision phase. Below, I will explain why.

In the theoretical chapter, stakeholders were defined as any group or individual who can affect or is affected by the achievement of the organization's objective. Furthermore, in that chapter I explained that engaging stakeholders is an important condition for responsible DDDM. First, I will discuss the importance of engaging individuals and groups that *affect* decision-making. Examples are healthcare organizations, housing cooperation's and citizens and citizen groups. As explained in 4.2, these organizations often provide data the government itself has no access to, which makes it important to engage them in the data phase (RG1, 7, 10, 13, 14, 15).

In the decision phase, engagement of organizations and citizen groups can provide additional, valuable information for the decision to be made. RG13 explains this for a data-driven project in the social domain in which stakeholders were actively engaged:

> *"We combined all sorts of participation things in the city with professionals who could all give their opinion […] engaging these stakeholders […] had impact on the instrument that we could offer, it showed what was feasible [according to the stakeholders]."*

Second, there are individuals and groups of stakeholders that *are being affected by* data-driven decisions of local governments. In the data phase, it is important to engage these stakeholders to check whether the data used in the process are correct. RE4 explains why this is essential:

> *"This farmer said 'how do you get this data [of my CO2 emission]? The stable that is standing there has not been in use for six years and you count it in your emissions [calculation]!' You will only find out about those kinds of things if you go there and actually talk to these people."*

Furthermore, again in the decision phase, actually talking to stakeholders is important in order to find out what the impact of the decision will be for the citizens and organizations subject to it and to deal with this in a responsible manner. RG4 and RG20 explain the importance of engaging citizens through so-called 'resident's evenings' to discuss the impact of the subsidence maps as discussed above:

> *"Residents were thinking 'well I have an [orange] map so I have to do research', or 'I have a green map so I don't have to do anything at all'. Whilst it was more intended as a guide and an indication. We did not mean it as: you have to do research or not. But it was interpreted like that.[…] and that is of course the risk with data, it is can really take on a life of its own and that was also the case here […] so [in the next resident's evening's] we looked together with these people at their maps to see what is [exactly] your situation?"* (RG4)

This statement shows that the decision to provide citizens with personal information on the maps caused some unrest amongst them. The civil servants managed this impact by not simply sending the citizens the maps, but also by inviting them to discuss each citizen's personal situations. RE4 confirms this by stating that in 'true' stakeholders' engagement: *"You have to think about the impact on citizens and for that you need to have an actual conversation with citizens, don't come up with it yourselves, that is a very important competency."* This statement shows the importance of 'going outside' and actually talking to stakeholders (RE1 to 4, 8; RG10, 11, 20).

To conclude, in DDDM processes, engaging stakeholders is an important competency in order to responsibly execute it. It entails physically going outside and engaging stakeholders to obtain relevant data they possess, to check the 'correctness' of the data that is used and to involve stakeholders in the final decision in order to assess and manage its (potential) impact. As none of the respondents mentioned a specific reason why this competency should be possessed by every single civil servant involved in the DDDM process, I conclude this is a competency that doesn't necessarily have to be possessed by everyone involved.

It is important to note that engaging stakeholders as referred to by these respondents is different from teamwork with third parties that take over part of the DDDM process, as described in the teamwork competency above. Engaging stakeholders is about involving stakeholders in a participative way in a DDDM process, not about paying a third party to execute part of the process. The latter will not necessarily make the process more responsible, whilst I argue that the former will.

4.3.6 Data analytical skills

The sixth identified competency is data analytical skills. This competency was discussed explicitly or implicitly by seventeen respondents of Gouda (RG1 to 5, 7 to 17, 20, 21) and seven experts (RE1, 3 to 9). It is an umbrella term for all kinds of skills that involve analyzing data. RE6 explains: *"it's about analyzing, visualizing, connecting, because data in itself is of course nothing."* Perhaps not surprisingly, this competency is therefore important in the data and information phase. As discussed in 4.2, these phases center around data collection, summarization, analysis and visualization.

Several respondents explicitly discuss that this is a competency that not everyone involved needs to possess (RE3, 4, 6; RG7, 9). That is because – according to them - a precondition to developing these skills is that you have to enjoy analyzing data. RE6 explains: *"I think you should intrinsically think that that [data analysis] is fun, and that it has added value. So if you [don't care] about data and presentation of data, if you are not a bit "beta", then you will not get there."* This is confirmed by RG7, who states: *"[Being able to analyze] data is not specifically necessary in my job, but it is useful if someone knows. You also see that many people do not necessarily like it, but I do."* These statements show that data analytical skills is a competency that should be possessed by at least someone involved, but not necessarily by everyone involved as not everyone will like it and/or naturally be good at it. However, as I will explain later on, this certainly doesn't mean that people cannot develop this skill at all.

In sum, being able to collect, organize, analyze and visualize data - all captured under the umbrella term 'data analytical skills' - is essential in the DDDM process. Where data literacy is about a rudimentary understanding of what data and data analysis entails, data analytical skills are about being able to actually perform this analysis. This is a competency that should be possessed by at least someone involved.

4.3.7 Innovativeness

The seventh identified competency is innovativeness. Table 1 shows several competencies that, based on the empirical material, I consider to fall within the umbrella competency of 'Innovativeness'. These are agility, ingenuity, courage and entrepreneurialism. All of these competencies were implicitly or explicitly discussed by eleven respondents of Gouda and (RG5, 6, 9, 10, 11, 12, 13, 15, 16, 17, 20) and eight experts (RE1 to 7, 10).

The umbrella competency innovativeness is very important in the data and information phase. As explained in 4.2, these phases center around data collection, organization, analysis and visualization According to RE1, innovativeness is important because of the nature of these phases: *"In my experience [data analysis] never succeeds at once. It's always a kind of trial and error. And that is fine, that is part of it. But you should not interpret that as a kind of personal failure."* RG17 explains all competencies within the umbrella term 'innovativeness', in describing the data and information phase of a data-driven project in the environmental and spatial planning domain:

> *"The lesson I have learned is: go where you want to go. However, that is not a fixed target, it moves, and you must be able to move along. You must be able to incorporate that flexibility into*

the process. Not being rigid like 'we had agreed on this way we will do it', no, you will gradually get new insights along the way. And you have to allow yourself to be guided by those insights."

This statement shows that courage and entrepreneurialism are needed to start analyzing the data with a degree of uncertainty about what the analysis is going to show. Ingenuity is needed to gain new insights along the way and agility is needed to act upon these new insights. Several respondents (RG2, 3, 4, 6, 11, 12, 15, 21, 22; RE1 to 5) described that curiosity is also an essential part of innovativeness. RE2 explains:

"Curiosity is the most important competence that a civil servant should have […] because the way you can solve a problem is changing at lightning speed, so you have to be very curious about these ways […] For example if you want to build a new building. The sources that you can use to gather information about the possibilities, the considerations, the interests, the circumstances, the time schedule, thousands of sources and thousands of parties from which you can get information, and you have to be very curious to do it in an innovative way every single time."

However, RE3 warns for the threat of 'unlimited' Innovativeness:

"This creates the feeling of 'we just keep going and everything is allowed' but that is a risk […] certainly for local governments where time, money and people are scarce […] you should also have the courage to just stop doing things. If you think it doesn't work, don't do it. Things can also be successful if at a given moment you can say it is better if we just drop it."

In sum, innovativeness (including agility, ingenuity, courage, entrepreneurialism and curiosity) is a competency that should be possessed by at least someone in the phases of data and information in the process of DDDM.

4.3.8 Political astuteness

The eight identified competency is political astuteness. In Table 1, this is referred to as a 'traditional' competency. Ten respondents of Gouda (RG1, 4, 6 to 10, 13, 14, 15, 17, 21, 22) and six experts (RE2 to 6, 9, 10,11) regarded this as an essential competency, especially because politics are so close to civil servants in local governments. This competency is important in the phases of data, knowledge and decision-making. I will explain this below.

According to RG14, political astuteness entails putting something on the political agenda and making sure it happens. This is in line with traditional political astuteness. However, in DDDM, this is slightly different. That is because DDDM pushes the decision-making process a bit further away from politics (RE6). According to RE6, politicians usually want to act immediately, but DDDM requires going through all the phases of data, information and knowledge before a decision is made. This prevents direct action. This makes political astuteness different, as explained by RE2:

"The competency would be that you dare to accept that you yourself do not know what an effect of something is going to be. And you also have the ability to tell politicians that you do not know it yet, but you can find the tools to do experiments to know better than you know at that moment."

This difference stems from the nature of the DDDM process as explained in the description of the previous two competencies: the process is often a matter of pioneering and working towards a moving target. Political astuteness then requires not only strategically putting things on the agenda, but also strategically creating room to execute data-driven projects by making explicit that this can be a pioneering process of which you yourself do not know the final outcome yet.

Again, similar to the 'traditional' competency domain expertise, the fact that political astuteness is important is probably not surprising considering the conclusion that in practice DDDM is actually often problem- or question-driven, and - as discussed in 4.2 – these questions are often posed by politicians. But even if the questions or problems are not the starting point of the DDDM process, according to RE11, engaging politicians is very important:

> *"You have to have a conversation [with politicians] before you start working with data […] because you don't want to get into the situation in which an alderman says 'I have never heard of this and now I am confronted with a fait accompli?' The council should know in advance what their civil servants are doing, that there are risks but also important benefits."*

This statement shows the importance of this competency in the data phase. However, political astuteness is also important in the knowledge and decision phase. In these phases, strategic prioritization of information in order to put something on the agenda and make it happen is very important (RG13, 14, 15). RG15 explains: *"Decision-making [for politicians] becomes easier if you can just substantiate it with data: last year this was the situation, we then did this, and now this is the situation."* RG13 specifically explains this for a decision that was made in the social domain:

> *"Eventually it comes down to political decision-making. I did the data analysis as a foundation for that decision-making. And it helped, it made a difference, because otherwise I think we would have had a lot of trouble pushing for [such a politically sensitive decision] […] and if we hadn't had that kind of analysis, I think we couldn't have pushed that through."*

In summary, political astuteness entails involving politicians in DDDM from the start and being able to strategically prioritize information in order to put something on the political agenda. As respondents did not mention a specific reason why this competency should be possessed by everyone involved in the process, political astuteness should be possessed by at least someone involved in the phases of data, knowledge and decision-making.

4.4 Hybrid competencies

Table 7 provides an overview of the eight competencies, in which phase of the DDDM process they are required, and if they should be possessed by everyone involved or at least by someone involved. Following this table and the discussion of the eight identified competencies above, I conclude that the process of 'hybrid' DDDM as observed in this study also requires 'hybrid' competencies because of two main reasons.

First, it requires both 'traditional' and 'new' competencies. Based on Table 1, domain expertise and political astuteness can be characterized as more traditional competencies. Data literacy, critical thinking, teamwork, engaging stakeholders, data analytical skills and innovativeness can be characterized as newer competencies. This mix is required because in hybrid DDDM the usage of new technologies requires newer competencies such as data literacy, data analytical skills and innovativeness. However, in hybrid DDDM the decision-making process in practice is still problem-driven and the decisions are eventually made by people who also use other sources of information than only data analysis. This requires the more traditional competency of domain expertise. Furthermore, because of the fact that ultimate decisions are often made by politicians, political astuteness is also an important competency. Lastly, responsible hybrid DDDM requires competencies such as critical thinking and engaging stakeholders.

Second, these competencies do not have to be possessed by everyone involved. This is in line with the assumption put forward in the theoretical chapter that on the level of a process, a lack of certain competencies possessed by one person can be compensated by the competencies of other people and vice versa. To underscore this, several respondents mention the need to bring people together so their competencies complement each other (RG3, 6, 12, 17, 19; RE5 to 10), or as three respondents of Gouda (RG9, 12, 17) refer to it, 'making sure the right people are at the right place'. The main reason for them to argue that complementaritity is essential, is that sometimes 'old' and 'new' competencies are contradictory, so you cannot expect one person to possess both (RG12, 13, 19). RG19 summarizes this contradiction:

> *"[In data-driven projects] you must be curious by nature […] but for an average civil servant, that is really difficult. They are usually fairly reserved. Local governments are extremely afraid of making mistakes, because they are always judged by that. And you cannot be curious and progressive without making mistakes."*

The implication of these two findings is that DDDM doesn't require a full focus on new competencies, it requires developing and rearranging both old and new competencies in such a way that they can together make the hybrid process of data-driven decision successful and responsible. In the last part of this chapter, the developability of the identified competencies will be discussed.

4.4.1 Developability of the identified competencies

In the theoretical chapter, it was explained that because I give meaning to the inductively identified competencies by linking them to pre-defined competencies, claims about the developability of these competencies can be made. Based on Table 1, I conclude that data literacy, critical thinking are skill competencies because they are defined in 21st century skills literature as such. I also conclude that teamwork, engaging stakeholders, data analytical skills and political astuteness are skill competencies. They are skills because they refer to specific, goal-oriented tasks. Domain expertise is a knowledge competency. It refers to tacit knowledge about content of issues and the wider political context of local governments. Lastly, all the competencies within the umbrella term innovativeness refer to things a person thinks or wants which causes action and consistent responses in situation. In line with Table 1, I therefore conclude that innovativeness as an umbrella term refers to motive and trait competencies.

Figure 5 plots these competencies in accordance with their type on the scale of the relationship between visibility and developability as introduced in section in Figure 1 in section 2.3.1. From Figure 5, it can be concluded that all but one of the competencies that are identified in this study as required in the process of DDDM are relatively easy to develop amongst civil servants. Only innovativeness is a competency that is relatively hard to develop.

Figure 5: Overview of the developability of the eight competencies identified in this study.

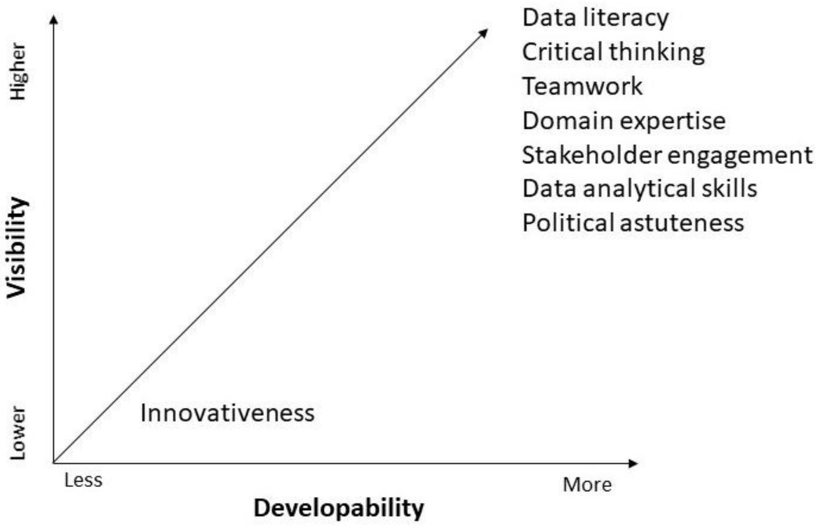


Table 7: Overview of the required competencies in the process of data-driven decision-making per phase, as identified in this study.

	Data	**Information**	**Knowledge**	**Decision**
Competencies that should be possessed by everyone	Data literacy Critical thinking Teamwork	Data literacy Critical thinking Teamwork	Data literacy Critical thinking Teamwork	Data literacy Critical thinking Teamwork
Competencies that should be possessed by at least someone in the process	Domain expertise Engaging stakeholders Data analytical skills Innovativeness Political astuteness	Domain expertise Data analytical skills Innovativeness	Domain expertise Political astuteness	Domain expertise Engaging stakeholders Political astuteness

5. Conclusion and discussion

Below, the findings of this study are summarized. Hereafter, the theoretical implications and points for practitioners that follow from these findings will be discussed. Lastly, some limitations of this study are outlined.

5.1 Summary of the findings

This study addressed the research question: *which competencies are required in the process of data-driven decision-making in local governments?* The identified competencies are data literacy, critical thinking, teamwork, domain expertise, data analytical skills, engaging stakeholders, innovativeness and political astuteness. I identified these competencies by first developing a preliminary theoretical model of required competencies in DDDM in local governments. This model allowed me to study how the process of DDDM takes place in practice in the 'typical' case of the local government of Gouda in the Netherlands. I used this model as the basis for the analysis of twelve expert interviews and twenty-two Behavioral Event Interviews (Spencer & Spencer, 1993) with civil servants of Gouda. From this analysis, I conclude that the DDDM process as observed in Gouda is hybrid. This is the case because data is used in ways beyond 'traditional' data analysis: providing insight into not only the past, but also the present and future. However the decision-making process itself is still structured in accordance with the traditional decision-making way: starting from a specific problem or question and basing decisions upon other sources than only the data, such experience, expertise and political wishes.

Building on these findings, I identified the eight competencies mentioned above. These competencies were triangulated by both the civil servants and the experts, and linked to existing competency definitions from academic literature. The ´new´ competencies of data literacy, data analytical skills and innovativeness are required because of the usage of new technologies that enable gaining insight into not only the past, but also the present and the future. The more ´traditional´ competencies of domain expertise and political astuteness are required because the decision-making process in practice is still problem-driven and the decisions are made based on other sources of information than only the data, usually by politicians. Critical thinking and engaging stakeholders are important competencies for responsible execution of the DDDM process. Critical thinking is required to check whether the data and its analysis correspond with reality. Engaging stakeholders is required to consider the impact of DDDM by actively involving the people it affects.

Furthermore, I included two additional assumptions. First, some of these competencies should be possessed by everyone involved in the process (critical thinking, data literacy and teamwork), whilst others should be possessed by at least someone involved (domain expertise, data analytical skills, engaging stakeholders, innovativeness and political astuteness). Second, some competencies are important throughout a whole DDDM process (data literacy, critical thinking, teamwork and domain expertise), whilst others are only important in some phases (data analytical skills, innovativeness, engaging stakeholders and political astuteness). From this I conclude: DDDM is hybrid process that requires hybrid competencies. It requires both traditional and newer competencies, that should be connected in different phases in the DDDM process.

5.1 Theoretical implications

These findings have some theoretical implications. First, the notion of hybrid DDDM and hybrid competencies is in line with scholarly literature on hybrid public organizations (Noordegraaf, 2007; Van der Wal & Van Hout, 2009; Van Hout, 2007). According to Van Hout (2007), hybrid organizations are characterized by a mix of pure, but often contradictive behavioral rationalities. Similarly, hybrid DDDM as observed in this study is a mixture of traditional decision-making and 'pure' data-driven-decision-making. These two rationalities to some extent contradict each other: pure DDDM requires starting from the data, whilst traditional decision-making requires starting from a specific problem. Moreover, pure DDDM requires the data to be the primary source of the final decision, whilst traditional decision-making requires other sources of information such as intuition, experience and political wishes, to come to a final decision. Similarly, the competencies that are required in this process serve different rationalities. Domain expertise and political astuteness are more traditional competencies, whilst innovativeness and data analytical skills are competencies that are specifically tailored to the 'pure' DDDM logic. It can therefore be expected that these competencies do not always naturally go together. This underscores the findings that some of the identified eight competencies only have to be possessed by at least someone involved in the DDDM process and not by everyone involved, based on the assumption that compensation on the level of the process is possible. However, the objective of this research was not to study the potential tensions between required competencies. Future studies could therefore study the process of DDDM on for example the level of teams to see to what extent the identified competencies contradict each other.

The fact that the DDDM process and the corresponding competencies are defined as hybrid also means they are subject to change (Van der Wal & Van Hout, 2009, p. 224). The 'new' technologies taken into consideration in this study are data analytics and the Internet of Things (IoT). These technologies were used in the local government studied. This study therefore did not take other technologies that might become more important in decision-making in local governments in the future into account. For example, literature suggests that the importance of technologies such as Artificial Intelligence (AI) in local governments will grow (Van den Hoven et al., 2017; Vetzo et al., 2018). In response to this, the hybrid combination of the traditional decision-making rationality and the pure DDDM rationality as currently observed in this study might change. Because of this, the eight competencies identified in this study might change as well. In other words, these competencies are not fixed. Future studies could use the preliminary theoretical model and the eight competencies to study to what extent they are subject to change under the influence of new technologies such as AI.

Second, this study provided a practical perspective on DDDM as it actually takes place in a 'typical' local government in the Netherlands. It thereby specifically distanced itself from futuristic theoretical models such as Höchtl's (2016). In Höchtl's (2016) E-policy cycle, policymaking is described as a process of constant, real-time evaluation based on data. This study provides evidence against this model by showing that in practice, there is often a lack of 'good' data or data is registered for different purposes, making it hard to link it. Furthermore, this study showed that local politicians are often the ones that put forward the questions or problems that start a DDDM process. Moreover, it showed that in the end, politicians are often also the ones making the final decisions, and in doing so, sometimes put the results of data analysis aside. I suggest that based on these findings, it is questionable whether models such as that of Höchtl (2016) will ever become a reality.

Lastly, this study leaves an unanswered question. I concluded that the identified traditional and new competencies should be connected in different phases in the process. This brings up the question: how can the connection of competencies on the level of the process of DDDM be brought about? This is an organizational structural challenge that was beyond the scope of this study. Future studies could study how local governments could connect the identified competencies through organizational structures.

5.2 Points for practitioners

The insights obtained in this study are important for practitioners. The empirically identified competencies can inform current human resource management practices of local governments that are already executing or taking the first steps in DDDM. The insights can be used in hiring, training, and rewarding civil servants (Getha-Taylor, 2008, p. 105). In respect to this it is important to note that this study provides evidence against studies suggesting that the competencies that are required in data-driven decision-making are ‘technology’ or ‘data’ competencies (Brown et al., 2011; Kim et al., 2014; Malomo & Sena, 2017). This study suggests that DDDM as it currently takes place in practice does not require only these new, technical competencies, but more traditional competencies as well. Local governments will not be able to use data in decision-making by simply focusing on hiring data scientists that possess these types of competencies. Instead, they should invest in connecting civil servants that possess newer competencies, but also more traditional competencies on the level of the process of DDDM.

Local governments should therefore invest resources into identifying which civil servants in their organization possess which competencies and in bringing them together in the process of DDDM. If however there are few civil servants who possess these ‘new’ competencies, governments would do well in developing these competencies, either by training their employees or by attending to these competencies in the processes of recruiting. As explained in the last section of the results chapter, all new competencies with the exception of the innovativeness competency should be relatively easy to develop amongst civil servants. This means that local governments could train their employees to develop newer competencies such as data literacy, critical thinking, data analytical skills and engaging stakeholders. Innovativeness on the other hand, is a competency that is harder to develop. It is therefore advisable to select civil servants that already possess this competency.

5.3 Limitations

This study also has some limitations. First, a theoretical limitation. This study focused on the micro level decision-making processes within the macro level process of policymaking. The main reason for this is that this study used the multimethod approach to identifying competencies. This starts from the work activities of people (Du Chatenier et al., 2010; Winterton et al., 2005) and focuses on the individual level experiences of these work activities by individuals (Spencer & Spencer, 1993). Competencies were identified trough expert interviews and BEIs in which the individual level experience and opinions of people were studied. This focus on individual level did not allow for a thorough investigation of the context in which the data-driven decisions observed in this study took place. I therefore did not study how competencies might differ per phase in the *policymaking* process (policy formation, policy adoption, implementation, and evaluation). According to scholars using the Knowledge Pyramid framework (e.g. Light et al., 2004; Mandinach, 2012; Mandinach et al., 2006; Schuyler Ikemoto & Marsh, 2007), context can matter for the eventual data-driven decision that is made. This means that the phase of the policymaking process at which the decision-making takes place could influence the competencies that are required in the decision-making process. Future studies could take the phase of policymaking at which decision-making takes place into account to see if the required competencies differ. This can for example be done by studying the DDDM process on the level of a team throughout a full policymaking process.

Secondly, the empirics of this study were derived from civil servants of a single case (Gouda) and from expert interviews. Even though Gouda can be considered a typical case and thus representative of many other Dutch local governments, and the competencies were triangulated by experts and linked to existing literature, it is still a single case study. Single case studies are limited in terms of external validity (Blatter & Haverland, 2012; Yin, 2013). Because of this, the preliminary theoretical model should be treated as a heuristic that enable learning and further development of theory, not as a models that perfectly represent reality (Yin, 2009). Further research could build on this heuristic to test its relevance for other (larger) local governments and potentially other governmental organizations. Furthermore, the identified list of competencies should be treated as an explorative list. Future studies could test these competencies for cases of other local governments.

Secondly, the competency method of Spencer & Spencer (1993) as employed in this study had its limitations. As discussed in the methods chapter, Spencer & Spencer (1993) discern three different ways of identifying competencies. In this study, the approach that focuses on single case studies to offer insights on future needs was followed. However, this is different from the 'classic' competency distillation approach that is recommended by Spencer & Spencer (1993). This classic approach is essentially a special form of experimental research comparing an 'average' and 'high performer' group. Based on this, one is able to distill competencies that distinguish average from high performers based on statistical significance. However, in this study, there were not enough current jobholders with enough experience in DDDM to be able to discern 'average' from 'high' performers. That is because the process of DDDM is still at its infancy in most local governments, including Gouda. Because of this, civil servants that had been part of at least one full DDDM process were selected, regardless of them performing better or worse in this process. In this sense, the relationship between the identified competencies and performance in the DDDM process should be treated carefully. The competencies identified in this study should thus be treated as indicative of the required competencies. Future studies could use the 'classic' Spencer & Spencer (1993) method to verify the competencies identified in this study. This can be done in local governments in which it is or it will be possible to make a distinction between average and high performers in DDDM processes.

Despite these cautionary words, the take-away message of this study is: data-driven decision-making in local governments is a hybrid process that requires hybrid competencies. Local governments need to invest resources in developing or selecting these competencies amongst their employees and in making sure the right people with the right competencies are put in the right place in the process of the DDDM process. This will help them exploiting the possibilities data offers in a responsible way, which is important in today's society in which the influence of new technologies will only increase.

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Appendix: Coding Tree