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A data analytics maturity assessment model for data-intensive organizations

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Abstract

Organizations across various domains increasingly rely on data to generate value for their stakeholders and customers. To gauge their proficiency in handling and analyzing this data, maturity models have been widely used. However, traditional maturity assessments based on qualitative metrics often involve tedious manual tasks and may introduce ambiguity and bias to the results.

In this research paper, we present a novel approach to maturity modeling that leverages quantitative metrics commonly found in organizations' IT systems. We propose a design method for creating a data analytics maturity model that incorporates these quantitative metrics. Our model aims to automate maturity assessments, streamlining the data collection, processing, and reporting activities.

To facilitate automated maturity assessments, we have developed an open-source tool that integrates the proposed maturity model. The tool enables organizations to conduct maturity assessments without significant time investments. Leveraging an inference engine, the tool automates the processing and reporting of both quantitative and qualitative metrics, employing techniques such as bottleneck and improvement analysis. It also identifies the most suitable data sources for automated extraction through data connections.

Our findings demonstrate the effectiveness of a maturity model composed of quantitative metrics in automating maturity assessments. The open-source tool we have developed provides organizations with valuable insights into their current and desired maturity levels. Additionally, it serves as a flexible platform for future research on automated maturity assessments.

In conclusion, our research offers a significant contribution to the field of maturity modeling and assessments. By introducing automation and quantitative metrics, we provide organizations with a more efficient and objective approach to evaluating their data analytics capabilities. The open-source tool opens up opportunities for further research and development in the domain of automated maturity assessments.

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Glossary

BA	Business Analytics
BD	Big Data
BI	Business Intelligence
CMM	Capability Maturity Model
CMMI	Capability Maturity Model Integration
Context characteristics	Maturity model characteristics related to its publication circumstances and validation
DA	Data Analytics
DM	Data Analytics
DW	Data Warehousing
DQM	Data Quality Management
IoT	Internet of Things
Inference engine	Method of converting maturity assessment data into maturity levels. Can be extended for other automatic calculations
MDM	Master Data Management
ML	Machine Learning
MM	Maturity Model
Procedure model	Methods for the design of maturity models
QA	Quality Assurance
QDAMM	Quantitative Data Analytics Maturity Model
Reference model	Part of the maturity model that mentioned maturity items and levels
Structure characteristics	Maturity model characteristics related to its structure, content, and inference engine
UI	User Inferface

1 Introduction

Due to the fast advancements in digitalization, more organizations employ data analytics processes to gain a competitive advantage (Korsten et al., 2022). Developments like real-time data analysis, cloud and edge computing, and big data analysis introduce new ways through which organizations can obtain insight and business value (M. Chen et al., 2014; Muller & Hart, 2016). If adopted successfully, these developments can increase productivity by 5% and profitability by 6% with respect to competitors (Barton & Court, 2012; Popovič et al., 2012), and help with decision-making and cost-cutting (Dinter, 2012). Business processes, organizational models, and stakeholders must be continuously realigned to reap the benefits of data analysis (Günther et al., 2017). Despite the benefits of adopting data analytics, one of the key challenges remains that organizations struggle with successfully implementing them (Ransbotham et al., 2015), often. This is because organizations often lack the required capabilities to optimally make use of these new developments (Al-Sai et al., 2020).

Much research has been done on identifying important data analytics-related capabilities, such as *Data management* (Peña et al., 2019), and *Data integration*(Popovič et al., 2012). These capabilities determine the degree to which organizations can generate value from data. Increased capabilities positively correlate to business value (Korsten et al., 2022). This indicates a need to assess the state of these capabilities and improve them. This as-is performance, or adequacy, of capabilities of organizations, is often expressed as *maturity*.

Maturity can be defined as "*the state of being complete, perfect or ready*" (Simpson et al., 2004). This implies that maturity is evolutionary progress in demonstrating a specific ability or accomplishing a target from an initial stage to a desired end stage (Mettler, 2009). Maturity models capture this process from an initial state to the desired end state and can guide organizations in assessing and developing organizational capabilities (Poeppelbuss et al., 2011). These models often have the same core characteristics and components (Lahrmann et al., 2011).

The models define *maturity dimensions*: specific capability areas, process areas, and design objects forming the field of interest. de Bruin et al. (2005) argue that these should be mutually exclusive and collectively exhaustive. Each dimension is decomposed into specific capabilities of which the maturity can be assessed using a comprehensive set of criteria, often named Key Performance Indicators (KPI). Methods of collecting KPI data for maturity assessments are, for example, semi-structured interviews (Shrestha et al., 2020) or Likert questions in a questionnaire, where each point corresponds to a maturity level (Peña et al., 2019). Sometimes KPIs are further broken down into *maturity metrics*, which are specific data points that can be measured. All of the maturity items that populate a maturity model form its *Reference model* (Ofner et al., 2009). This model refers to the scope that the maturity model covers, expressed on its maturity items. The way in which the maturity levels are linked to the particular maturity items in the reference model is called the *Assessment model*. This model allows for maturity levels to be assigned to specific items based on input data. Pöppelbuß & Röglinger (2011) refer to this part of maturity models as its *Decision calculus*, stating that its needs to be defined to draw meaningful conclusions from the collected data. This then indicates how collected data leads to the assignment of maturity levels and can help decision-makers to base their maturation decisions on data (Peterson, 2017).

The *maturity levels* of a maturity model form different stages of a maturity item's maturity. They often start from level 1, indicating low maturity, to level 5, showing very high maturity. For each capability, all maturity levels have a distinguishing description that clearly describes the characteristics that a capability must exhibit before attaining that maturity level (Lahrmann et al., 2011). They are structured according to an underlying *maturity principle*. Maturity models can be continuous or staged. Continuous models define maturity levels per capability, allowing the scoring of activities at different levels. Staged models require all capabilities to attain a specific maturity before reaching a total, over-arching maturity level. They specify the number of goals and essential practices to achieve these predefined levels. Continuous maturity models allow for different maturation paths; meaning that organizations can follow multiple routes when maturing instead of always having the same set of requirements to reach the next maturity level

Maturity models can be used as an evaluative tool for tracking the maturity of capabilities and subsequently improving them (de Bruin et al., 2005). The evaluations are called *maturity assessments* and consist of three main activities: data collection, data processing, and data reporting (Shrestha et al., 2020). The data collection activity refers to using a method of data collection, to extract the required data from a certain data source. In current literature, these data sources always refer to the tacit knowledge of humans. This data is collected through either interviews, surveys, or other qualitative data extraction methods. The data that needs to be collected is defined by the reference model. The assessment model/decision calculus can then be used to process the data. The calculus can be qualitative or quantitative. For example, qualitative decision calculus could describe the needed capabilities for maturity level X. The data is then collected through a survey, and an expert assigns the correct maturity level after an analysis. An example of quantitative decision calculus is a formula that uses data collected from KPIs to calculate the associated maturity level. Prescriptive maturity models can utilize quantitative criteria to implement bottleneck identification into the maturity assessment results (Lukhmanov et al., 2022). This activity of processing the maturity assessment data is the second of the three activities. The third main maturity assessment activity is the reporting of the results; Data reporting (Shrestha et al., 2020). This can be done in the form of verbal or textual reports, or through visualizations, like was done by Pinzone et al. (2021); Schumacher et al. (2016); Caiado et al. (2021). This also depends on the assessment type; self-assessment, where the maturity model was designed to be used by organizations themselves, or third-party assisted assessments. The three maturity assessment activities are often performed manually. This is because the data collection needed for the capability assessment criteria is often through questionnaires or interviews. Lastly, maturity models can support maturity assessment that output either descriptive, prescriptive, or comparative data. Descriptive maturity models only show the current maturity of the organization and do not provide recommendations on how to mature. Prescriptive maturity models provide improvement suggestions to help organizations mature further, helping them to create a maturation roadmap for future improvements. Comparative maturity models are designed with benchmarking across industries or regions in mind (de Bruin et al., 2005). His allows organizations to compare their performance to other maturity model users. For such purposes, a high adoption rate is beneficial.

Problem statement

Maturity models have received a lot of criticism regarding their design, characteristics, and implementation. Models can, for example, be too large and therefore incomprehensible and expensive to implement(Steenbergen et al., 2010). The lack of standardized terminology is also noted (Sacu & Spruit, 2010), as well as a lack of consensus of essential maturity items and levels (Wagire et al., 2021; Cates et al., 2005).

Regarding the design of new maturity models in general, many researchers note the lack of a (detailed) design methodology (Raber et al., 2012; Frick et al., 2013; Dikhanbayeva et al., 2020). Due to many newly proposed ad-hoc developed maturity models, researchers proposed maturity model design methodologies (de Bruin et al., 2005; Mettler, 2009), also called *Procedure models* (Röglinger et al., 2012). However, these procedure models are often fairly old and do not mention the possible automation of the maturity models. The partially automated models proposed in the literature have also not been designed according to these procedure models. Another common limitation of maturity models is their lack of documentation and availability (Chuah & Wong, 2011). Often, the paper does not include information regarding the model structure, content, or its inception. It is also noted that many models are not grounded in literature, i.e., by not performing literature research on older models before designing a new one (Poeppelbuss et al., 2011). This causes near-duplicate models. Lastly, many maturity models are not empirically validated, causing their usefulness to be unproven (Dinter, 2012).

Further criticism is related to the nature of the data collection and how conclusions are drawn from them. Manual maturity assessments are criticized for being expensive in manpower and resources (Devaraju & Huber, 2021; Shrestha et al., 2020). Performing lots of interviews to gather the required data takes time. Furthermore, it is argued that maturity assessments conducted by humans vary in terms of results (de Carvalho et al., 2016) and that a lack of maturity models allows for automating this process. Krivograd et al. (2014) mention several advantages of automating the maturity assessment process. Some benefits are lower costs, execution of more regular assessments, and better improvement recommendations. The need for continuous maturity assessment would also be fulfilled (Szelagowski & Berniak-Woźny, 2022).

Furthermore, Vasarhelyi et al. (2012) note that audit automation is beneficial and places it at the highest maturity level in their Audit maturity model. A handful of models incorporate either automated inference engines or automated data collection, but not both. This is because they often require qualitative data, a datatype that is much harder to automate. (Shrestha et al., 2020). Shrestha et al. (2020) mention the automatic collection and processing of process output data, as opposed to survey questions, as an interesting venue for future research. No research has yet been done on designing such a maturity model containing quantitative KPIs retrieved directly from the processes and IT tooling of organizations. This study aims to expand on the automation capabilities by using a quantitative decision calculus that infers, among others, recommendation suggestions from the collected maturity assessment data. Following work published by Farshidi (2020), this thesis henceforth calls the expanded decision calculus an *Inference engine*.

This research aims to use an adapted procedure model that incorporates the need for automated maturity assessments. This model is then used to systematically design a new prescriptive maturity model by documenting all design choices. The resulting maturity model has qualitative and easily automatable quantitative KPIs and an automated inference engine. This maturity model is built into a tool that allows for automation and visual reporting of the maturity assessment results. Such a tool will enable data-intensive organizations to follow the guidelines outlined by the reference model and allows easy, cheap, and continuous assessment and reporting of their current maturity. It also improves this maturity by following the improvement suggestions generated by the inference engine.

2 Research Approach

This chapter explains the research approach that was used to conduct the research and answer the research questions.

2.1 Research questions

Maturity assessments are currently often performed through interviews, a very cost en time-intensive process. To lay the foundation for research into automated-assisted maturity assessment through specially designed maturity models, the following main research question (MRQ) was elicited:

MRQ: *How can a data analytics maturity model be developed and validated that automatically quantifies KPIs to support decision-makers at data-intensive organizations?*

This research question focuses on maturity models in the data analytics domain. This is deliberate as this domain overlaps with the target group of this research; data-intensive organizations. These are organizations that use or generate data through their processes. Combined, these two requirements ensure that the results of this research are relevant for all organizations to practice data analytics.

To build a solid theoretical foundation for the to-be-designed artifacts, and to ensure their proper design and validation, the main research questions has been split up into five sub-research questions (RQ) to guide the research:

- **RQ1**: *Which data analytics maturity models exist in literature?*

The above research questions aim to gather data on the contemporary landscape of data analytics maturity models. A set of maturity models, and other relevant sources, is collected which can be used as a basis from which to answer sub-question 2.

- **RQ2**: *Which features and concepts are common in data analytics maturity models?*

Through the effort of answering this research question, a set of important and frequent characteristics is obtained that can be used in the design process of the proposed maturity model. The structure, maturity levels, and maturity items of the model can be based on frequency analysis of the collected data, and a gap analysis of maturity model performance and limitations can show which threats to maturity model performance should be mitigated. Automation possibilities of the maturity assessment process are also assessed to see how a maturity model can be extended to support automation.

- **RQ3**: *How can a data analytics maturity model's performance and effectiveness be evaluated?*

The third sub-question is designed to steer and form the process that is later used to implement and validate the proposed maturity model. An analysis is maturity model design methods can indicate what characteristics are important in maturity modeling. These characteristics can then be used, together with data on common validation techniques found in literature, to elicit a validation protocol that can be implemented using expert interviews.

- **RQ4**: *How can a new data analytics maturity model be designed to support automatic maturity assessment?*

The fourth sub-question is concerned with the design of the data analytics maturity model. Previously gained knowledge on important maturity model content and relevant structures, as well as knowledge on extending the model for automation support, is used to inform the design of the proposed maturity model. Maturity areas are linked with a set of maturity levels, and for each combination of maturity item and level criteria are created to allow for maturity assessments to be performed using the model. Validation of the model also falls under this sub-question and is informed by the results of sun-question three.

- **RQ5**: *Do the proposed maturity model and tool help in attaining a higher maturity level?*

Lastly, the fifth sub-question relates to the implementation and validation of the proposed maturity model through an industrial case study in an effort to empirically ground it. The automatability and ease of use of the proposed artifacts are validated by collecting input data and using this to perform a maturity assessment. The expected result of answering this sub-question is data and knowledge on the performed maturity assessment, as well as quantitative and qualitative data on the potential of the maturity model. Upon answering the sub-question, and all questions before, the main research questions will have been answered.

RQs 1 to 3 are answered using a systematic literature review (SLR) and are related to the state-of-the-art maturity models described in the literature. Data will be extracted and analyzed, resulting in an overview of current maturity models, their characteristics, maturity dimensions, capability, KPIs, and automatability. This data will then be used to propose a new maturity model. RQ4 involves expert interviews and refers to the elicitation and validation of the maturity model. RQ5 concerns the validation of the proposed model through an industrial case study. Table 1 provides an overview of the research methods and questions used.

2.2 Research methods

The research questions defined in section 1.2 will be answered using different research methods. These methods are *Literature research*, *Expert interviews*, *Design science*, and *Case study* Table 1 shows the research questions with their respective methods. These methods are further explained in the following sections.

Research questions		**Research methods**			
		Literature study	Expert interviews	Design science	Case study
MRQ	*How can a data analytics maturity model be developed and validated that automatically quantifies KPIs to support decision-makers at data-intensive organizations?*	X	X	X	X
RQ1	*Which data analytics maturity models exist in literature?*	X			
RQ2	*Which features and concepts are common in data analytics maturity models?*	X			
RQ3	*How can a data analytics maturity model's performance and effectiveness be evaluated?*	X	X		
RQ4	*How can a new data analytics maturity model be designed to support automatic maturity assessment?*	X	X	X	
RQ5	*Do the proposed maturity model and tool help in attaining a higher maturity level?*			X	X

Table 1: Research methods used to answer the research questions

2.2.1 Literature study

A systematic literature review (SLR) was performed to gather information about the state-of-the-art of the research domain. This ensures that the proposed model is grounded in contemporary literature and that the problems in the domain are clear and can be mitigated. The aim is to collect maturity models, their characteristics, relevant KPIs, and maturity model limitations. Implementation barriers and maturity characteristics like the used maturity levels are also collected. The used protocol is described below, while the results are described in Chapter 2, and used for the creation of the maturity model in Chapter 3.

Kitchenham (2004) describe a protocol for performing SLRs, consisting of eleven phases: Problem formulation, research questions, review protocol (search strategy), search process, searching, screening, inclusion/exclusion criteria, quality assessment, data extraction, analyzing and synthesizing data, and reporting.

The **Problem formulation** phase starts the research protocol. First, the domain and its challenges must be understood to ensure the relevancy of the research. Relevant papers are found, and the contribution of the study becomes evident. **Research questions** are then elicited, which help structure the research and expected results. A **Review protocol (search strategy)** was drafted and used during the SLR. The eleven phases of protocol proposed by (Kitchenham, 2004) were condensed into five phases. Phase one contained the search process, searching, and screening. This resulted in the first set of papers. The second phase involved eliciting inclusion and exclusion criteria and assessing the collected papers. These papers were then graded on quality in the third phase. The fourth phase involved data extraction from the remaining papers, after which the data was analyzed, synthesized, and reported in the fifth phase. The **Search process** is the process of manually collecting relevant papers for initial hypothesis formulation based on the elicited research questions. The papers found during this phase generate the search term, which is later used in the *Searching* phase. This literature study included sources from four libraries: *IEEE Xplore*, *Springer*, *ACM DL*, and *ScienceDirect*. Furthermore, only papers written in English and published after 2009 were included to ensure relevancy. **Searching** was performed to collect the to-be-assessed papers. Based on papers found for initial hypothesis formulation, a set of key terms was combined into a search term (see section 3.1.2). This search term was entered into the four digital libraries, and several search parameters, like publication date, were set. The results were exported in CSV format and combined into a spreadsheet. Collected characteristics were the Title, Url, Authors, Abstract, Keywords, Year of publication, Citations, Venue, and Venue Ranking.

During the **Screening** part of the process, all papers are checked using their abstract, keywords, and title. The paper is then given a relevancy score of *None*, *Low*, *Medium*, or *High* depending on its relevancy to the research. **Inclusion/Exclusion criteria** were created to decide with which papers to proceed in the SLR. These criteria were based on the relevancy of the paper defined earlier in the screening phase, the quality of the venue, citations, publication year, and research type. **Quality assessment** was then performed to assess the quality of the remaining papers. Information like the used research methods and types (quantitative or qualitative), data collection methods, and validation methods were extracted. Furthermore, each paper was checked on whether it had a clear problem statement, research questions, research challenges, statement of findings, and whether the authors mentioned real-world use cases. Based on this data, each paper was graded on its quality, and based on this, the final set of papers for data extraction was created.

All relevant data were collected from the remaining papers during the **Data extraction** phase. This selection of to-be-extracted data is based on the earlier defined research questions. Data about the nature of the paper in the domain of Maturity modeling was collected, as well as data about proposed maturity models and other maturity-related concepts. The data was stored in a large spreadsheet, and a definition was extracted for each concept to ensure the consistency of the dataset. **Analyzing and synthesizing the data** was then performed to clean up the dataset. Due to many extracted concepts, some duplicates were extracted separately instead of being grouped. During the synthesis phase, the duplicates were resolved, and similar items were grouped based on their definition. A changelog was kept containing notes of all changes. Further data analysis was performed to gather insight to help answer RQ1-3. **Reporting** was performed as the final step of the SLR. The result can be found in Chapter 2 of this research.

2.2.2 Design science

The purpose of this research is to propose a new maturity model and a design method to create this model. The Design Science methodology by A. Hevner & Chatterjee (2010) was used to facilitate this and ensure rigor. This methodology was developed to support research projects in the IT domain and facilitates the introduction of new artifacts into an existing environment. The method consists of three cycles: the Relevance cycle, the Design cycle, and the Rigor cycle. Figure 1 shows the Design Science model.

The Relevance cycle ensures the proposed artifact tackles a relevant problem or opportunity. It involves understanding the application domain and its gaps and improvement opportunities. Not only does this cycle initiate research into the requirements of the artifact, but it also defines acceptance criteria for correctly evaluating the research results. The conducted SLR will help with understanding the application domain and possible requirements. These can be refined during the expert interviews.

The Rigor cycle is concerned with evaluating and improving the current knowledge base of the domain. The application domain should be thoroughly researched for state-of-the-art methods and techniques to ensure the research is novel, not just routine design. The knowledge base can contain scientific theories, engineering methods, experiences, expertise, and existing artifacts. The proposed maturity model is based on thorough domain analysis and is validated through expert interviews and a case study to ensure novelty and relevance.

As A. Hevner & Chatterjee (2010) state: "*The internal design cycle is the heart of any design science research project.*". The Design cycle iterates between the construction of the artifact, its validation, and its subsequent refinement. Requirements for the artifact's design are retrieved from the Relevance cycle, while the design and validation methods are drawn from the Rigor cycle.

The research will lead to a relevant, rigorously designed, and validated artifact if all three cycles are correctly executed.

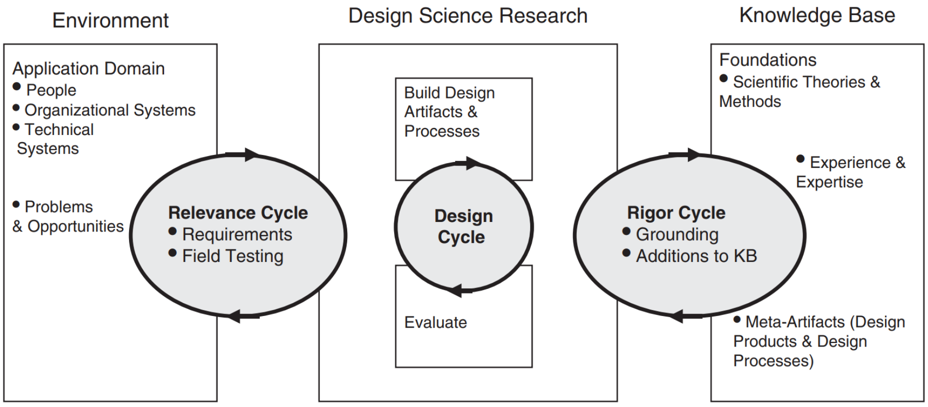

Figure 1: Systematic Literature Review process (adopted from (A. Hevner & Chatterjee, 2010))

2.2.3 Expert interview

Expert interviews were conducted to validate the findings from the SLR and gather new information from the practitioners' perspective while also being used to validate the proposed maturity model. The interviews consisted of two rounds. The first round consisted of exploratory semi-structured interviews, meaning a predefined list of questions was designed to allow for a more free conversation than when conducting structured interviews. This round aimed to collect essential maturity items and considerations without showing the proposed maturity model. This was only done during the second round of interviews, after slight revisions based on the collected data. The second round consisted of experts validating the maturity model using a template proposed by Salah et al. (2014). Based on this data, the maturity model could be finalized, and sub-question four answered.

The experts were invited after a screening phase where it was determined what their expertise was. Experts who were either experts on maturity models, data analysis, or both were considered. This is because the structure and characteristics of the maturity model needed to be validated, as well as the data analysis-related content of the model. Fifty-eight experts were considered, of which 39 have been invited to an interview. Ultimately, 11 interviewees accepted the invitation.

The first round of interviews typically lasted around 45 minutes and followed a protocol that indicated the questions and interview phases. The protocol is found in Appendix. E. First, questions about relevant maturity model characteristics and data analysis processes were asked. Then the interviewees were shown the answers of other interviewees so they could agree or disagree with different notions. For the second round, the interviewees were shown the proposed maturity model (sometimes, it was sent to them due to time constraints). They then answered Likert questions about the model's completeness and usefulness. Ultimately, not all interviewees responded to the invitation for a second round, with only six providing feedback on this matter. The validation template was retrieved from Salah et al. (2014).

2.2.4 Case study

A case study is conducted after the SLR and Expert interviews to validate the proposed model in an industry setting. The case study was conducted at InTraffic, a data analytics company in the public-transport domain. A total of 9 case study participants were shown the maturity model and automated maturity assessment tool. The results of a maturity assessment were discussed with them as well as the strengths and weaknesses of the tool. This was done through a TAM questionnaire (Davis, 1989). The case study protocol can be found in Appendix. H.

2.3 Contributions

This research aims to provide a contemporary overview of the domain of maturity modeling through a systematic literature review. This grants insights into currently used maturity models and their characteristics. Limitations of current maturity models are also identified. Furthermore, the automatability of KPIs and inference engines within maturity models is researched to identify opportunities to reduce the resource costs of maturity assessments.

The scientific contribution of this research consists of the results from the systematic literature review. A maturity model containing quantitative KPIs is proposed to reduce the costs and bias of maturity assessments and allow for automation. A tool is then built and validated to help with conducting and reporting the results of the maturity assessments conduct and report the maturity assessment results.

3 Literature study

This chapter contains the results of the SLR conducted according to the protocol proposed by Kitchenham (2004). The SLR aimed to provide this thesis with a solid theoretical foundation. Through this study, RQ1, RQ2, and RQ3 are answered, and a contribution is made to answering RQ4.

3.1 Research protocol

First, the SLR protocol is elaborated to show the research phases conducted. Each step is explained, and the choices that were made are substantiated. The researched maturity models are discussed. Their application domains, limitations, and characteristics are presented, and their usefulness to the to-be-designed maturity model is elaborated upon. More results of the literature study are described in Chapter 3. Here, the design process of the proposed maturity model is discussed. For each maturity model item, e.g., capabilities and KPIs, frequency analysis is used over the literature study results to determine whether to include the maturity item in the new model.

3.1.1 Search strategy

During the SLR, four main digital libraries were used to collect papers. These are ACM Digital Library (ACM DL), Springer Publishing (Springer), IEEE Xplore Digital Library (IEEE Xplore), and ScienceDirect. These four libraries were chosen since they offer high-quality papers valuable to the scientific community. Grey literature was not included in the SLR, except during the *Initial hypotheses* step, to guarantee the scientific value of the research. For this reason, Google Scholar was not used as a digital library after the Initial hypotheses step. Maturity models with a practitioner origin are therefore not included in this study.

Based on the limited domain knowledge at the start of the research process, and the designed research questions, a small set of search terms was created to gather papers from the four digital libraries. These were: (1) *Automated maturity model*, (2) *Data analytics maturity*, (3) *Maturity assessment*, (4) *Maturity model*, (5) *Maturity model elicitation*, and (6) *Maturity model evaluation*,

This Initial hypotheses step served to help gather an understanding of the domain. This gave an overview of relevant research topics and substantiated the research questions that were created. This initial set of research papers, labeled *Initial hypotheses* papers, contains 456 articles, of which the relevancy was assessed. 126 of these papers were deemed relevant enough to be used for the search term creation, which is explained in a later section. Although not used whenever possible, Google Scholar and grey literature were included during this research step as no data was collected from the papers. Only their titles were used. Based on these papers, search terms were generated to collect the actual set of to-be-analyzed papers.

3.1.2 Search process

During this phase, papers were extracted, which will be used for the data extraction phase. Grey literature is discarded from here on out, and Google Scholar sources are only kept if they have many citations and are deemed highly relevant. Figure 2 gives an overview of the different SLR phases, the outcomes of each step, and the number of papers involved.

The titles of the papers in the Initial hypotheses set were used to create a new search term. This was done using Frequent word analysis using an online tool: SketchEngine. This resulted in a set of frequent terms, which was subsequently divided into *Focus* and *Domain*-related terms. Based on the online tool's score, the most relevant terms in both categories were combined into a search term. This term represents currently pertinent domains of the maturity modeling field and harbors the created research questions. The search term is:

("maturity model" OR "maturity level" OR "maturity assessment" OR "analytics maturity" OR "capability maturity model" OR "evaluation of maturity" OR "maturity model development") AND ("big data" OR "bi" OR "business intelligence" OR "development of maturity" OR "development of maturity models" OR "data governance maturity")

This search term was entered into each of the four digital libraries, and some filters were applied. An example is to include papers published after 2009. The resulting papers were exported and put into an Excel sheet, and duplicates were removed from the list. Then several empty or wrongly parsed cells were restored. The total pool of papers at this point was 1988. During the assessment phase of the SLR, each paper was marked as a potential candidate for backward snowballing. However, no backward snowballing was performed due to the sufficient number of papers.

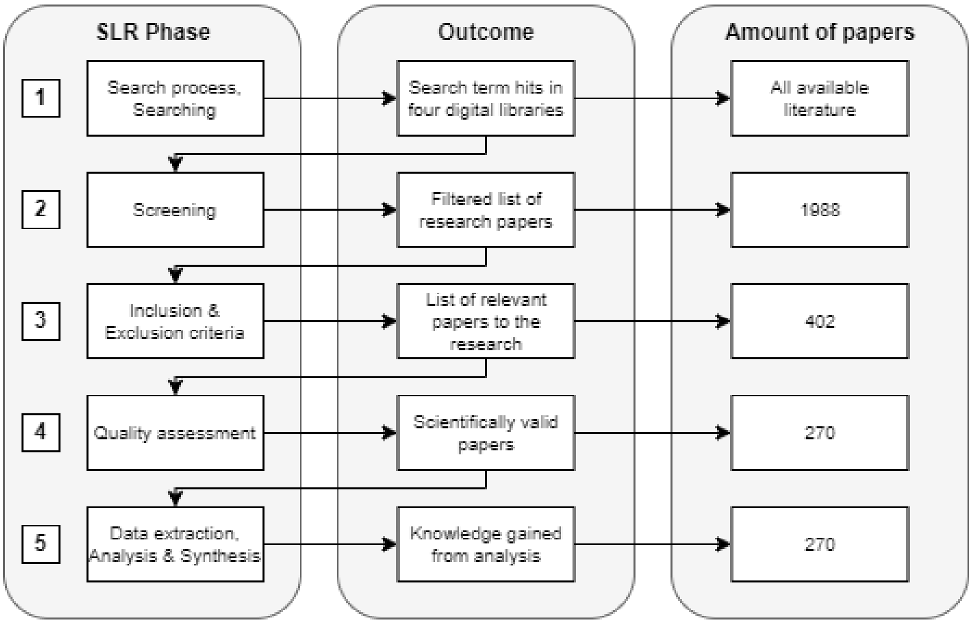

Figure 2: Systematic Literature Review process (adopted from (Farshidi et al., 2020; Farshidi, 2020))

3.1.3 Inclusion and exclusion criteria

During this SLR phase, the remaining papers underwent a screening process in which they were evaluated. The goal was to filter out papers that were not relevant to this research or that were published in poorly-graded venues. The papers' abstracts, titles, and keywords were read for this process. A brief scan of the paper was also performed. The papers were then ranked based on their relevance to the research. This relevancy could be *None*, *Low*, *Medium*, and *High*. A further set of characteristics was extracted from the papers. These are the year of publication, citation count, venue, and venue ranking. Based on these factors and the relevancy, a score was calculated for each paper, and a threshold was set for the inclusion or exclusion of papers. The parameter values are documented in the dataset for transparency. The aim was to keep papers with high relevancy, which are published in highly-regarded and contemporary venues. Therefore, an older publication year meant a lower score, while the number of citations boosted the paper's score. Grey literature was immediately dropped by setting the score to zero. A total of 402 proceeded to the next phase of the SLR.

3.1.4 Quality assessment

The Quality assessment phase concerns assessing the quality of all the papers. For this purpose, the research methods that the papers reported on were extracted and analyzed. Five criteria were considered during this assessment. These are shown in table 2. For each paper, these five criteria were marked using a dichotomous ("Yes", "No") answer. A score was then generated based on these criteria. A paper was only included in the next phase of the SLR if its score was higher than the threshold, indicating its high scientific value. In total, 270 papers continued to the data extraction phase.

Besides the criteria listed below, the research, data collection, and evaluation methods were also extracted. These have not been used as inclusion/exclusion criteria, however.

Quality criteria	**Definition**
Clear problem statement	Does the study contain a clear problem statement?
Research questions	Does the study contain research questions or hypotheses?
Clear research challenges	Are the clear research challenges of the study explained?
A clear statement of findings	Are research results elaborated clearly and understandably?
Real-world use cases	Does the study contains a real-world use case?

Table 2: Quality assessment criteria (retrieved from (Kitchenham, 2004))

3.1.5 Data extraction, analysis, and synthesis

Data was extracted from the 270 papers that got through all previous research phases. The distribution of the publication years is shown in figure 3. Many papers are recent, while papers become less numerous as we go back in time. This is partly due to the way in which the inclusion/exclusion criteria formula was designed, where older papers were given a lesser grade than newer papers. A few papers from before 2010 are also shown. These were included in the study due to their high citation count and relevancy in the field of maturity modeling.

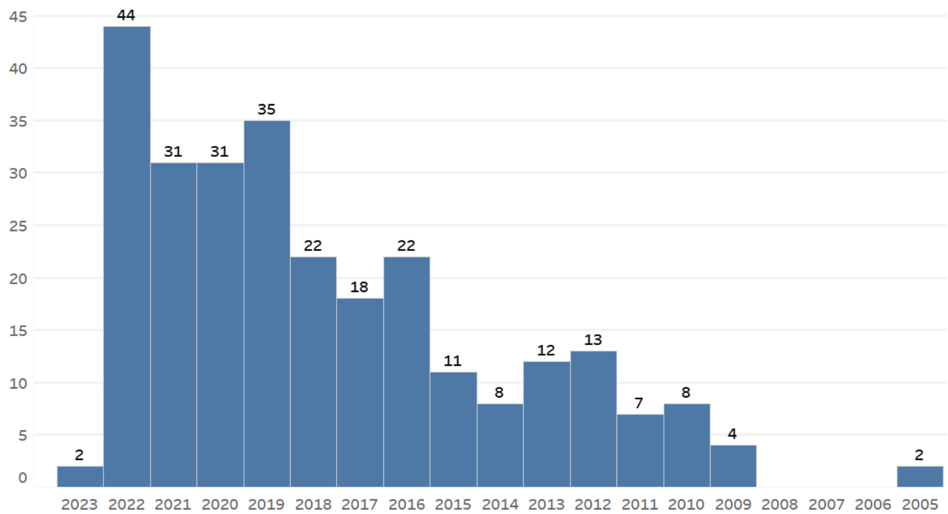

Figure 3: Distribution of research papers' publication years

The papers have been analyzed and categorized according to a categorization proposed by Wendler (2012). This categorization refers to the research content of the paper and consists of 8 paper types, as shown below. The authors furthermore propose the categories of *application domain* and *developed/used maturity model*. The distribution of the paper in this categorization is shown in figure 4. Due to the rigorous assessment of paper quality and relevance, most papers included in the data extraction phase propose a maturity model or map relevant models. On the other hand, very few models produced little to no useful data for this study.

- *Concept/construction*: articles where a maturity model is developed (conceptual) or constructed (design-oriented)
- *Description*: articles where existent maturity models are described for presentation purposes or as applicable methods or instruments
- *Mapping/comparison*: articles where existent maturity models are compared and mapped to each other or to other maturity-related concepts
- *Assessment*: articles where the maturity of industries, organizations, etc. is assessed (not the assessment, in terms of validation, of the model itself)

- *Transfer*: articles where an existing maturity model is applied to another domain or research field without changing the model or developing a new one
- *Empirical study*: articles where an empirical study (qualitative, quantitative, and mixed) has been conducted to develop, apply, or validate maturity models, take out assessments, or other purposes
- *Theoretical reflection*: articles where theoretical implications of maturity models are discussed; for example, applicable theories, measurement approaches, theoretical benefits, and others
- *Others*: articles that could not be classified into the before-mentioned concepts

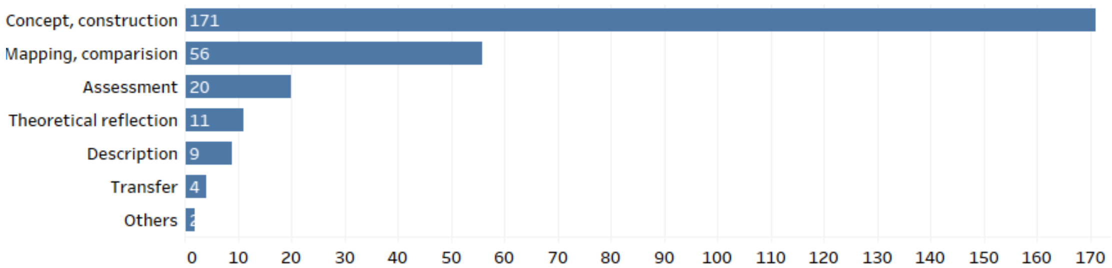

Figure 4: Distribution of research papers' content according to the categorization by Wendler (2012)

The domains in which a research paper is positioned were also extracted and can be seen in figure 5. First, all domains and sub-domains were extracted from the research papers to come to this set of domains. An example of this is a research paper with domain *Business Intelligence* and sub-domain *Enterprise business intelligence (EBI)*. Based on this set of domains and sub-domains, a grouping was made for the domains to avoid a long list of domains with occurrences of 1 or 2. The groupings are explained below. The sub-domains can be found in the dataset (Appendix A).

- *Business Operations and Digital Transformation*: refers to the management of business processes and use of digital technologies to improve and optimize various operations, processes, and functions.
- *Data Management and Analysis*: Refers to the collecting, organizing, maintaining, and analyzing of data to derive insights and make informed decisions. This domain encompasses, for example, Business Intelligence and Data analysis.
- *Knowledge Management*: Refers to papers in the field of Innovation, Knowledge management, and Knowledge creation.
- *Information Technology Management*: Encompasses domains like Information system management, IT governance, and Software ecosystem.
- *Software Development Methodologies*: articles where the maturity of industries, organizations, etc. is assessed (not the assessment, in terms of validation, of the model itself)
- *Cybersecurity and Monitoring*: Refers to research papers in Cybersecurity, Auditing, and Monitoring of, for example, performance.
- *Urban Development and Sustainability*: This domain encompasses the domains of Smart Cities and Sustainability/Environmental performance.
- *E-government*: Research articles in the Open Government and E-government field fall under this domain.
- *Supply Chain and Operations Management*: articles related to managing and improving supply chains and relations operations and processes.
- *Healthcare Information Systems*: This domain refers to maturity modeling research in the field of Healthcare, or, for example, Healthcare Information Systems.

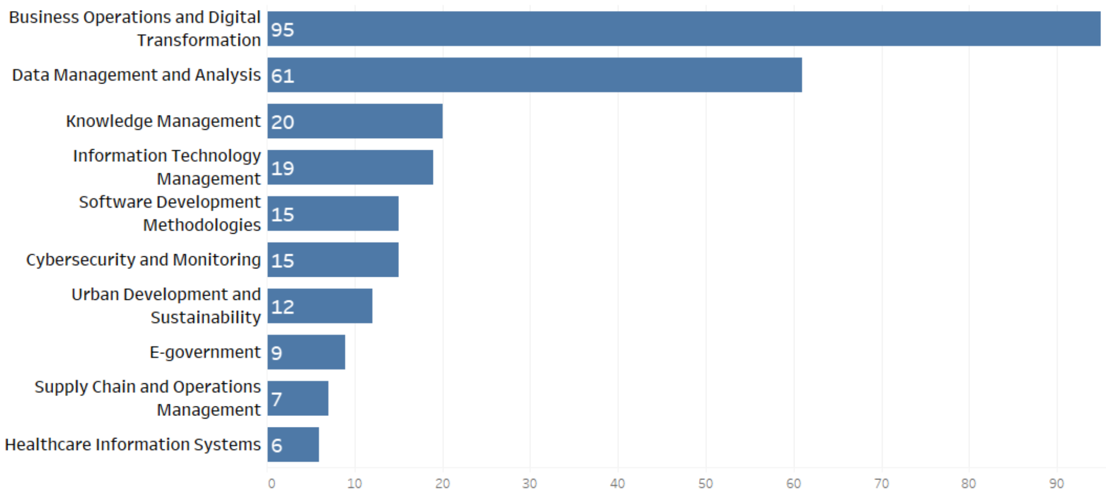

Figure 5: Distribution of research papers' domains

Other data was extracted from the research papers. From papers that proposed a maturity model, the content was extracted and marked in the dataset for data analysis. This includes the maturity levels, maturity dimensions, mentioned capabilities, and relevant KPIs. This is reported upon in Chapter 3, related to the development of the proposed model. Furthermore, it was checked if these papers propose a maturity assessment tool other than the model itself, which could be analyzed. Used datasets were also marked down if these were mentioned.

All types of papers mentioned possible limitations of current maturity models. These limitations have also been extracted and written down as these are useful to consider during the design of the maturity model. Furthermore, possible implementation barriers are also extracted for the same purpose.

During the whole data extraction phase, a list of definitions was used to keep track of the extracted elements. This was done to limit threats to internal validity. After the completion of the data extraction, the dataset was cleaned. Duplicate items were combined, and similar items were combined, if logical, based on their definitions. All changes during this phase were recorded in a changelog so that the whole process is documented and transparent.

3.1.6 Data reporting

The final part of the literature study protocol as described by Kitchenham (2004) is the reporting of the findings. The next section reports on the characteristics of all found maturity models. More in-depth findings related to the content of the models can be found in the next chapter. Here, the proposed maturity model is built by performing frequency analysis on the content of all domain-relevant maturity models that were found through the literature study.

3.2 Maturity model characteristics

This section reports on the general limitations and characteristics of maturity models. These provide insight into the different aspects and adoption barriers of the models. The limitations are mitigated through the proposed model while the set of maturity model characteristics is used to determine the structure of the proposed model. Through these findings, sub-question 2 regarding common concepts and maturity items found in models is answered. Note that literature study findings related to the maturity items are also partly presented in Chapter 4 where it is used to inform the design of the proposed maturity model.

3.2.1 Maturity model limitations

A list of maturity model limitations was extracted from the research papers. These limitations were often mentioned in the problem statement of papers and then addressed in the proposed models. However, it also occurred that researchers mentioned a limitation but did not try to mitigate it in their proposed maturity model. The limitations cover all aspects of maturity modeling. Some refer to the content and structure of maturity models, while others refer to the design process or its application. Table 3 provides an overview of the most commonly mentioned maturity model limitations. Only limitations that were mentioned more than 3 times are shown. Concrete examples of these mentioned limitations are described below the table.

MM Limitation	**Frequency**	**Description**
Model incomplete	34	Maturity models risk being too simple, thereby not accurately representing the (whole) domain. The balance between simple and complex should be considered during the scoping phase of the design process (Lahrmann et al., 2011)
Not grounded in literature	32	Maturity models should be based on extensive literature study, and not only on an organization's case. Many maturity model design methodologies include a literature review step to mitigate this limitation.
Automated could be incorporated into the model	21	Automating, for example, the inference engine of maturity models, or implementing an automated maturity assessment tool provides insight into the maturation process and helps save on resources and time.
Not prescriptive	20	(Mittal et al., 2018), amongst others, mention that there is a lack of roadmaps and prescriptive models, which hinders the usefulness of maturity models as no improvement recommendations can be made.
Lack of empirical validation	19	Many models are not empirically validated, and if this is done then the empirical data resulting from the application of a maturity model is rarely publicly accessible (Dinter, 2012).
Continuous evaluation neglected	16	The continuous evaluation of an organization using a MM remains neglected in many models (Otto et al., 2020).
Maturity items are vague	15	Some models have maturity items that are vague and have no clear scope, making their assessment difficult.
No/little documentation	12	A common characteristic of maturity models is that they are poorly documented - often on one or two pages. Some of them are incomplete or are not described well enough (Lahrmann et al., 2011).
Evaluation by humans may vary	10	Since maturity levels are assessed by humans, the human factor of the evaluation may lead to possible uncertainties, e. g., because of different evaluators or different physical and mental conditions of the same evaluator on different days (Schmitz et al., 2021).
Neglect the existence of multiple maturation paths	10	Some maturity models only specify 1 path to high maturity levels, when in reality multiple of these paths can exist.
No design method was mentioned	10	Maturity models need to have been designed according to some design method. This method needs to be clearly documented and substantiated.
No standardized terminology	9	Models often use different terminology due to a lack of prior research on maturity models in their domain.
Model too large	8	Models that are too large and detailed (and not focused) are too resource-intensive to implement.
Steps to evaluate readiness missing	8	Mittal et al. (2018) mention the lack of readiness assessment steps as an important research gap. Models should include an assessment of whether organizations are ready to implement a specific technology.
Too generic	6	In addition, there is an indication that a lot of models are too generic to be applied to any particular industry and, as such, are not designed to offer specific guidance (de Leon, 2016).
No consensus on important maturity aspects	5	In some domains, still no consensus exists among researchers on important maturity aspects to be included in maturity models (Wagire et al., 2021).
Lack of visualization report	4	Al-Sai et al. (2019) argue that maturity models should include a reporting tool making use of visualizations to convey the state of the maturation process.
Model not suited for small companies	4	Smaller organizations have limited resources for the implementation of maturity models. Therefore, models that are too heavy cannot be used (Limpeeticharoenchot et al., 2022).
Models are outdated	4	Maturity models are often not updated. This results in them not including state-of-the-art developments in the model domain (Muller & Hart, 2016).

No standardized measurement	4	Existing maturity models often have their own criteria and focus of measurement. Some focus on the business aspects, while others are concentrated on technical aspects, making it difficult to select one model for overall maturity assessment (Muller & Hart, 2016).
Relation between the Maturity dimension and improvement is not clear	4	It is argued that not enough research has been done on whether improvements in maturity also improve organizational performance (Kwak et al., 2015).
Fixed-level models are flawed	3	Fixed-level maturity models are not geared to expressing interdependencies between maturity dimensions and provide little guidance on the order of improvement implementation (Steenbergen et al., 2010).
Generic maturity levels are flawed	3	IT is argued that the variation in levels between different maturity models suggests that the assumption of the existence of generic maturity levels is an oversimplification.
The implementation framework of MM is poor	3	Maturity models often provide little documentation on how to implement the model and perform and interpret maturity assessments.
Lack of an advisory tool	3	Maturity models should include a roadmap. It is argued that an advisory tool could be built which proposes improvements based on this roadmap.
Little data for automation at low Maturity	3	Organizations at low data analytics maturity levels do not yet possess the data and capabilities to automate the maturity assessments (Lahrmann et al., 2011).
Maturity levels are vague	3	Some models do not use clearly defined maturity levels. This creates an unclear scope and maturation goal.
Models are not configurable	3	Some are not configurable to a specific domain and are therefore too specified/specialized.
Models not free	3	Some are only commercially available and require extra costs (Overeem et al., 2022).
Models transferred without checking suitability	3	Sometimes models are transferred from one domain to another without checking literature to see if this is even suitable. Furthermore, base models like CMMI could be used when not applicable
Models lack quantitative measures	3	Models lack quantitative measures. Incorporating these measures into a maturity model allows for easier and more consistent maturity assessments.

Table 3: Maturity model limitations found in literature

Several limitations are closely linked together. For example, the limitation 'Fixed level models are flawed' is related to 'Neglect the existence of multiple maturation paths'. Steenbergen et al. (2010) mention that fixed-level maturity models fail to express the interdependencies between processes, while Renteria et al. (2019) argue a similar point in mentioning that maturity models whose levels have a limited uni-dimensional description fail to take into consideration the different maturation paths that lead to the same maturity. There are also limitations that are opposite each other. An example of these is the limitations related to model size and model incompleteness (Cates et al., 2005; Dinter, 2012), and limitations related to maturity models being specialized to a certain domain versus generalized. It is argued that some models are too generic to be useful while others mention the lack of transferability of maturity models between domains (Teichert, 2019). This consideration of specialism vs generalism is also mentioned for maturity levels (Otto et al., 2020). Another criticism of maturity models is that their content, i.e. maturity items, is vague. For example, Özden Özcan Top & Demirors (2019) argue that unclear and unstandardized terminology in the maturity model and maturity assessment method may allow for results with poor construction validity. Related to this is the most often-mentioned limitation of maturity models being incomplete. Many authors mention that other proposed maturity models in a certain domain fail to include a process or set of processes (Schreckenberg & Moroff, 2020; Lahrmann et al., 2011). It is argued that this can be partly due to poor empirical validation of the maturity models, which leads to models not being complete, relevant, and representative of the real-world (Salah et al., 2014). Hence why *Scoping* is a phase that occurs in almost all procedure models that were found through the SLR.

There are also several limitations related to assessment and automation, that are relevant to this research. Having to perform the three maturity assessment activities manually is argued to be costly in terms of manpower of money (Devaraju & Huber, 2021). A proposed solution to this limitation is the use of surveys to collect data. However, this has been argued as not being automated, as well as still allowing for bias and ambiguity. It is also argued that employees may try to present the current maturity better than it actually is due to the stakeholder pressure (Shrestha et al., 2020).

Shrestha et al. (2020) mentioned in their future work section that a solution involving the implementation of quantitative KPIs into maturity models allows for more accessible and more understandable automation of the maturity assessment procedure. Furthermore, such an automated tool allows for more continuous maturity assessments, which are not subject to human variance and are less costly than manual assessments. Such tools can also include a prescriptive component/engine and are implicitly well-documented through KPI thresholds. They can also easily include a visualization component. The overview also shows potential pitfalls in implementing automated solutions, such as low-maturity organizations having little data to automate.

Discussing these limitations in the context of the proposed maturity model, the model is grounded in ample literature research through the thorough literature study. As automation is the focus of this thesis, this limitation is also tackled, and the model allows for continuous evaluation. The model will be prescriptive through the use of an Inference engine and will contain visualization capabilities. All these requirements point to the need for a maturity assessment tool, which allows for data to be collected for the built-in maturity model. Through such a tool, documentation can also be included, and bias negated, as quantitative data can be gathered through an organization's IT systems.

The following section describes common maturity model characteristics; see table 4. These characteristics are used to make decisions in the maturity model design process. The above-mentioned limitations will help steer this process by indicating which characteristics are desirable and which are not. For example, the limitation *Lack of empirical validation* strongly suggests excluding from the design process those maturity models that are not empirically validated.

The maturity models collected during the SLR do not adhere to all extracted characteristics and limitations. For example, only 12 articles mentioned some automation in the maturity model. Tools which were created for this purpose are also never publicly available. The significant variance between the mentioned maturity levels and items confirms the presence of those limitations. Around half of the extracted maturity models were descriptive, showing the lack of maturity models which suggest improvement items. Furthermore, 63 of the 130 extracted models did not explicitly mention an implementation strategy, and many models did not mention an assessment strategy or inference engine. See section 3.3.1 for more information on this topic.

3.2.2 Maturity model characteristics

Maturity models have a set of characteristics that define them. This thesis categorizes them as either *context characteristics* or *structure characteristics*. Context characteristics refer to the design, documentation, and evaluation of maturity model performance. Examples are the method used to validate a maturity model, whether it is available and accessible, and the domain in which the model is proposed. Structure characteristics refer to the maturity model's purpose, content and components, and target group. For example, whether the model proposed an automated component, which type of inference engine it uses, and what maturity dimensions, capabilities, KPIs, and metrics make up its reference framework.

The list of characteristics was collected as follows: during the SLR, all papers were marked that mention maturity model design methods, also called *Procedure models* (Röglinger et al., 2012). These papers mention relevant design phases in the elicitation of new maturity models and, in doing so, propose characteristics and design choices that need to be considered. From all these papers, the set of mentioned characteristics was noted. The characteristics were then grouped, and several characteristics were combined based on their definitions. This was documented in a changelog. Afterward, all characteristics with an occurrence of 1 were removed from the list, removing nine characteristics. Table 4 shows all maturity model characteristics and their definitions. Appendix B. contains tables regarding the elicitation of these characteristics.

ID	Characteristic	Definition
Char 1	Application scale	The intended scope of use can vary depending on the number of entities and regions the model is designed to assess (de Bruin et al., 2005).
Char 2	Assessment data type	The nature of the data that is used in a maturity model to assess the maturity of an organization or process. This characteristic determines whether the data is quantitative, based on numerical data and statistical analysis, or qualitative, based on descriptive and subjective data (Adrian et al., 2016).
Char 3	Assessment methodology	An Assessment methodology needs to be present and feature a procedure model and advice on eliciting the assessment criteria and adapting or configuring the criteria according to organization-specific situational characteristics. Assessment methodologies should also share knowledge from previous applications – if available (Poeppelbuss et al., 2011).
Char 4	Assessment tool	An Assessment tool for maturity models provides a streamlined and standardized approach to conducting assessments. It can help organizations identify improvement areas and track progress over time.
Char 5	Automation	The degree to which the assessment of a maturity model can be automated by automating data collection. A maturity model with high automation allows the assessment process to be largely or fully automated using computerized tools, software, or other technologies. A maturity model with low automation requires a more manual assessment process that is often time-consuming and resource-intensive.
Char 6	Availability	Whether a model is, or is not, openly and freely available for general use.
Char 7	Capability areas	Dimensions are specific capability areas, process areas, or design objects structuring the field of interest. They should be exhaustive and distinct. Each dimension is further specified by several measures (practices, objects, or activities) at each level (Lahrmann et al., 2011).
Char 8	Inference engine	The logic or reasoning used to interpret the assessment results and determine the appropriate action. This can be manually performed, encoded in logic, and automated.
Char 9	Definition of underlying notion of maturity	Refers to the underlying concept or idea of what maturity means within the context of the maturity model. The definition of maturity is the conceptual foundation of the model and informs the structure and content of the model.
Char 10	Description of domain & components	Maturity models must define the application domain's central constructs. These include common terms and definitions relevant to the setting in which the maturity models are supposed to be applied (e.g., in the form of a glossary that defines terms like business process) (Poeppelbuss et al., 2011).
Char 11	Design process documentation	The design process should be documented, including the extent to which the model has been subject to empirical validation (Poeppelbuss et al., 2011).
Char 12	Focus of model	The domain in which the maturity model would be targeted and applied. Focusing on the domain will distinguish the proposed model from other existing models. Focusing the model within a domain will also determine the specificity and extensibility of the model (de Bruin et al., 2005).
Char 13	Granularity mentioned	Maturity models can be structured hierarchically into multiple layers referring to different levels of granularity of maturation (de Bruin et al., 2005).
Char 14	Implementation guide	The extent to which the model guides on implementing the model in practice. This may include guidance on conducting a maturity assessment, interpreting results, and developing and implementing improvement plans.
Char 15	Improvement measures	Specific actions or recommendations provided to organizations based on the results of a maturity assessment and a prescriptive engine.
Char 16	Knowledge from older MMs	The extent to which the model incorporates new knowledge, concepts, or best practices that differentiate it from previous maturity models.
Char 17	Maturation paths	The basic purpose of maturity models is to outline the stages of maturation paths. This includes the characteristics of each stage and the logical relationship between them (Poeppelbuss et al., 2011).
Char 18	Maturity concept	Three different maturity concepts (or understandings of maturity) can be distinguished. People (or workforce) capability defines "the level of knowledge, skills, and process abilities available for performing an organization's business activities.". Process maturity defines "the extent to which a specific process is explicitly defined, managed, measured, controlled, and effective.". Object (or technology) maturity defines the individual level of development of a design object (Lahrmann et al., 2011).
Char 19	Maturity level	Levels are archetypal states of maturity of a certain dimension or domain. Each level has a distinguishing descriptor providing the intent of the level and a detailed description of its characteristics (Lahrmann et al., 2011).
Char 20	Maturity model type	Refers to the model being descriptive, prescriptive, or comparative. The Maturity model type characteristic provides a clear understanding of the functionality, purpose, and maturity assessment results of a maturity model (de Bruin et al., 2005).

Char 21	Maturity principle	MMs can be continuous or staged. Continuous MMs allow the scoring of activities at different levels. Therefore, the level can be either the (weighted) sum of the individual scores or the individual levels in different dimensions. Staged models require compliance with all elements of one level. They specify a set of goals and key practices to reach a predefined level. Staged MMs reduce the levels to the defined stages, whereas continuous MMs open up the possibility of specifying situational levels (Lahrmann et al., 2011).
Char 22	Method of evaluation	Whether the data collection is based upon a self or a third-party assisted assessment.
Char 23	Origin	The Origin of the model refers to whether it has its source from academia or practice
Char 24	Purpose	The specific problem or challenge that the model is designed to address. The purpose may be related to a particular industry, function, or process and may be focused on improving performance, increasing efficiency, or achieving specific goals.
Char 25	Reliability	How well the maturity model has been validated. Untested means the model has not been verified or validated. Experts have evaluated a verified model, while a validated model has empirical evidence supporting it.
Char 26	Respondents	Respondents are stakeholders responsible for providing data for maturity assessment using the maturity model
Char 27	Target group	The intended Target Group of a maturity model concerns the stakeholders involved in designing and using the maturity model (de Bruin et al., 2005).
Char 28	Visualization	The maturity model should provide a means to visualize the results of maturity assessments. This could be extended into dashboards showing the maturity model and improvement suggestions

Table 4: Common maturity model characteristics

3.2.3 Maturity model automation

When looking at the main phases of maturity assessments: data collection, data processing, and data reporting, automation could be applied to improve several aspects of the maturity assessment process. A lot of varying maturity models are found in the literature, covering a lot of domains. These models also differ in both structure and hierarchy levels. However, A common theme is that authors often mention the lack of such automatability in the maturity assessment process, as mentioned in the section on maturity model limitations. However, a few sources provide insight into how automation can be used in the field of maturity modeling.

The more common applications of automation are for eliciting new maturity modeling or classifying maturity levels. Research by Meding et al. (2021) uses machine learning to order a set of pre-defined maturity items based using machine learning. As for the classification of maturity, Lismont et al. (2017) mention clustering of organization characteristics to categorize them into four groups. These groups, *no analytics, analytics bootstrappers, sustainable analytics adopters, and disruptive analytics innovators*, form a growth path that organizations follow when investing in the maturation of their analytics processes. Analytics here is related to the application of computer-supported programs to process data. While this is a novel and automated method of performing maturity assessments, a limitation of the work might be that such an inference engine is not interpretable and non-prescriptive. Furthermore, such an inference engine only works when coupled to a staged maturity model, which provides maturity levels only on the highest level. The authors indicate which organization characteristics lead to which maturity level and how organizations might try to manipulate and mature these. The data for these approaches is often gathered using long surveys with Likert questions used as quantitative data for the analyses (Aleem et al., 2016; Marsina et al., 2015; Abu-Shanab, 2015). Another example of such an article is by Raber et al. (2012): "*Using Quantitative Analyses to Construct a Capability Maturity Model for Business Intelligence*", where the quantitative analysis consists only of Likert-question answers converted to numerical values. Furthermore, several papers present maturity models that incorporate fuzzy logic alongside the Delphi method for more efficient use of the Delphi method to gather maturity items for new maturity models (Marlina et al., 2022).

This research aims to lessen the manual effort required for maturity assessments. For the research by Lismont et al. (2017), however, the data input is still manual, as is the reporting and, to a certain extent also, the processing. Vásquez et al. (2021) presents a sustainability maturity model using machine learning to classify an overall maturity score. This research suffers from the same limitation as earlier-mentioned work, where to process from input data to output cannot be adequately explained. Furthermore, the machine learning models used are supervised in nature, thus requiring a large dataset of labeled data. They do not, however, present this dataset for future research. Several more sources were found that employ automation for the classification of maturity levels (Gupta et al., 2017; Limpeeticharoenchot et al., 2022); however, due to the process not offering much interpretability, as well as still requiring lots of manual work, it was chosen not to implement such a method for this research.

Some authors also present work that includes maturity models that are supported by tooling to a certain degree. Like work that shows the maturity model in a website or mobile app Limpeeticharoenchot et al. (2022), or interesting work by Jansen (2020) that describes the creation of a web application to design maturity models online. or Furthermore, wwork by Siedler et al. (2021); Steinlechner et al. (2021) that uses visualizations for the data reporting of the maturity assessment. In these works, the implementation of automation remains limited to one phase of the maturity assessment process, which is often data reporting. Not a single source was found that tried to incorporate quantitative metrics to facilitate automation into the design of the maturity model, to allow for data collection to be automated. Work that is most closely aligned with the aim of this research is by Devaraju & Huber (2021), who propose a tool to measure progress toward FAIR research data. This tool is capable of processing data and reporting it in a limited manner, however, the tool does not use quantitative data and is also not open source and thus not transferable to other domains and maturity models. Furthermore, Shrestha et al. (2020) propose a tool that automates the data processing and reporting activities. However, the data reporting output of their tool is limited to very high-level visualizations, lacking drill-down and trend analysis capabilities. They furthermore mention their use of surveys for data collection as a limitation of their work, stating that research could be conducted on using output data of an organization's processes and IT tooling directly as quantitative input for the maturity assessments to fully automate the data collection activity.

4 Maturity Model Design

This chapter concerns the creation of the reference framework of the maturity model. First, a set of steps for the design of the model is outlined based on other often-used methods. Then an overview is given of all extracted maturity models and the domains in which they were published. This set of models is then filtered on relevant domains and maturity model characteristics. Afterward, the remaining set of maturity models is used to elicit the maturity dimensions, capabilities, and KPIs. The chapter then continues by describing the results of the expert evaluation round, which is used to validate the proposed maturity model. The maturity model is named the *Quantitative Data Analytics Maturity Model* (QDAMM). The last section is related to the design of the maturity assessment tool in which the maturity model is instantiated. The tool has been named the Automated Maturity Assessment Tool *AutoMAT* as it supports the automation of all maturity assessment activities.

4.1 Procedure model for designing automated maturity models

A design method was chosen to develop the maturity model that includes quantitative metrics. The design method describes the steps of the design process and ensures the maturity model is relevant, explicitly documented, and grounded in ample literature and empirical evidence. During the SLR, all papers that mention maturity model design methods, also called *Procedure models* (Röglinger et al., 2012), were marked. Based on the set of resulting characteristics, two relevant procedure models were chosen and adapted into a new procedure model that contains activities on populating the model with quantitative metrics (Caiado et al., 2021; Steenbergen et al., 2010). It furthermore contains activities on the automation of the three maturity assessment activities: data collection, processing, and reporting (Shrestha et al., 2020). The procedure model also helps mitigate identified limitations of maturity models. The thorough design and evaluation process ensures that the maturity model is complete, relevant, and grounded in ample literature and empirical data. The focus on automation and quantitative metrics mitigates the threat of maturity assessments being costly and ambiguous. Other benefits of the focus on automation are that the limitation related to the lack of continuous maturity assessment possibilities is also addressed, as well as the threat of the maturity models not being prescriptive through their inference engine (Otto et al., 2020).

Figure 6 shows the elicited procedure model. It consists of three sections. The left section *Phase* indicates the phase name and the research methods that are utilized to execute the related design activities. The *Activities* section shows the activities that are performed per phase and their interdependencies. The *Output & Related section* part of the procedure model indicates what each phase contributes to the design process, and where in this thesis this is described.

The model consists of four phases, each involving activities related to the scoping, designing, populating, and testing of the maturity model. This procedure model is used to design the proposed maturity model which will be validated during the expert interview phase. This then answers RQ4: *How can a new data analytics maturity model be designed to support automatic maturity assessment?* The model's phases are described below. The application of some steps has already been described in previous sections

Phase 1 - Scoping

This step concerns conducting a literature study and examining the domain to determine which maturity models and resources already exist. The scope of the maturity model is determined based on this data and the desired set of maturity model characteristics. The application of these steps is described in Chapter 2 and partly in this chapter. Through this phase, the possible limitations of incompleteness, vagueness, and a lack of knowledge from previously proposed maturity models are mitigated. The output is a clear scope and definition of the to-be-designed maturity model (Steenbergen et al., 2010).

- A1. Selection of relevant domains - Before starting the design process, the relevant domain(s) must be chosen first. This will then steer the domain in which the literature study is conducted. This research was done during the SLR.
- A2. Identification of existing MMs - Existing maturity models need to be identified and written down for later analysis.

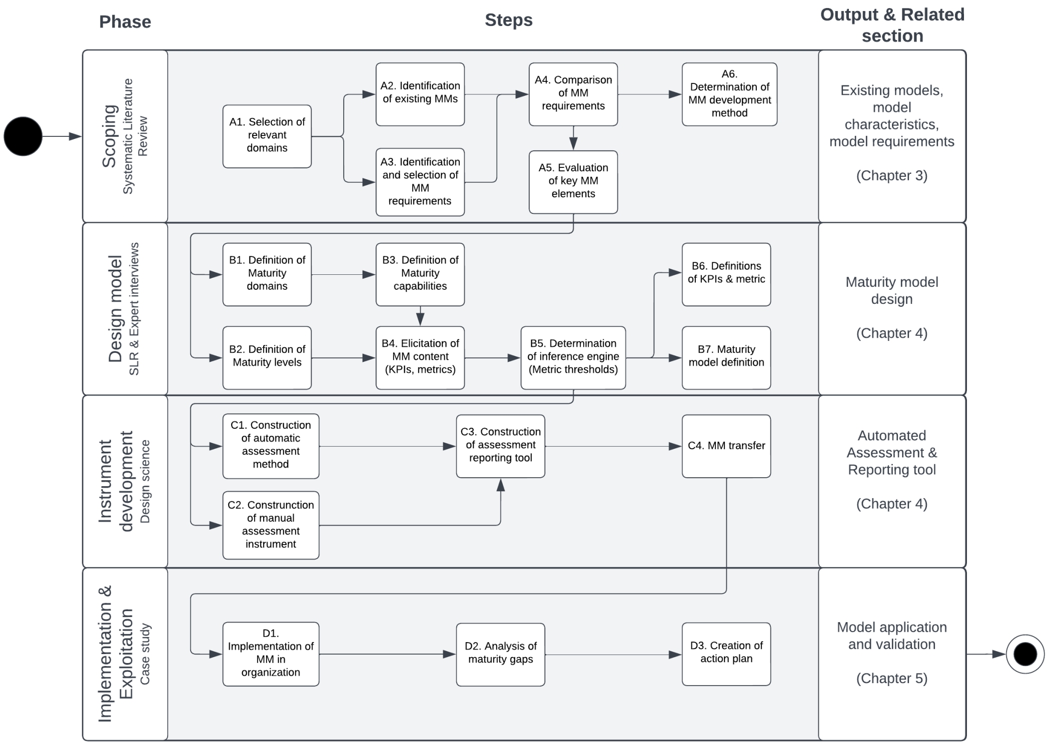

Figure 6: Procedure model for designing an automated maturity model (adopted from (Caiado et al., 2021; Steenbergen et al., 2010))

- A3. Identification and selection of MM requirements - Relevant maturity model characteristics must be identified. Section 3.6.1. shows this research's implementation of this step.

- A4. Comparison of MM requirements - The extracted maturity models need to be assessed using the discovered relevant maturity model characteristics.

- A5. Evaluation of key MM elements - Based on the analysis from step A4, a set of maturity model characteristics that must be addressed in the new model can be constructed.

- A6. Determination of MM development method - Related to the choice of which research methods to apply for the creation and population of the proposed maturity model and how to apply them. This thesis describes the used research methods in Chapter 2.

Phase 2 - Design model
This phase refers to the design of the maturity model. The content of the model is populated based on the results of the previous phase through a top-down approach. After all maturity items are determined down to the KPI level, the KPIs are populated with quantitative metrics (if possible) through a bottom-up approach. The inference engine, consisting of the metric thresholds and calculation logic is determined and created so that conclusions can be drawn from data collected through maturity assessments. The next sections describe the execution of these steps.

- B1. Definition of Maturity dimensions - Based on the SLR, maturity dimensions are chosen to be included in the maturity model.

- B2. Definition of Maturity levels - Based on the SLR and chosen maturity model characteristics, maturity levels are designed or copied for inclusion in the maturity model.

- B3. Definition of Maturity Capabilities - Based on the SLR and expert interviews, capabilities are chosen to populate the maturity dimensions.
- B4. Elicitation of MM content (details, KPIs) - KPIs are designed to link to the capabilities. These will be used to perform the maturity assessments. It is possible to further drill down these items into maturity metrics.
- B5. Determination of inference engine (KPI thresholds) - The type of inference engine is determined, and thresholds are determined for the KPIs and maturity levels.
- B6. Definitions of KPIs - The KPIs and their thresholds are documented and explained.
- B7. Maturity model definition - The maturity model as a whole is documented, and its characteristics and initial design choices are explained.

Phase 3 - Instrument development
An implementation instrument should be developed so that the maturity model can be tested and used in practice. This model should contain an automated component in the form of data processing and visualization, but should also allow for manual data input. This is then built into a tool that is transferred to an organization. The end of this chapter describes the development of the assessment tool.

- C1. Construction of automatic assessment method - The automated part of the assessment method is designed as a tool. The tool incorporates the KPIs and their thresholds and automates the data collection, inference engine, and, possibly, the improvement suggestion engine parts of the maturity model.
- C2. Construction of manual assessment instrument - The manual aspect of the maturity assessment method is created. This can be a survey or interview protocol. Possible extensions could be the automation of these methods as well, by, for example, automating the processing of survey answers.
- C3. Construction of assessment reporting tool - The automated tool is extended by adding a reporting method through dashboards.
- C4. MM transfer - The designed maturity model is transferred to the case study organization through training and documentation.

Phase 4 - Implementation & Exploitation
The maturity model and assessment tool are implemented in the last phase. The outcome of using the tool to conduct maturity assessments is then used to further mature the organization. Chapters 5 and 6 describe the application and validation of the tool through an industrial case study.

- D1. Implementation of MM in organization - The maturity model is implemented at the case study organization. The automatic maturity assessment tool can be fine-tuned, and a maturity assessment is performed and documented.
- D2. Analysis of maturity gaps - Based on the maturity assessment, the maturity gaps are analyzed to identify bottlenecks. This, as well as activity D3, can be performed by the automated improvement suggestion engine.
- D3. Creation of action plan - An improvement plan is created automatically by the inference engine, and proposed to the organization as part of the iterative maturation process.
- D4. Improve maturity model iteratively - The maturity model should be iteratively improved through case studies and future research to keep it relevant.

The procedure model is used in the following section to design the maturity model. The gathered literature study data is also analyzed and filtered by the defined phases and activities.

4.2 Conceptual framework

As described before, maturity models can be used to guide organizations in assessing their current maturity and in creating a maturation plan to reach higher maturity models (Poeppelbuss et al., 2011). Maturity models consist of a set of maturity items possibly categorized on different hierarchy levels. Together these maturity items cover all relevant processes according to the maturity model's scope (de Bruin et al., 2005). The relation that a maturity item has to each maturity level, i.e. the maturation criteria, is used to assess the maturity. Data can be gathered for each of these criteria through a maturity assessment in the form of either qualitative data or quantitative data (Shrestha et al., 2020). The aim of this thesis is the automation of the three maturity assessment steps. Therefore, an effort is made to make the inference engine explicit so that it can be reasoned with. Articles often fail to note the actual implementation of the maturity model and the required calculations on the data. For example, Jansen (2020) provides a useful meta-model for focus area maturity models wherein they mention *Instantiation* as a component of the maturity items. To expand on this notion of instantiation, a conceptual framework was designed to guide the maturity model and tool elicitation process (see Figure 7). This framework is a novel contribution of this research to the data analytics and maturity modeling domains as it describes the creation, but also instantiation and automation of the maturity model and maturity model assessment process.

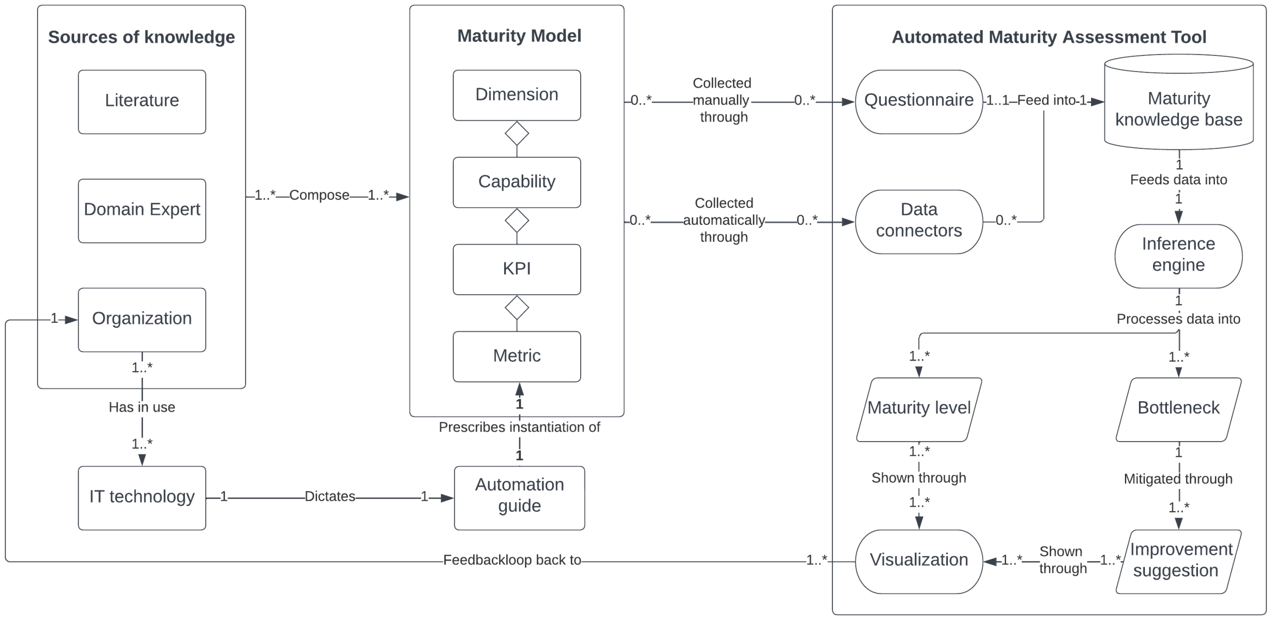

Figure 7: Conceptual framework of design, composition, and implementation of maturity models

The framework consists of three components that are all related: *Sources of knowledge*, *Maturity model*, and *Automated Maturity Assessment Tool*. The firstmentioned component concerns the elicitation of the maturity model. Data must be collected from a set of sources, namely from literature, domain experts, and from organizations. This ensures that the maturity model is grounded in ample academic and practitioner data. This component is linked to the Maturity model component through a *'Compose'* relation. Note that another connection exists that is related to the Data collection maturity assessment activity. The framework denotes that organizations have data sources in the form of IT technology, and how automation guides can be created to automatically collect metric data from these data sources. This automation eliminates the need for manual tasks, thus saving on resources and time (Devaraju & Huber, 2021). The Maturity Model component itself consists of four hierarchy levels: Dimension, Capability, KPI, and Metric. Maturity models in literature always propose structures consisting of (a set of) the first three components. This study adds metrics as a representation of automatable data points that help quantify KPIs. The maturity model can be implemented through an Automated

Maturity Assessment Tool; the third component of the framework. This component states the two possible ways of data collection: manual and automatic (Shrestha et al., 2020). Relations to the database then show how this data is stored in inputted into an inference engine containing the calculation logic. The framework also denotes the expected output of the inference engine, and how this is reported back to the user (Al-Sai et al., 2019); this being the organizations that have instantiated the maturity model through the tool. The conceptual framework implies that the maturity model is prescriptive in nature through the bottleneck and improvement analysis (Lukhmanov et al., 2022; Mittal et al., 2018). The automation also allows for continuous evaluation, a characteristic that other maturity models lack (Otto et al., 2020).

Through the use of the conceptual model, certain design choices in relation to the proposed maturity model have been made. Namely, as mentioned before, the model needs to be prescriptive at least, and support automation. Furthermore, the model needs to have been validated by experts and also through a case study at an organization. Only through this last research method is the automation of the data collection activity possible. The maturity model also needs to be documented extensively, meaning both the used maturity items, as well as the logic of the inference engine. This mitigates reported maturity model limitations related to a lack of explicit documentation and assessment methods (Lahrmann et al., 2011). This framework, and the maturity model characteristics that are mentioned in Table 4, are used in the following sections to create a maturity model and compare it to other models in the domain.

4.3 Related work

The maturity models that were collected as a result of the SLR were proposed in varying domains and have different characteristics. The set of models is filtered based on these attributes so that a set of maturity models remains of which the content is useful to this thesis. The filtering is first done over the application domain and then on the characteristics.

After analyzing the publication domains shown in figure 5 and their sub-domains, it was chosen only to include models in the *Data Management and Analysis* domain as this corresponds best to the application domain of the proposed maturity model. Table 5 shows the distribution of the maturity models in this domain. Based on this decision, the total pool of maturity models decreases from 130 to 32. The domains cover a wide range of topics related to data and data analytics. This is useful for ensuring that the proposed maturity model has adequate coverage of the data analytics domain. This also explains why the study is not just using the Data analytics subdomain-related maturity models.

Domain	**Sub-Domain**	**Models in domain**
Data Management and Analysis	Business Intelligence (BI)	10
	Big Data (BD)	8
	Data management (DM)	6
	Data analytics (DA)	5
	Machine Learning (ML)	2
	Data warehousing (DW)	1

Table 5: Distribution of maturity models in the domain *Data Management and Analysis*.

Table 6 provides an overview of the selected set of maturity models. The maturity models have been published in a domain that is closely related to the domain of this thesis. Therefore, the models provide a good scientific reference for related work. The models are examined over several aspects based on the conceptual framework (Figure 7 that was designed. Columns two and three are related to the design of the maturity model. According to Pöppelbuß & Röglinger (2011) and Dinter (2012) scientific and empirical validation are vital in the creation of new maturity models. Several maturity models lack either a thorough literature review or a research method for empirical validation. This thesis aims to cover both of these bases through an extensive set of conducted research methods. Regarding data collection, some maturity models have been elicited based on qualitative data only. Columns six through eleven are related to the maturity model itself and its implementation. Note that some components that are mentioned in the conceptual framework are discussed later in this section. Regarding the datatype of the maturity level criteria, most maturity models employ qualitative data. Most maturity models have been designed for self-assessments and a questionnaire is often published to help with this. These questionnaires are populated with Likert questions that, even though they can be converted to numerical data, are still qualitative data that cannot be easily automated. Raber et al. (2012) propose a method to use the Rasch algorithm for the automatic weighting of maturity model items. However, they only conduct interviews with three experts to collect data so the evaluation is lacking. Limpeeticharoenchot et al. (2022) propose a maturity model that uses Latent class analysis for automatic data processing and use a tool for data reporting. However, these components are not open-source, and the data collection is also still manually done, costing a lot of time according to the authors. Work by Peña et al. (2019) applies a Fuzzy ELECTRE model for a multicriteria evaluation of big data maturity. This automates the processing of the input data, however, the results of this analysis offer no suggestions for improvement. The maturity model is descriptive in nature, and no case study was performed to substantiate this as a viable maturity assessment method. Lismont et al. (2017) proposes similar work that suffers from the same limitations as mentioned earlier, and again, does not have a valid real-world application.

As can be seen, there is a gap in the set of currently available maturity models with regard to automatability. Another observation is that almost no maturity models make use of quantitative data, even though this can help with the automation of the data collection process Shrestha et al. (2020). To populate the proposed maturity model with maturity items, a top-down analysis is done of common maturity items. The set of maturity models is filtered further so that they exhibit the desired characteristics that make them suitable to be analyzed. The characteristics of models are split into context and structure characteristics. First, the models are filtered based on the context characteristics (see table 22). It was determined to exclude ch1 - *Application scale* from the filtering, as almost no paper explicitly mentioned this. Regarding ch6 - *Availability*; of the 32 models, 25 are fully available, and 7 are only partly. In all of these seven cases, this is due to a proposed tool or questionnaire not being published in the source or anywhere online. However, these models were not excluded based on this characteristic as their maturity models were still documented and could contain useful data. The remaining maturity models are now filtered based on their context characteristics. Table 7 shows these maturity models and their context characteristics. Characteristics for the proposed maturity model have also been added to show how the model differentiates itself from related work.

Based on Table 7, it becomes evident that some maturity models do not possess the required context characteristics to be included in the design process. Some authors did not offer extensive enough documentation for their proposed models for them to be included in the design process. Filtering was performed based on characteristics 9, 10, 11, and 16, which all relate to the extensiveness of the design process and documentation of the maturity models. The following maturity models were excluded based on these characteristics: *Big Data & CRM analytics MM*, *Organizational maturity model*, *ITPM3*, *BACF*, *LOBI*, *Evolutionary business intelligence maturity model*, *EBIMM*, *Analytic Process Maturity Model*, *Data maturity model*, *IoT DQM3*, and *Machine Learning Process MM*. The *LOBI* model is also the only model to be of practitioner origin, so excluding it is even more substantiated. Regarding the maturity models' reliability (ch25) of the remaining 21 models; 15 are empirically validated, 4 are verified through expert interviews, and 2 are completely untested. It was chosen to exclude the untested maturity models as their performance has not been validated.

4.4 Maturity model structure

Through the filtering process, related to activity A4 from the procedure model, a total of 19 maturity models remain. These maturity models have been published in a domain relevant to this thesis and have beneficial context characteristics. Next, the maturity models are evaluated based on their structure characteristics. An overview of the maturity models and their structure characteristics can be seen in Table 8. Some characteristics are not included in the model and are either discussed below or mentioned in a later section in this chapter where they are relevant. An example is characteristics 2: *Assessment data type*. Only 8 models mentioned quantitative measures like KPIs or Likert surveys. 3 models of these 8 models also mentioned qualitative measures. 8 models mentioned only qualitative measures, while 3 models did not include an assessment component and thus mentioned neither quantitative nor qualitative measures. These models are only used to elicit the maturity dimensions and capabilities. Regarding characteristic

Study	R. Method	Data Col.	Year	MM Name	Assessment Method	Assessment Instrument	Domain	Level set	Criteria datatype	Autom. sup.
This study	SLR Experts Design Science Case study	Mixed	2023	Quantitative Data Analytics Maturity Model (QDAMM)	Self assessment	Automated Maturity Assessment Tool (AutoMAT)	DA	Nameless	Mixed	Fully
(Korsten et al., 2022)	SLR Delphi study Survey	Mixed	2022	ADA-CMM	Third party assisted	Questionnaire (4-point Likert)	DA	Ad-hoc	Qualitative	-
(M. O. Gökalp et al., 2022)	SLR Case study	Qualitative	2022	BDA process capability assessment model	Self assessment	-	BD	SPICE	Qualitative	-
(Limpeeticharoenchot et al., 2022)	Survey Experiment	Quantitative	2022	BDMM b	Self assessment	Latent class analysis model	BD	Nameless	Mixed	Data Processing, Data Reporting
(Marlina et al., 2022)	SLR Delphi study Experts	Mixed	2022	RDM readiness model	Self assessment	-	DM	Nameless	Qualitative	-
(Akkiraju et al., 2020)	SLR	Qualitative	2021	ML implementation maturity workflow	Self assessment	Questionnaire (4-point Likert)	ML	Ad-hoc	Qualitative	-
(Daraghmeh & Brown, 2021)	SLR Design Science Survey Case study	Mixed	2021	EHR-MM	Self assessment	-	BD	Nameless	Qualitative	-
(Hausladen & Schosser, 2020)	SLR Case study	Mixed	2020	Airline network planning BDA MM	Self assessment	Questionnaire (5-point Likert)	BD	Nameless	Qualitative	-
(Peña et al., 2019)	SLR Experiment	Mixed	2019	Fuzzy ELECTRE big data maturity model	Self assessment	Fuzzy ELECTRE model	BD	Ad-hoc	Quantitative	Data Processing
(Thomas et al., 2019)	SLR Case study	Mixed	2019	DMM model	Third party assisted	-	DM	Nameless	Qualitative	-
(Carvalho et al., 2019)	SLR Design science	Qualitative	2019	HISMM-DA	Self assessment	-	DA	Ad-hoc	Qualitative	-
(Gastaldi et al., 2018)	Case study	Qualitative	2018	BI maturity model	Not mentioned	Questionnaire (4-point Likert)	BI	Ad-hoc	Qualitative	-
(Lismont et al., 2017)	Survey	Quantitative	2017	DELTA model	Self assessment	Survey	DA	Ad-hoc	Qualitative	Data Processing
(Comuzzi & Patel, 2016)	SLR Experts	Qualitative	2016	BDMM a	Self assessment	-	BD	CMM(I)	Qualitative	-
(Spruit & Pietzka, 2015)	SLR Design science Experts Case study	Mixed	2015	Master Data Maturity Model (MD3M)	Self assessment	Questionnaire	DM	COBIT	Qualitative	-
(Dinter, 2012)	SLR Experts	Qualitative	2012	biMM a	Self assessment	Questionnaire (5-point Likert)	BI	Ad-hoc	Qualitative	-
(Raber et al., 2012)	Experts Case study	Qualitative	2012	biMM b	Self assessment	Questionnaire (5-point Likert)	BI	Ad-hoc	Qualitative	-
(Sen et al., 2012)	SLR Design science Experts	Qualitative	2012	DWP-M	Third party assisted	Questionnaire (5-point Likert)	DM	CMM(I)	Qualitative	-
(Popovič et al., 2012)	SLR Focus group	Mixed	2012	BIS Maturity model	Not mentioned	Questionnaire (7-point Likert)	BI	No levels	Qualitative	-
(Hüner et al., 2009)	Focus group Case study	Mixed	2009	CDQM maturity model	Not mentioned	-	DM	Nameless	Qualitative	-

Research method (R. Method) (including Master Thesis(MT), Report).

Table 6: Analysis of domain-relevant maturity models (adopted from (Farshidi, 2020))

18: *Maturity concept*, which refers to the categorization of 'People', 'Process', and 'Object' as proposed by Lahrmann et al. (2011). No model was mentioned as having a People maturity concept, 1 had an Object maturity concept, 5 had a Process maturity concept, and the other 13 mentioned a mixed maturity concept. It was therefore chosen to ignore this characteristic in the decision-making as it would not result in significant changes to the structure. During the expert evaluation phase, experts also mentioned the automatability of Object and Process-related maturity items to be great, while that of People-related measures was less so. A mix of these maturity concepts will therefore improve the performance of the overall model. Characteristic 26 refers to the Respondents of the maturity models. Meaning those who provide data during

Source	Maturity model name	Domain	Def. of maturity	Descr. of domain	Design doc.	MM knowledge	Origin	Reliability
This study	Quantitative Data Analytics Maturity Model (QDAMM)	DA	X	X	X	X	Academic	Validated
M. O. Gökalp et al. (2022)	BDA process capability assessment model	BD	X	X	X	X	Academic	Validated
Comuzzi & Patel (2016)	BDMM a	BD	X	X	X	X	Academic	Validated
Limpeeticharoenchot et al. (2022)	BDMM b	BD	X	X	X	X	Academic	Validated
Hausladen & Schosser (2020)	Airline network planning BDA MM	BD	X	X	X	X	Academic	Validated
Tiefenbacher & Olbrich (2015)	Big Data & CRM analytics MM	BD		X	X		Academic	Untested
Daraghmeh & Brown (2021)	EHR-MM	BD	X	X	X	X	Academic	Validated
Peña et al. (2019)	Fuzzy ELECTRE big data maturity model	BD	X	X	X	X	Academic	Validated
Klievink et al. (2017)	Organizational maturity model	BD	X	X	X		Academic	Validated
Becker et al. (2009)	ITPM3	BI		X	X	X	Academic	Validated
Cosic et al. (2012)	BACF	BI	X	X	X		Academic	Untested
Cates et al. (2005)	LOBI	BI	X	X			Practitioner	Validated
Sacu & Spruit (2010)	Business Intelligence Development Model (BIDM)	BI	X	X	X	X	Academic	Untested
Dinter (2012)	biMM a	BI	X	X	X	X	Academic	Validated
Raber et al. (2012)	biMM b	BI	X	X	X	X	Academic	Verified
Russell et al. (2010)	Evolutionary business intelligence maturity model	BI	X	X		X	Academic	Verified
Chuah (2010)	EBIMM	BI	X	X		X	Academic	Untested
Popovič et al. (2012)	BIS Maturity model	BI	X	X	X	X	Academic	Verified
Gastaldi et al. (2018)	BI maturity model	BI	X	X	X	X	Academic	Validated
Lismont et al. (2017)	DELTA model	DA	X	X	X	X	Academic	Validated
Grossman (2018)	Analytic Processes Maturity Model (APMM)	DA	X	X			Academic	Untested
Carvalho et al. (2019)	HISMM-DA	DA	X	X	X	X	Academic	Verified
Korsten et al. (2022)	ADA-CMM	DA	X	X	X	X	Academic	Validated
Muehlbauer et al. (2022)	Data maturity model	DA	X	X		X	Academic	Validated
Spruit & Pietzka (2015)	Master Data Maturity Model (MD3M)	DM	X	X	X	X	Academic	Validated
Hüner et al. (2009)	CDQM maturity model	DM	X	X	X	X	Academic	Validated
Devaraju & Huber (2021)	FAIRsFAIR	DM	X	X	X	X	Academic	Untested
Kim et al. (2022)	IoT DQM3	DM	X	X	X		Academic	Validated
Marlina et al. (2022)	RDM readiness model	DM	X	X	X	X	Academic	Verified
Thomas et al. (2019)	DMM model	DM	X	X	X	X	Academic	Validated
Sen et al. (2012)	DWP-M	DW	X	X	X	X	Academic	Validated
Akkiraju et al. (2020)	Machine Learning Process MM	ML	X	X		X	Academic	Untested
Schreckenberg & Moroff (2020)	ML implementation maturity workflow	ML	X	X	X	X	Academic	Validated

Domain abbreviations: BD - Big Data, BI - Business Intelligence, DA - Data Analytics, DM - Data Management, DW - Data Warehousing, ML - Machine Learning.
Characteristic abbreviations: Def. of maturity (ch9. Definition of underlying notion of maturity), Descr. of domain (ch10 Description of domain & components), Design doc. (ch11. Design process documentation), MM knowledge (ch16. Knowledge from older MMs), Origin (ch.23), Reliability (ch.25).

Table 7: Context characteristics of maturity models in the domain *Data Management and Analysis.*

the data collection. 8 of the 19 models did not mention who should provide the data through, for example, surveys. Management was mentioned in 1 paper, while the staff was mentioned in 2 others. Most often, a mix of these groups was mentioned as being respondents. Regarding ch27: *Target group*, all papers mentioned the target group being of internal origin. This comes as no surprise as maturity modeling is often used to gain insight into the performance of internal processes. Furthermore, as opposed to standards like ISO or ISAE, which provide certifications and reports for external publication, maturity models do not have such standardized corroboration. Like with Table 22, a row was added showing the characteristics of the maturity model proposed for this study. This shows how to proposed maturity model differentiates itself from related work.

Maturity model	**Assess. met.**	**Assess. tool**	**Automation**	**Cap. areas**	**Focus**	**Granularity**	**Implem. guide**	**Improv. measures**	**Matur. paths**	**MM type**	**Maturity principle**
Quantitative Data Analytics Maturity Model (QDAMM)	X	X	X	X	Domain-specific	X	X	X	X	Prescriptive	Continuous
BDA process capability assessment model	X			X	General	X	X	X	X	Prescriptive	Staged
BDMM a	X			X	Not mentioned	X			X	Prescriptive	Staged
BDMM b	X	X		X	General	X			X	Descriptive	Staged
Airline network planning BDA MM	X	X		X	General	X	X	X	X	Comparative	Staged
EHR-MM	X			X	General	X			X	Descriptive	Staged
Fuzzy ELECTRE big data maturity model	X			X	Domain-specific		X		X	Prescriptive	Staged
BI maturity model	X	X		X	General		X		X	Descriptive	Staged
biMM a				X	General	X	X	X	X	Prescriptive	Staged
biMM b	X	X		X	General	X	X	X	X	Comparative	Staged
BIS Maturity model				X	Domain-specific	X				Descriptive	Staged
ADA-CMM	X			X	General	X	X		X	Descriptive	Staged
DELTA model	X			X	General	X	X	X	X	Descriptive	Staged
HISMM-DA				X	General					Descriptive	Staged
CDQM maturity model	X		X	X	General	X			X	Prescriptive	Continuous
DMM model	X			X	Domain-specific	X	X		X	Comparative	Continuous
Master Data Maturity Model (MD3M)	X			X	Domain-specific	X	X		X	Prescriptive	Continuous
RDM readiness model				X	Domain-specific	X				Prescriptive	Continuous
DWP-M	X			X	Domain-specific	X	X		X	Descriptive	Continuous
ML implementation maturity workflow	X			X	General	X	X	X	X	Prescriptive	Continuous
Frequency:	15	4	1	19	Gen:12, D-S:6, Not m:1	16	12	6	16	Desc:8, Pres:8, Comp:3	Staged:13, Cont:6

Characteristic abbreviations: Assess. met (ch3. Assessment methodology), Assess. tool (ch4. Assessment tool), Automation (ch5.), Cap. areas (ch7. Capability areas), Focus (ch12. Focus of model), Granularity (ch13. Granularity mentioned), Implem. guide (ch14. Implementation guide), Improv. measures (ch15. Improvement measures), Matur. paths (ch17. Maturation paths), MM type (ch20. Maturity model type), Maturity principle (ch21. maturity principle).

Table 8: Structure characteristics of maturity models in the domain *Data Management and Analysis*.

When looking at Table 8, some interesting points arise. It shows that not all maturity models include an assessment methodology component, meaning they have no inference engine that allows for collecting and interpreting maturity assessment data. A large part of the models is descriptive, meaning that no improvement items can be designed based on the maturity assessments. This is further shown by some models' lack of maturation paths. Organizations implementing maturity models without such paths cannot reach a higher maturity as there are no guidelines to follow. The above points all diminish the usefulness of maturity models as a tool for maturation. Furthermore, most models allow for self-assessment, but not all models mention this. This, coupled with some models' lack of assessment and implementation methods, points to some models' poor usability. These findings confirm the maturity model limitations found during the SLR. The proposed maturity model will feature some characteristics which appear to not be the most frequent. These characteristics are related to the automation and extensiveness of maturity assessments and are included in the model because it is believed that these will improve the model's performance. The model will be a Domain-general, Prescriptive, Self-assessment maturity model with an Assessment methodology and tool, supporting automation. This means that the presence and elicitation of improvement items and maturation paths are described. An implementation guide will be provided as well. Most models in Table 8 were staged instead of continuous. However, the proposed model is of continuous nature as this allows for more granularity. The risk of losing usability through the greater level of detail is mitigated through the use of a visual reporting component in the form of an automation tool.

4.4.1 Maturity dimensions

To design the Maturity dimensions for the maturity model of the maturity model, research has been done on the maturity dimensions found in the extracted maturity models. The dimensions have not only been collected from the 19 domain-relevant maturity models but from all collected models. This should indicate whether the maturity models in the Data Management and Analysis domain have maturity dimensions that are similar to the most common dimensions of all models.

Not all maturity models explicitly mention their granularity. The extraction of the maturity dimensions was not always straightforward because of this. Terminology for the maturity dimensions also differed. Synonyms are: *Domain*, *Focus Area*, or *Capability area/domain.* These terms were collected along with the definitions to make the grouping of maturity dimensions as systematic as possible. Furthermore, this variance in used terminology confirms the maturity model limitation of a lack of standard terminology and also violates the presence of key maturity model characteristic 'granularity'.

From all 130 maturity models, 301 domains were collected, of which most had an occurrence of 1 (172). The granularity of the domains varied a lot based on the different maturity models and their purpose. For example, a maturity model for Information system management might have a domain *Cybersecurity.* In contrast, a maturity model specifically for Cybersecurity might already split this domain through its maturity dimensions. Therefore, the dataset contains a lot of maturity model items that are mentioned as both a maturity dimension and capability. These dimensions often only occur once, however.

A set of maturity dimensions appear to be more common than others. In line with the maturity model characteristic 'Maturity concept' (Lahrmann et al., 2011), the domains *People*, *Process* and *Object* (in the form of *Product* or *Technology*) often appear in maturity models. Table 9 shows the ten most common maturity dimensions across all extracted maturity models. The most common domain, *Technology*, only occurs in 46 of the 130 maturity models. The other domains occur even less often. And while this can be explained by the models having their own focus, which does not have to be related to technology or an organization, it also confirms the absence of standardized maturity model components. Also, the tenth model common domain is a combination of two more common domains, which violates the design rule of maturity models being non-overlapping.

The same set of dimensions arises when looking at the maturity dimensions of the 19 domain-relevant maturity models. These models have 69 maturity dimensions combined, of which only 13 occur more than once. These maturity dimensions are shown in table 10. Dimensions *Technology, Organization, Strategy, People, Culture, Governance*, and *Data* often occur in both lists. The table below also shows maturity dimensions that are closely related, like *Data governance* and *Data quality.* For the proposed maturity model, it was decided to use these maturity dimensions, although with slightly different names, as capabilities under dimension *Data.* The maturity model will also use the other set of common maturity models mentioned above.

The maturity model will contain the following maturity dimensions: *Data*, *Governance*, *Organization*, *Strategy*, and *Technology.* It was chosen to include *People* and *Culture* as capabilities

Maturity dimension	Frequency
Technology	46
Organization	41
Strategy	35
People	34
Culture	24
Data	21
Governance	21
Information Technology (IT)	21
(IT) Infrastructure	18
Processes & organization	16

Table 9: Maturity dimensions from all extracted maturity models.

Maturity dimension	Frequency
Organization	8
Data	6
Technology	5
People	4
Strategy	4
Culture	3
Data governance	3
Data quality	3
Information Technology (IT)	3
Governance	2
Information delivery management	2
Usage & Ownership	2

Table 10: Maturity dimensions from the 19 domain-relevant maturity models.

under *Organization* due to overlapping capabilities. Other common dimensions like *Information Technology*, and *Data quality* were included under *Technology* and *Data* respectively.

In the next section, common capabilities are further analyzed to populate the maturity dimensions mentioned above.

4.4.2 Capabilities

To populate the elicited maturity dimensions with capabilities, all capabilities mentioned in the 19 domain-relevant maturity models were extracted. It was chosen to exclude capabilities mentioned in the total pool of 130 original models as these are not related to data analytics. The aim is to categorize the capabilities under the set of 5 maturity dimensions. To do this, all parent maturity dimensions were extracted for each capability. The collected definitions were used to group or combine capabilities if relevant. In some cases, the parent maturity dimension is not present in the group of 5 that is used in the new maturity model, as the related maturity dimension was disregarded. In that case, the capability is placed elsewhere if that is deemed logical based on the definitions. If this is not possible, then the capability is dropped.

Some capabilities like *Data management* and *employee skills* occurred a lot and were placed under a maturity dimension. However, when looking at their related KPIs, it became clear that the granularity of some capabilities slightly differed. For example, Data management had multiple KPIs and papers referring to it, while *Employee skills* was mentioned as a capability but only had 1 KPI: which was Employee skills. Due to this difference in granularity, some capabilities are later used as KPIs (if their extracted definitions indicated that this was possible). *Data quality*, which was also mentioned as maturity dimension has been combined with frequent capability *Data management*. Several capabilities like *Training*, *Innovation*, and *Data architecture* were initially placed in the maturity model as capabilities, but were later transformed into maturity metrics as there were changed from qualitative measures to quantitative measures. This was done in line with the collected definitions and granularity of the models from which they stem. As some models gave capabilities thresholds for each level, the conversion to maturity metrics could be made.

Table 11 shows the proposed capabilities linked to maturity dimensions. As can be seen, the maturity dimension *Data* has the most capabilities. This is in line with the purpose of

Maturity Dimension	Capability	Description
Data	Data Analytics	Related to the processing of data to provide insight. Envelops the tools that are used, the types and analysis, and coverage,
	Data Management	How well the data is managed when in the organization's care. Concerns policies and standards for data storage and structure.
	Data Sources	This capability concerns data gathering from external parties.
	Data Reporting	This capability concerns reporting the analyses to stakeholders.
Governance	N/A	All practices related to governance. There is no overlap with data management, however.
Organization	People	Concerns the employees, staff, and users of an organization. Competencies, training, and commitment are relevant.
	Culture	Related to the culture of an organization. Concerns how well data analytics has been integrated into the culture, and if new initiatives have management backing.
Strategy	N/A	Related to the strategy of an organization
Technology	N/A	Concerns the IT/Data analytics infrastructure that is used by the organization.

Table 11: Capabilities of the proposed maturity model.

the proposed maturity model, situated in the field of Data Analytics. Maturity dimensions *Governance*, and *Strategy* have no capabilities as there was no need to divide this dimension. Dimension *Organization* has capabilities *People* and *Culture*, as was indicated in section 3.2.2.

The next section concerns linking KPIs to the mentioned capabilities. These will be used for data collection to be used for maturity assessments.

4.4.3 KPIs & metrics

As was the case for the maturity capabilities, a vast amount of KPIs was collected. These KPIs correspond with the before-mentioned capabilities. Some KPIs have a one-to-one relation with capabilities, and as such, this capability has been written down as a KPI in the maturity model. The KPIs encompass aggregations of measurable data points, i.e. *maturity metrics*, which together express value regarding the maturity of a capability. These metrics are measurable, and thus automatable. Each metric has a threshold value for each maturity level so that the data can be converted to a maturity score. The collection of this data, as well as its processing and reporting, can therefore be automated. These thresholds are often directly retrieved from the systematic literature study by transforming a qualitative measure into a quantitative one. In some cases, the thresholds were already quantitative.

The maturity dimensions and capabilities were designed using a top-down approach. For the population of the capabilities with KPIs and maturity metrics, a mixed approach is used. First, all frequent KPIs are collected and placed under capabilities if that makes sense according to their definitions and original parent capabilities. Then the KPIs are populated with maturity metrics. These are seldom reported in papers as quantitative measures are a novel research concept. Therefore, a bottom-up approach is used to place the metrics retrieved from literature and interviews under the present KPIs. When a metric is deemed as relevant to a maturity dimension and capability but cannot be placed under a KPI, a new KPI is elicited if that makes sense for the overall coverage of the proposed maturity model.

The proposed maturity model is validated through expert interviews, of which the results are found in section 3.4. The full maturity model can be found in table 24 in Appendix C. An alternative visualization of the maturity model, as well as extended documentation of all maturity components, can be found in Appendix D.

Note that the nature and implementation of the KPIs are not discussed here. Only when the model is prepared for implementation will the method of data collection be discussed. The KPIs and their metrics and thresholds are not organization-dependent, meaning they are generalized and relevant for all organizations. As the maturity model is designed with automatic data collection in mind, almost all maturity metrics can be measured using surveys with Likert-based questions which can later be replaced by automated counterparts. Regarding the respondents of the data collection process, a mix will be needed of employees and managers to get the most complete picture.

However, the aim of this research is to automate the maturity model. This envelops the data collection, processing, and reporting part of the model. An effort should therefore be made to automate the implementation of the maturity model by, for example, automating the processing of the survey's answers. But for the most part, the surveys for measuring maturity metrics should be replaced by real-time automated counterparts. The implementation guide and maturity assessment tool of the maturity model should incorporate this switch from manual to automatic maturity assessments and allow for both. This helps negate the Maturity model limitation of low-maturity organizations not yet having the data to allow for automation.

4.4.4 Inference Engine

Regarding the Inference engine, an analysis was done of 130 extracted maturity models to get an overview of the used methods. This overview can be seen in table 12. The most common type of inference engine is quantitative, i.e. a formula with or without weights to calculate the overall maturity score. Maturity models which are untested are likely to not include a valid inference engine in the maturity model; 13 of 27 untested models (+-48%) as opposed to 8 of 81 validated models (+-10%).

As the aim of this thesis is to propose an automated maturity model, a quantitative inference engine will be used. It was chosen not to include weights in the formula to keep the maturity model more interpretable. There are qualitative and quantitative maturity metrics, which have thresholds using their respective datatypes. These thresholds were created by converting the thresholds found in papers from qualitative to quantitative or by slightly altering the object/metric that is measured. These thresholds were reviewed by experts to ensure that the thresholds make sense. The data from the maturity assessments are parsed and compared to these thresholds to calculate the maturity level of that metric. The metrics are then averaged to calculate the KPI averages, and again for the capability and maturity dimension averages. This granularity is still interpretable due to the visual reporting component of the maturity model.

A quantitative inference engine like the one described above also allows for bottleneck calculation by automatically comparing the maturity levels to check which maturity metrics are holding the average back. Furthermore, goal-setting is also possible and can even be used to generate customized maturation suggestions. It is possible to scale up the logic of the inference engine further to include dependencies, weights, and more detailed improvement suggestions if the architecture of the automated maturity assessment tool is solid. Adding logic on the relative weights and dependencies of KPIs is added to the inference engine of the proposed maturity model and tool, however. This choice was made as no specific research was conducted into collecting these relations from literature or eliciting them through other methods.

Inference engine type	**Freq.**	**Definition**
Textual description of requirements per maturity level	30	For each capability and maturity level, a textual description was given of the required level of performance to reach that maturity level.
Not mentioned	29	The authors did not mention how to perform maturity assessments, and how to convert the outcome into a meaningful conclusion about maturity.
Formula for calculation without weight	27	A possibly automatable formula which does not involve weights for maturity items. An example is a Likert-based survey where each question corresponds to a maturity level
Formula for calculation with weight	21	A more sophisticated inference engine formula where each maturity item has also been given weight.
Assignment based on interviews	13	A third-party, i.e. auditor, interviews stakeholders in the company and assigns a maturity level based on the results.
Capabilities linked to maturity level	10	Each maturity level has a set of unique capabilities which must be attained in order to reach that maturity level.

Table 12: Types of Inference engines

4.4.5 Maturity levels

A variety of maturity levels are used in maturity models to indicate an organization's progression in improving its capabilities. The set of maturity levels is important in showing the maturity progression that organizations can achieve. Therefore, maturity levels must have a clear title and short description (Poeppelbuss et al., 2011). Comuzzi & Patel (2016) argue that including a level 0 is also beneficial as many maturity level sets cannot indicate a complete lack of awareness and capability. Spruit & Pietzka (2015), on the other hand, chooses against the usage of level 0 precisely because it does not often occur in other maturity level sets.

For all 130 maturity models, the maturity levels were extracted. If the authors mentioned the use of an existing maturity level set then this was recorded. In all cases, the used maturity levels were written down with their definitions if these were provided. It should be noted that the meaning of these levels changes depending on the maturity model principle, e.g. staged or continuous. An overview of the used maturity level types is shown below in table 13. Afterward, the most common and well-known maturity level sets are discussed.

Maturity level set	**Freq.**	**Description**
Ad-hoc levels	67	A set of maturity levels that the authors newly designed. These range vastly in terms of the number of levels, the meaning of the levels, and their granularity.
Nameless levels	31	These levels do not have a description. Often these maturity levels are assessed based on a formula-based inference engine.
Maturity score	8	Instead of levels, a maturity score is given in the range of 1-100.
No levels	6	These maturity models do not indicate any maturity levels.
Existing maturity level sets	18	Maturity levels are copied from already existing and well-known maturity models. These include, among others, the Capability Maturity Model (CMM) and its successor Capability Maturity Model Integration (CMMI) (Humphrey et al., 1987; S. E. Institute, 2010), and COBIT 4.1 (I. G. Institute, 2007).

Table 13: Distribution of used maturity level types

A maturity model of which the maturity levels were most often used is the Capability Maturity Model (CMM), and its successor Capability Maturity Model Integration (CMMI) (Humphrey et al., 1987; S. E. Institute, 2010). This maturity model is perhaps the most well-known of them all. It is a staged maturity model with five maturity levels: 1 - Initial, 2 - Repeatable, 3 - Defined, 4 - Managed, and 5 - Optimizing. Note that the most mature level still offers room for further improvement as an organization is never 100% mature. The successor model CMMI changes levels 2 and 4 to Managed and Quantitatively Managed respectively. Another well-known model is the COBIT framework (I. G. Institute, 2007). This framework proposed 6 maturity levels, including a level 0: 0 - Non-existent, 1 - Initial, 2 - Repeatable, 3 - Defined process, 4 - Managed and measurable, and 5 - Optimized. Note that level 5 here is worded more as an end-point of the maturation process. Some ad-hoc maturity level sets were very similar to those of CMM and COBIT. For example, Kayikci et al. (2022) propose the following maturity levels: 0 - Non-existent, 1 - Executed, 2 - Managed, 3 - Established, 4 - Predictable, 5 - Optimized. It is easy to see the similarities to the above-mentioned models, but as the authors never cite these sources, they were not categorized as using their maturity levels.

Regarding the 19 domain-relevant maturity models: 8 models used ad-hoc levels, 2 used CMMI levels, 1 model used COBIT, 1 model used SPICE, 4 models used nameless levels, 2 models used a performance %, and 1 model indicated no maturity levels. As for the size of the maturity level sets, 9 of the 16 sets with actual maturity levels had 5 different stages of maturation. Furthermore, 13 of the 19 maturity models used a stages maturity level set, while only 6 used a continuous maturity principle. Based on this, it was chosen that the maturity level set that will be used in the maturity model indicates 5 stages and support the staged maturity principle. And since CMMI is by far the most well-known and supported maturity model, it was chosen to use these maturity levels in the reference framework.

4.5 Expert evaluation

The proposed maturity model was validated through a set of expert interviews, conducted in two rounds. The outcome of this is a validated maturity model that can be integrated into the automated maturity assessment tool, thus answering sub-question 4. The process is explained in section 1.3.4 and the interview protocols for both rounds are found in Appendices E. and F. Data on the experience and expertise of the interviewed experts can be found in Table 14.

During the first interview round, each time an item was mentioned and experts were positive, the item got was marked with 'Y' which was equal to 1 positive point. Each negative mentioned was indicated with a 'N' which was equal to -1 point. The tables shown below reflect the total of this sum.

Title	**Skills**	**Years of Experience**	**Education Degree**
Lean/Agile coach	CMM assessor	25	bachelor's degree
Data scientist	Data Science, Informatietechnologie	4	Msc
Test- en requirements consultant	Quality assurance	25	Msc
QHSE Officer	CMMI, Quality assurance	17	Msc
CMMI Coach	CMMI	25	bachelor's degree
Quality Assurance Officer	Quality assurance	7	bachelor's degree
CEO	Testing and quality assurance	20	Msc
Backend & Data Developer	Power BI, Data mining	4	Msc
Data Analyst	Big Data Analytics, Statistical programming	5	Msc
Azure Consultant	Data Visualization	3	Msc
Data Architect	Data modeling	19	Bsc

Table 14: Demographic data of interviewed experts.

4.5.1 Characteristics

All experts except for one, a data analysis expert, had experience with using maturity models in the work. Curiously, CMM(I) was the only maturity model experts mentioned which also was found during the SLR. This may indicate a need to include gray literature in future research on collecting maturity models. CMM(I) was mentioned 7 times by experts, and TMMI, SPICE, and the Data Analytics Ladder were mentioned 3 times. Less often mentioned were COBIT 5 and the CO2 ladder, while SAFE, Gartner MM, I3, and DAMA DMBOK were only mentioned once.

Experts mentioned that data collection was always done through interviews and/or document analysis. The intervals of data collection ranged from once every two or three years to every few months or on an ad-hoc basis. The total time that this takes ranged from several hours to a few days, and even 16 weeks of analysis. No experts mentioned the data collection and processing as being automated, while 9 expressed that automation of the data processing would be very beneficial to the process. 1 expert was opposed to this notion. As for the data collection, 8 experts saw benefit in this while 2 were opposed to the idea. Overall, experts saw automating this part of maturity assessments as more difficult. They were also wary of completely replacing interviews, as some experts stated that maturity items belonging to the *People* maturity concept cannot be automated due to the intangible knowledge of employees. Maturity items belonging to the other two elements would be better suited to automation, however. The majority of experts also saw potential in the automation of data reporting through adaptive visualization.

4.5.2 Limitations & Requirements

The experts were also asked about the limitations and pitfalls of using maturity models. The mentioned limitations are shown in table 15. They coincide with the limitations that were found during the SLR. Interestingly, some experts mentioned that an academic foundation does not guarantee that the maturity model is useful, while a limitation that was often found in literature stated the opposite. Lack of empirical validation was confirmed as a limitation of some maturity models, as well as a lack of standardized terminology, models being too abstract, continuous evaluation being impossible, and maturity items being contradictory or vague. A limitation that

Limitation	Frequency
Risk of being reduced to 'list of checkmarks' (level hunting)	7
MMs could prescribe goal that company does not want	6
Maturity assessments are very expensive	5
Automation: proof still needed	5
MM/KPIs too abstract	3
Costs not included in maturity level items consideration	3
Foundation in literature not equal to a useful model	3
Maturity models do not support continuous evaluation	3
Maturity assessments are too large and infrequent	3
KPIs could go against best practices	1
KPIs could contradict each other	1
Fixed-level MM not desired	1

Table 15: Maturity model limitations mentioned by experts

was not found in the literature is related to maturity models and their levels being reduced to a set of checkboxes. A parallel was drawn to a 'concrete life jacket'. The item may appear like a life jacket when looking purely at the specifications, but this does not guarantee that it works. The same goes for maturity models, where there is a risk that companies try to achieve the highest maturity levels solely for this purpose of certification. They then completely ignore the process changes and benefits that need to be taken into consideration. Or as another expert put it: "Hitting the target, but missing the point". A similar limitation that only experts mentioned is that an organization might beautify its results to obtain a higher maturity level for the recognition of its stakeholders. Automating the data collection to be based on an organization's IT systems and processes eliminates this threat as the data is not based on human judgment.

Lastly, a frequently mentioned limitation was that the organization might not want to achieve the highest maturity level for all maturity items. This might be due to, for example, domain or cost-related reasons. The automated maturity assessment tool will include goal-setting functionality to help organizations track their own goals and progression. No characteristics of the proposed maturity model were seen as wrong so no changes were made to the structure.

4.5.3 Automation possibilities

Automation possibilities were discussed with the experts, whose opinions differed on the different benefits. All 11 experts saw the benefits of automatic data processing to reduce the time between data collection and reporting. This could be in the form of a simple Excel sheet or in more sophisticated forms, like including an inference engine with bottleneck identification. Automated generation of improvement suggestions was also seen as a good development. The automation of the data reporting in the form of interactive analytical reporting was mentioned by 7 experts, all of whom agreed on its usefulness. The automatic collection of data was mentioned by all 11 experts. 8 saw this as a very useful feature, while 1 expert was neutral and 2 experts were against this idea. They mentioned the loss of data context as a major pitfall, as well as the difficulty in creating 'universal' data connectors which can adapt to the differing IT structures of organizations. It was also mentioned how this automation possibility is dependent on the maturity of the organization, where a lower maturity means fewer data sources from which to automatically draw data. Some experts remarked how this process of increasing maturity according to the maturity model should go hand-in-hand with increasing automation opportunities. When discussing the implementation of ML to classify maturity levels, like was proposed by Lismont et al. (2017), some experts noted that this degrades the quality of the insights that can be gained. They noted that the main aim of maturity assessments is to inform the team or organization of their as-is and to-be situation. An understandable and detailed maturity assessment is needed for this, something which they argued cannot be adequately achieved through the use of classification algorithms.

Other automation possibilities include involving an organization's goals in the inference engine so that bottlenecks can be identified in relation to how the organization wants to mature. Ethics were mentioned as a potential danger as there also lie automation possibilities in maturity metrics related to personal data. This should be carefully considered. As one expert put it:

"The People-part of the maturity model is hard to automate". This is in line with the opinions of some experts saying that subjective opinions cannot be automated.

These findings from the expert interviews impact the requirements of the to-be-developed automated maturity assessment tool. Automated data collection is not implemented as a core component of the tool. For each maturity metric, a recommendation is given on how to automate the data collection and from which tools and systems the data could be collected. Automated data processing and reporting are fully implemented, however, as well as the bottleneck engine.

4.5.4 Content

The content of the maturity model was extensively validated during the second round of expert interviews with six interviewees, using the evaluation template proposed by Salah et al. (2014). However, during the round, the maturity model was not yet shown. Here, experts were asked which factors they deem important in a Data Analytics environment. The mentioned items were noted and shown to the experts after they mentioned all of their own ideas.

As for maturity dimensions, the experts' mentioned maturity dimensions mainly coincide with the maturity dimensions of the maturity model. Dimensions *People* and *Culture* are placed under *Organization*, while *Software development* does not appear in the maturity model as a maturity dimension. It is covered, however, by the KPIs and metrics that are found under the *Data* and *Technology* dimensions. KPIs like *DA architecture*, *Data integration*, and *Data quality* all are related to the development of software to process the data. However, these all focus more on the outcome of the development, and not on the development process itself. Curiously, experts also mentioned KPIs related to this maturity dimension, like *Velocity* which was mentioned twice, and *Lines of code* which was mentioned more often but about which experts were very negative. Ultimately, due to the focus and domain of the thesis, and the lack of software development in the maturity models found through the SLR, it was chosen to not include this maturity dimension in the maturity model. Furthermore, dimensions *Test* and *Management* are also not explicitly included as these are only mentioned once and already are partially covered by existing KPIs. The mentioned maturity dimensions are found in Table 16.

Maturity Dimensions	**Frequency**
Data	8
Technology	7
Software development	6
Strategy	6
Governance	5
Organization	5
People	4
Culture	2
Test	1
Management	1

Table 16: Maturity dimensions mentioned by interviewed experts.

Maturity capabilities were mentioned less as experts would often talk about high-level domains (i.e. maturity dimensions), or lower-level items like KPIs. The capabilities that they did mention are found in Table 17. The two most common capabilities are either already present in the maturity model or captured through a higher-level maturity dimension. All other mentioned capabilities were mentioned far less often with some, like *Machine learning*, even getting a lot of negative responses. For this capability, in particular, it was argued that most organizations do not yet employ machine learning and that underlying metrics would not yield a representative picture as the application context of machine learning greatly influences the desired output in terms of accuracy and prediction speed. Like with earlier mentioned cases, some capabilities are already represented in the maturity model. This is the case for *Configuration management*, *CICD*, and *Innovation*. After the round of expert interviews, capability *Ethical considerations* was added to the maturity model due to it not being covered in any way by the existing set of maturity items. Initially, *Machine learning* was marked as KPI in the maturity model. This was removed after the expert evaluation round due to the negative responses that its capability counterpart got.

Maturity Capabilities	Frequency
Data Reporting	7
Data governance	6
Configuration management	3
Risk management	3
CICD	3
Ethical considerations	3
CRISP-DM	2
Validation	1
Innovation	1
Change management	1
ML	-2

Table 17: Maturity capabilities mentioned by interviewed experts.

Table 18 shows all KPIs that were mentioned by the experts. Note that during this part of the interviews, there was no distinction between KPIs and maturity metrics to not introduce any unnecessary complications to the creative process. If possible (through analysis of the interviews and definitions), the wording of KPIs that were mentioned by the experts has been slightly altered to make to coincide with KPIs that are already present in the maturity model. Following from this is a list of KPIs that are mostly all already in the maturity model. This is expected as the proposed maturity model was grounded in a rigorous SLR. The most negative KPI was *Lines of code*, about which experts argued that it is a very bad metric of quality and productivity. Following from this list, KPIs *Use case coverage* and *DA report creation time* were removed from the maturity model. It was argued that these KPIs are hard to standardize as they depend heavily on the context of an organization. In line with earlier comments about the capabilities, all machine learning-related KPIs also got negative responses. Besides these KPIs, most were confirmed to be useful, and some had opposing responses. These have therefore not been added to the maturity model.

Afterward, the thresholds and definitions of the maturity metrics were also discussed with the experts. A selection of these has been altered according to the comments from the experts. For example, experts argued that for some maturation steps, like *Code coverage*, implementing the first test is way more complicated than implementing the N^{th} test. Therefore, the threshold curve was made less steep for lower levels as gains in coverage were harder initially. Many definitions were also slightly altered to better represent the scope and possible considerations.

Based on the results of the first expert interview round, the maturity model was revised as described above. The maturity model was then added to a document, along with a short explanation and the evaluation template by Salah et al. (2014). The resulting document was used for the second round of interviews where six interviewees participated. The results of this interview round can be found in Table 19. The evaluation template by Salah et al. (2014) can be used as a standardized method of evaluating the proposed maturity model. It consists of five-point Likert statements, spread across different maturity model components. Component *Maturity levels* has questions related to Sufficiency; *The maturity levels are sufficient to represent, all maturation stages of the domain*, and Accuracy; *There is no overlap detected between descriptions of maturity levels.* Component *Processes and Practices* has questions related to Relevance; *The processes and practices are relevant to the domain*, Comprehensiveness; *Processes and practices cover all aspects impacting/ involved in the domain*, Mutual Exclusion; *Processes and practices are clearly distinct*, andAccuracy *The indicator levels for each KPI and Capability are correctly assigned to their respective maturity level*, while factor *Automatability*; *The automatability of the indicators is logical* was added for this study. Component *Maturity Model* consists of questions related to Understandability; *The maturity levels are understandable*, *The assessment guidelines are understandable*, *The documentation is understandable.* A factor is *Ease of use*; *The scoring scheme is easy to use*, *The assessment guidelines are easy to use*, *The documentation is easy to use.* Lastly, factor *Usefulness and Practicality* with questions; *The maturity model is useful for conducting assessments*, *The maturity model is practical for use in industry.* Note that the last three factors are derived from TAM (Davis, 1989).

Maturity KPIs	Frequency
Code testing coverage	6
Data usage/accessibility	5
Type of data analysis	4
Code tests coverage	4
Executive sponsorship	4
Aim of visualisation	4
Employee competencies	4
Data warehousing	3
Pipeline/deploy success	3
Data cleanliness	3
Documentation of datasets	3
End-user proficiency	3
Velocity	2
Report frequency	2
Data definitions	2
Business understanding	2
Decisions made based on DA reports	2
Up-to-date-tooling	2
Aggregation	1
Last time updating definitions	1
Data & dashboard ownership	1
DA report feedback frequency	1
Stakeholder management	1
Data completeness	1
Metadata	1
Data retention	0
Budget	0
DA report relevancy	0
Use case coverage	-1
ML prediction speed	-1
ML accuracy	-2
DA report creation time	-2
Lines of code	-5

Table 18: Maturity KPIs mentioned by interviewed experts.

Overall, the maturity model scored highly on most aspects. The lowest scoring element is related to the maturity levels and their overall descriptions (Accuracy). One interviewee noted that using the maturity levels of CMM(I) is not very useful as these are textual descriptions of how well an organization grasps a specific capability. While this can still apply to maturity models with quantitative data, this is less useful. The progression of maturity is now expressed numerically, and it is impossible to clearly define how these different numbers relate to specific textual descriptions of maturation. Following this discussion, it was chosen to abandon the use of CMM(I)'s maturity levels and move more towards to the focus area approach described by Steenbergen et al. (2010).

All interviewees indicated that the maturity items in the maturity model are entirely relevant to data-intensive data analytics practicing organizations. They noted that the processes are relatively comprehensive but suggested adding new items, like the above-mentioned ethical consideration capability. These suggestions were then reviewed to deem if they fell within the scope of the proposed maturity model. Regarding the automatability of the mentioned maturity items, this was seen as very reachable, with most experts offering a long list of datasets that could be used for this purpose.

Lastly, the understandability (UP 1 & UP2) of the maturity model was seen as good across all metrics with high average means. The interviewees had no trouble understanding the maturity model's composition and the relation of different maturity items to the maturity levels. Overall, the maturity model was evaluated very positively. Although the small sample size hinders the validity of the results.

		Descriptive Statistics		Summary of Responses				
				1	2	3	4	5
		Mean	St. Dev.	Strongly Disagree	Slightly Disagree	Neither Disagree Nor Agree	Slightly Agree	Strongly Agree
Maturity Levels	Sufficiency	4.17	0.41	0.00%	0.00%	0.00%	83.3%	16.7%
	Accuracy	3.67	0.82	0.00%	0.00%	50%	33%	16.7%
Processes and Practices	Relevance	4.84	0.41	0.00%	0.00%	0.00%	16.7%	83.3%
	Comprehensiveness	4.17	0.41	0.00%	0.00%	0.00%	83.3%	16.7%
	Mutual Exclusion	3.84	0.41	0.00%	0.00%	16.7%	83.3%	0.00%
	Accuracy	4.67	0.52	0.00%	0.00%	67%	33%	67%
	Automatability	4.34	0.82	0.00%	0.00%	16.7%	33%	50%
Understandability	PU1	4	1.27	0.00%	16.7%	16.7%	16.7%	50%
	PU2	4.17	0.76	0.00%	0.00%	16.7%	50%	33%
	PU3	4.67	0.52	0.00%	0.00%	0.00%	33%	67%
Ease of Use	PE1	4.67	0.52	0.00%	0.00%	0.00%	33%	67%
	PE2	4	0.9	0.00%	0.00%	33%	33%	33%
	PE3	4.5	0.84	0.00%	0.00%	16.7%	33%	50%
Usefulness and Practicality	UP1	4.84	0.41	0.00%	0.00%	0.00%	16.7%	83.3%
	UP2	4.67	0.52	0.00%	0.00%	0.00%	33%	67%

Table 19: Results of the evaluation expert interviews

4.6 Automated maturity assessment tool

A tool was built to apply the proposed and expert-validated maturity model, which introduces automation features to the maturity assessment process. Because the maturity model contains quantitative elements, automation of various process parts is possible. The tool is described below, and some example pictures can be found in Appendix G. Appendix J. provides an implementation guide explaining how to instantiate and apply the tool to perform automated maturity assessments. The usefulness of the tool, as well as the maturity model, is tested through the industrial case study, which is described in Chapter 4.

As mentioned before, the tool does not automate data collection, but it does lessen the need for manual tasks. It also gives recommendations for automated data collection per maturity metric, but these data connections need to be created by the organization and adapted to its internal IT landscape. The data reporting component of the tool is built in Tableau, while most of the data processing is done in Excel. These sheets are embedded in the Tableau part of the tool. The Excel consists of a set of sheets for processing logic, a data input sheet, and a 'Maturity model documentation' sheet. This last sheet functions as configuration management for the tool. From here, all maturity components and their thresholds, maturity levels, definitions, and other desired components are declared. These changes are automatically implemented throughout the tool to update the embedded maturity model immediately. This makes it easy to continuously improve and adapt the embedded maturity model or change it completely. This aspect also makes it easier to transfer the tool to other application domains and research.

Data can be inputted in two ways, depending on the nature of the data: quantitative or qualitative. The quantitative data, extracted from the organization's tooling and processes, can be inputted into a sheet with a timestamp. The data is extracted and sorted from this sheet using sorts and regexes. This makes the processing more flexible and less notation-dependent. The qualitative data can be inputted through a survey accessed through the tool's dashboarding part. Here, on the *Data collection* page, a survey for inputting this data can be found, as well as a survey where users can indicate their goals for each maturity metric. The inputted data is immediately processed into maturity levels, which are then used to calculate bottlenecks and improvement suggestions. This is all done instantaneously, and the results are instantly displayed on the dashboards. Below, the four pages of the automated maturity assessment tool are discussed. Images of the tool, with filled-in data, can be found in Appendix G.

The above-mentioned *Data collection* page is one of four pages, each with a different use. The main page is the *Maturity overview* page. This page shows the different maturity levels through a spiderweb graph. Turning off/on other visual elements like labels and scores is possible. It is also possible to remove or add an overlay of the goals if an organization has indicated those. Using a set of buttons, users can move between different aggregations of maturity items to drill down into values that they find interesting. More in-depth data is displayed in the right-most panes depending on which maturity item the user has last hovered over.

The *Inference engine* page shows data about bottlenecks in the maturation process. It displays data on the lowest-level maturity items: the maturity metrics. It is possible to choose from four different types of analysis: 1. All bottlenecks 2—biggest bottlenecks 3. Best performers 4. Gaps to goal. Based on the selected analysis, the tool displays different bottlenecks and how much of an impact that has on the overall maturity of the KPI. Based on which maturity item the user hovers over, the correct description is shown, and a list of improvement suggestions can help improve the score of that maturity item.

The *data collection* page shows data in the inputted data. The collection method is shown for each maturity metric, and a timestamp indicates the latest data retrieval time. Automation suggestions for the data collection process are also shown here. This page also contains embedded surveys that can be used to input the goals that an organization strives for and the qualitative data.

The *Maturation path* page shows data on the current progress of singular maturity items with more detail than the other pages. Here, the thresholds for all maturity levels are shown alongside the raw data of a maturity metric that lead to its current maturity level score. An overview of the historical data and maturity levels of all maturity metrics is also given. This allows organizations to analyze their past performance and try and improve their future efforts to mature.

5 Application of the DA maturity model

An industrial case study is performed to test and validate the proposed maturity model and the automated maturity assessment tool. The aim is to test whether the maturity model is helpful in practice and whether the assessment tool adds value to the whole maturity assessment process. This chapter first describes the company where the case study is performed. Afterward, the implementation is discussed, starting with the performed steps and the collected data and ending with a section on using a Technology Acceptance Model (TAM) survey. The results of the implementation are discussed in Chapter 6.

5.1 The Case company

The case study was performed at InTraffic, a company offering IT services in the public transport domain. It employs around 150 people. The company performs many services and operations, from software development to consulting, to data analysis, and has data analytics as a core business asset. The organization is part of a larger group, *ICT Group*, which covers a set of organizations focusing on a broader set of domains and IT-related operations. InTraffic itself has one data analytics team, team *DSS* (meaning Data Services & Solutions), that busies itself with performing data analysis over, for example, logging data, system status data, and network occupation data. The day-to-day activities of this team include retrieving log data through scripting in Bash. Data is parsed through transformation scripts, often written in Python, Pyspark, or Java, and then stored in the Datalake. The team can then extract data to create analyses and visualizations for their customers and other relevant stakeholders. This team comprises eight people and makes up the set of case study participants. The team's systems and processes are used to collect the quantitative data. At the same time, the employees are asked to provide qualitative data and assess the designed maturity assessment tool.

This case company is of medium size, with only one data analytics team. When implementing the maturity model and tool at a larger company, choices need to be made regarding the application scale. The data resulting from the maturity assessments will be most helpful if it has a high level of detail. It would therefore be most beneficial to implement a tool in a smaller scope; for example, all data analytics teams could have their implementation of the tool. It is beneficiary, however, if such a subsection of the organization still employs data analytics processes over the whole chain. This provides the most Representative insight into its data analytics maturity landscape. If some processes are not deemed relevant, goal-setting can indicate this.

5.2 Maturity model & tool implementation

The case study was performed according to the protocol found in Appendix H. This protocol states the goal of the case study, the participants, the executed steps, and the to-be-collected data. The case study was performed through one-on-one sessions with a member of InTraffic's data analytics team. To minimize the variability of the sessions, a closed-off room was used, and interviewees were shown the same tool and data. Furthermore, after explaining the proposed maturity model and tool, the interviewer left the room and allowed the interviewees some time to play around with the tool before filling in the TAM questionnaire. This was done not to give the participants the feeling of having to answer positively because the interviewer was sitting beside them. All eight interviews went smoothly without any interruptions. All sessions lasted between 20 and 35 minutes except for the first data collection session. This session lasted close to 90 minutes. All sessions were held within eight days of each other, so collecting more up-to-date data on the IT landscape would not have yielded much different data.

The automated maturity assessment tool was hosted on the digital environment of InTraffic. This gives an example of how the tool's implementation could work. The data required for the maturity assessments were then collected with the first case study participants. As no automated data collection methods yet exist, the data were manually retrieved from the relevant IT systems and processes, and an automation guideline was created. This guideline is not utilized during this case study as it falls outside of the scope of this thesis, but it was agreed upon by the case study participant, who found it very helpful for future actions. The case study participant also provided the necessary qualitative data through the questionnaire and indicated their goals for future maturation.

This data populated the dashboards, and the inference model provided data on bottlenecks and historical growth. All subsequent case study participants assessed this on both UI and content and then were asked to fill in the TAM questionnaire and provide tips and tops to help further improve the tool. Demographic data on the eight participants are found in Table 35 in Appendix H.

5.2.1 Data collection

The data that was collected forms a snapshot of the performance and maturity of the organization at a specific point in time. It is outside the scope of the case study to perform multiple maturity assessments to track maturity. Therefore, data on historical performance was not collected. To ensure that the dashboards had enough data, some data was mocked to fill the gaps. This was done for maturity metric *Code testing coverage*, a maturation development that In-Traffic is currently undergoing. Some historical data was estimated based on past developments in this field. The data collection process was easy for the case study participant. The maturity metrics and their descriptions were seen as straightforward, and they often knew immediately where to search for the data to extract it.

Besides this, the retrieved data could generate a complete maturity overview. The results of this are discussed in Chapter 6. Data for the 29 quantitative maturity metrics was entered in the input sheet, while data on the 26 qualitative maturity metrics was entered through the questionnaire. As mentioned earlier, it was chosen not to express some metrics quantitatively as this could involve personal data and could therefore pose privacy risks. This data, combined with the indicated maturation goals and historical data mockup, forms all input data required for the automated maturity assessment. Note that the raw input data is not provided in this thesis due to this containing company-sensitive data.

5.2.2 Automated maturity assessment results

A part of the output of the assessment is the calculated maturity levels. This is calculated from the maturity metrics up to the maturity dimensions. As mentioned earlier, a tool page provides interactive data on this. The maturation goals are presented alongside this to have a graphical way to show maturation priorities. Bottlenecks, i.e., bad-performing maturity metrics, are automatically calculated based on the input data. These bottlenecks can be based on a set of parameters that the user can choose based on what they desire to see. Furthermore, improvement suggestions are shown for each maturity metric. These typically consist of general methods to increase performance related to that maturity metric. The page showing historical data can then be used to check in hindsight whether improvement efforts have worked or how different maturity metrics influence each other. In contrast to maturity assessments done through interviews, this automated tool cannot take into consideration the context of the current situation through the richness of qualitative data but is much more capable of considering a company's past maturity. It becomes more valuable when maturity assessments and automated data connections are created.

5.2.3 TAM

After showing case study participants the dashboard populated with data, they were asked to fill in a Technology Acceptance Model (TAM) questionnaire and two open questions related to the good and bad parts of the tool. The questionnaire that was used can be found in Appendix I and is based on the work of Davis (1989) and Babar et al. (2007). TAM can be applied to gauge how and when individuals will adopt new technologies and is, therefore, useful to measure the sentiment of the case study participants towards the artifacts. To remove any pressure on the case study participants, the interviewer left to ensure they did not feel pressured to answer more positively due to the interviewer's presence. Afterward, the results were averaged and analyzed and are reported in the next chapter. The results of the two open questions are also discussed here. These open questions were related to the strengths and weaknesses of the tool and to potential use cases for which the tool can be extended. The interviewees received a short explanation of the origin of these questions and were then all able to answer the questions without hindrance.

6 Results

This chapter reports the findings of the case study. The implementation of the maturity model and automated maturity assessment tool generated data on the maturity of InTraffic. This output data, combined with the input data, and the results from the discussion with case study participants, is reported here.

6.1 Results of implementation at InTraffic

The proposed maturity model and tool were validated through a case study with the Data Analytics team at InTraffic. Data was collected for the maturity assessment and inputted into the tool. 8 case study participants were then asked about their experience with using the tool.

6.1.1 Input data

As mentioned in section 5.2.1., three types of input data were collected. The most senior team member was chosen as the first case study participant. This session was used to collect all data on the processes and IT systems of the data analytics team. The quantitative data was read from the systems, the qualitative data was collected through the embedded questionnaire, and the goals (to-be situation) were also gathered through this method.

The quantitative input data can be found in table 36, in appendix K. Note that this data is copied directly from the dataset used by the tool. This shows that it is very easy to input the data. The list of quantitative metrics is shown along with the measurement unit and a description of the scope and meaning of the maturity metric. The next column then starts with a timestamp and contains the numerical values for all metrics. This data denotes a part of the current maturity (as-is situation) of the data analytics team at InTraffic. Since only one session was dedicated to data collection, data is only available for a specific time. To showcase the historical trend visualization capabilities of the tool, the dataset was duplicated four more times with different timestamps. The only change was to maturity metric *Code testing coverage*. An estimate was made to predict this metric's future situations based on the team's backlog. Therefore, the total maturity assessment data consists of five columns with data, where most of the same except for one metric. Some values deliberately also include text in the form of measurement units. This is to test the tool's ability to filter the input data and extract only the numerical value. This was done through regexes.

As for the input to the qualitative maturity metrics, this can be found in table 37. Answering the questions proved easy for the case study participant, taking less than 10 minutes. For this case study, only one participant answered the questions. In future research, all participants could answer the research question and the mode of the responses could be used as the 'truth'. This would also allow for analyses into the sentiment differences that the employees experience on some topics.

Related to the goals that the data analytics team wants to strive towards, these are found in table 38. The participant indicated that the organization wants to achieve the highest maturity level, level 5, for most maturity metrics. However, for some metrics, they indicated that they are fine with the as-is situation. These metrics were mostly related to the types of analyses they could provide or the processing capabilities of different data types. They marked these advancements in maturity as not in line with the team and the company's current roadmap and strategic goal. Furthermore, some maturity metrics got low goals because the company did not *yet* want to invest in maturing this metric. This brings up the notion that some organizations may already have a maturation plan in place without performing a maturity assessment or using a maturity model. It was good to notice that the case study participant could incorporate this maturation plan in their goal-setting of the different maturity items.

These three data types together form the data collection phase of the maturity assessment process. The data processing phase entails combining this data by the inference engine and transforming it into a certain output. This data is reported back to the users by the tool. The execution of these last two phases in the context of this case study is reported below

6.1.2 Automated maturity assessment results

This section discusses the output the inference engine provided when given the input data explained in the section above.

Table 39 in Appendix K. shows the assigned maturity levels for each maturity metric and the indicated goals by the case study participant. The maturity levels were calculated based on quantitative or qualitative data, compared to the different thresholds of the maturity levels of a particular maturity metric. A good sign is that the maturity values that the inference engine assigned to the maturity metrics are all lower than the goals set. Some are equal, however, which means that the organization does not have to spend any effort in trying to mature further in this area.

Figure 39 shows the data reporting of the inference engine output through the tool's dashboarding side. As an example, the mouse currently hovers over KPI *Data quality* to show the current maturity level and goal of the KPI (left), the maturity levels and goals of its metrics (bottom-right), and relations to other maturity items in the maturity model (top-right). The data analytics team really struggles with getting the data quality right. Case study participants confirmed this during the discussion sessions. The team is planning to introduce PyDeeQu into their coding environment to automate input and output controls over their data streams. This lack of automated control and documentation is accurately reflected in the tool through these metrics having maturity levels 1. They score a bit better on the other maturity metrics, but, as seen by their indicated goals, they aim to mature a lot in this area. This is understandable, as data quality is the cornerstone for all types of data analyses. As for the data source automation recommendation, they were recommended to automatically extract PyDeeQu output data once this is implemented to get real-time insight into their data quality.

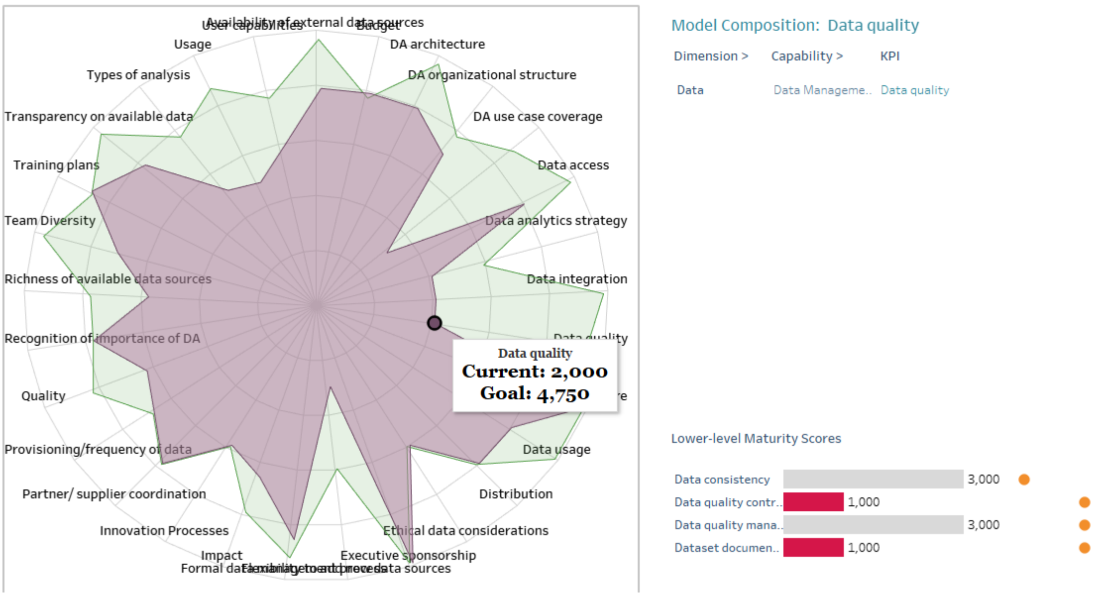

Figure 8: Screenshot of (part of) Maturity overview page of the automated maturity assessment tool, showing the output of the maturity levels as outputted by the inference engine.

This type of analysis on the maturity metric and KPI level can be performed for all 29 KPIs if the organization desires. The tool allows for easy navigation between data points and fields of interest. However, this thesis does not elaborate further on this type of results besides showing the overview in the figure above, through the tables in Appendix K.

If we look at the maturity levels 1 level higher, on the capability level, we can see the organization's maturity from another angle. Figure 9 shows the average maturity level for each capability. An interesting insight from this visualization is that the data analytics team actually has the lowest maturity score for capability *Data analytics*. After some thought, the case study participants were very interested in these results but could confirm that this seems logical as they struggle with some key components of this capability. They were interested in the bottleneck page to check which recommendations could be used to mitigate this gap in maturity. Furthermore, regarding this page, some participants hid the maturity levels and sometimes even the labels. In contrast, others argued that the option to remove this should not even be present as it is vital information. This provides an interesting topic for the future validation of the tool and its UI.

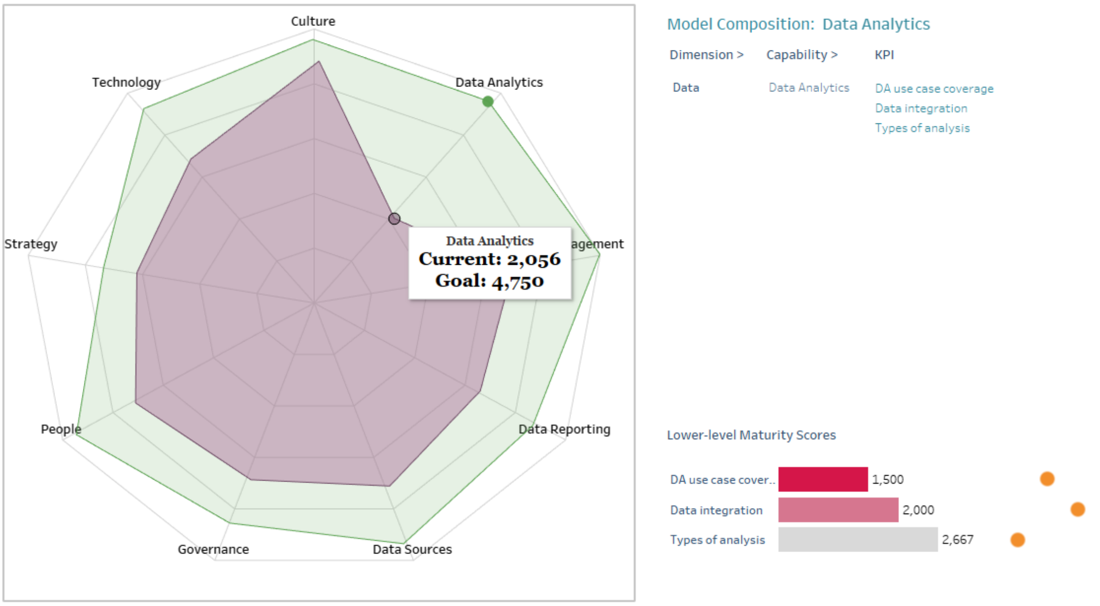

Figure 9: Screenshot of (part of) Maturity overview page of the automated maturity assessment tool, showing the maturity levels for the capabilities.

Figure 11 shows the Maturation page. This page shows historical data and maturity level thresholds for all maturity metrics. This allows users to look at their past and current performance and the criteria for the next maturity level to plan out their maturation approach. As mentioned before, the data for this maturity metric was mocked as only 1 data-gathering session was performed. This data was mocked based on the expectations of the team members.

The graph clearly shows the team's (mocked) progression in implementing tests over all their scripts. The input value, here the percentage of tested scripts, is shown for each data collection timestamp. The maturity levels that the organization reach are also shown through the use of color and displayed for each of the data points. A clear positive trend can be seen between the timestamps, so the team is maturing in this aspect. Maturing of this metric will also improve the maturity of all above maturity items, all the way to the *Data* maturity dimensions. A dotted line shows the average value for this metric over 30 days. This is useful as the team may postpone writing tests for their new scripts, briefly causing their maturity level to fall. Taking the average value for this metric provides a more representative picture of the situation. This is also relevant for, for example, maturity metric *Uptime of DA reports*. The team should see that improvements in the code testing coverage maturity metric will also positively impact their maturity on other maturity metrics like *Script execution success rate*.

6.1.3 Improvement suggestions

The automated maturity assessment tool also provides insight into the biggest bottlenecks and gives recommendations on how to improve this. The case study participants were very interested in this page because it allowed them to deep-dive into the performance of specific maturity metrics and compare that to the performance of other related metrics. The most often used inference engine modes were *Biggest Bottlenecks* and *Gaps to Goal*. The maturity metrics that came up as bottlenecks for these two modes were very similar. An example of such a metric is metric *Alerting* for KPI *DA report quality*. The team indicated that this was an area with easy-to-attain gains but with little priority, as there were other higher-priority tasks to do. Therefore the maturity level of this metric remained low. The tool provided improvement recommendations

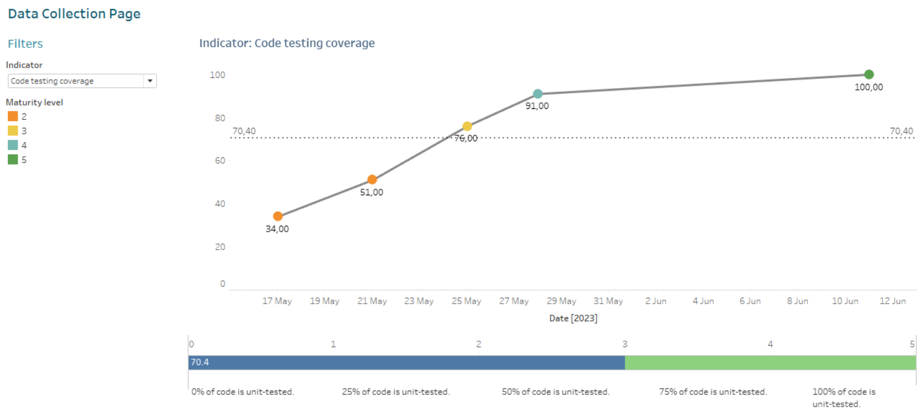

Figure 10: Screenshot of the Maturation page of the automated maturity assessment tool, showing the historical data for maturity metric *Code testing coverage*.

to improve the maturity level of this metric. Examples of suggestions are defining alert trigger conditions and customizing alert and delivery methods according to end-user. When looking at the gap to the goal, this maturity metric lags three maturity levels behind the desired maturity. This shows that the team is very much behind on their target here.

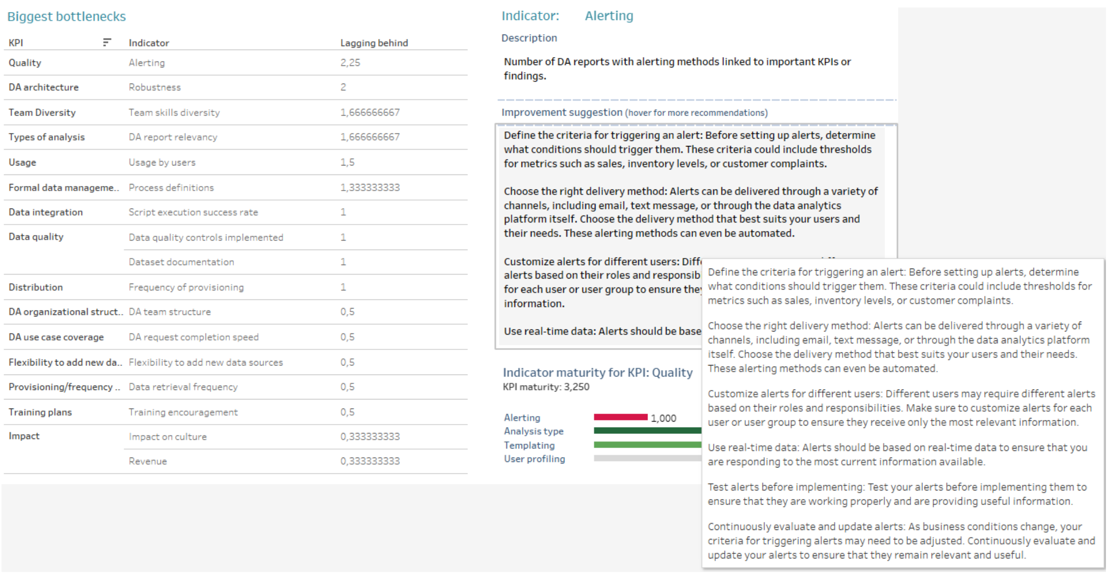

Figure 11: Screenshot of the Inference Engine of the automated maturity assessment tool, showing the all bottlenecks, here with an overview of improvement suggestions for maturity metric *Alerting*.

6.1.4 Data collection automation suggestions

Regarding the data collection automation suggestions which are elicited during the first data collection session, several data sources were identified for the data analytics team at InTraffic. Almost all of the automation suggestions relate to quantitative maturity metrics as this datatype is much easier to work with and automate than qualitative data. Automating datastreams of this datatype is a nice topic for future research, however.

For InTraffic, the biggest data sources by far to automatically extract data from are the PostgreSQL data source from Tableau and the Azure DevOps datasets which can be connected through an OData data connection. The Tableau dataset contains data on DA report uptime, usage, relevancy, update time, and access rights. Meanwhile, the Azure DevOps datasets contain data from both the Azure board, which the team uses to track their progress and plan their sprints, and data from Azure Synapse which the team uses to write code and deploy their pipelines. Creating data connections to these data sources could automate the extraction of almost half of the quantitative maturity metrics. Several other data sources were identified which can be used as a basis to automate the data collection. An example of this is the collection of Finance-related Excel sheets used by the team manager. Another is the internal cv-tool which is used to keep track of the individual skills of the members of the team. However, using this data source comes with ethical risks and considerations, a warning that is reflected in the suggestions from the automated maturity assessment tool. For some other metrics, the automation advice is to first create adequate documentation of the current situation in such a format that data can be automatically extracted from it. For example, the data analytics team of InTraffic does not document a lot, and therefore they sometimes did not even know the status of some datasets or processing pipelines. The maturity model demands this information to reach higher maturity levels, and therefore, the effort to automate this datastream overlaps with the effort to increase the maturity of said metric.

The before-mentioned data connections were not created for this study but could be created as part of a follow-up study where the maturation of the organization is tracked. In case these data connections are indeed made, then the Data Collection page of the tool will reflect this by showing the data sources and the latest time of the extraction for all maturity metrics. The aim is that by increasingly using the automated maturity assessment tool, and by automating the datastreams and collecting historical data, the tool will become increasingly powerful and valuable to the organization.

6.2 Discussion results

This section discusses the findings and results of the discussion that was had with the case study participants after they used the automated maturity assessment tool.

6.2.1 Inference engine output

The participants were asked to play around with the tool to discover its capabilities, strengths, and possible flaws. They could ask questions to the researcher if they liked it until they were satisfied with their understanding of the tool. They were also asked to look at the maturity levels they achieved on certain metrics. Generally, participants were interested to find out their relative lack of maturity over processes falling under the *Data analytics* capability. Upon drilling down further into the maturity model and their scores, they could grasp the reasons for this low maturity level.

Another thing that was generally like was the information available on the inference engine page. Participants were most happy with this page as it gave them an idea of what maturity metrics to mature and how to mature them. They were also more interested in more considerable bottlenecks, i.e., maturity items that lagged behind the KPI maturity level the most, as opposed to the more minor bottlenecks. Some participants noted that the spread in bottleneck 'size' was representative of the priority list of the team. This was especially true when relating the bottlenecks to the goals that were indicated by the team. This is to be expected, but still good validation of the inference engine's calculations.

Participants also noted how a portion of the maturity metrics could be improved by documenting more. They indicated that they would like to see even more maturity metrics' data sources in IT systems and tooling instead of documentation, which is often still a manual task. There are methods to automate the documentation process; however implementing these could require a significant time investment, making the net gain worthless.

The case study participants were also very interested in the maturation page. The trendline that is present on this page, showing the progress in maturation, gave them a good sense of the as-is situation. It also shows the maturity level thresholds, something they like as it gives them an understanding of how the inference engine draws results from the input data. Hiding this data from the end user makes the tool more user-friendly. However, this comes with the downside of making the tool-less interpretable. To counteract this, a link to the full maturity model is included in the tool on every page. The user is transported to an online document showing the maturity model by clicking on it. Participants indicated this a not very user-friendly, however, as they are transported away from the tool when clicking this link. An improvement point here is to find a way in the current (or slightly altered) UI to put the model so that users can easily access it. Another wish mentioned by one participant was the creation of a landing page. Currently, the user is first shown the maturity overview page as this page gives a high-level summary of the maturity levels the data analytics team attained. However, some indicated this page was a bit overwhelming on first viewing. Also, upon first using the tool and wanting to input qualitative data or indicating maturity level goals, the data collection page is the first page that is needed. It was mentioned that a landing page with a short explanation of the tool helps get users up to speed without them being lost in the UI and features of the tool. A mitigating factor here is that the case study participants were not shown the implementation guide present in Appendix J. This was done due to time constraints. However, offering the participants this guide first instead of explaining it during the session may have helped them understand the tool better. Subsequent uses of the tool would also improve their proficiency in using the tool. This is also represented in the answers to the TAM questions.

6.2.2 Technology Acceptance Model

Case study participants were asked to fill in a Technology Acceptance Model (TAM) questionnaire after their time with the maturity model and tool. The TAM framework was proposed by Davis (1989) and is applied to gauge how and when individuals will adopt new technologies. The framework suggests the existence of three components in this choice of adoption: *Perceived Usefulness*, *Perceived Ease of Use*, and *Self-predicted future use*. The last factor, related to the self-reported willingness of participants to adopt an artifact in the future, is determined by the first two factors. Perceived Usefulness relates to the potential and possible increase in performance that employees perceive in the tool. Higher perceived usefulness will make participants want to use the tool in the future for its benefits. Perceived Ease of Use refers to the degree to which participants find an artifact difficult to use or learn. If more effort is needed to apply the artifact then participants may be less willing to use it in the future. According to TAM, a correlation exists between the Perceived Usefulness and Self-predicted future use factors, and between Perceived Ease of Use and Self-predicted future use. To confirm this, and to be able to perform statistical analyses on these factors, a questionnaire is used. A set of statements related to the three factors is added to collect data on them. The statements are adopted from Babar et al. (2007) and slightly altered to represent the proposed artifacts of this study. They are asked in the form of seven-point Likert questions. This form of question can be used to indicate the degree of agreement or disagreement with the statements. The seven points all relate to a different sentiment: Extremely disagree (1), Quite disagree (2), Slightly disagree (3), Neither (4), Slightly agree (5), Quite agree (6), Extremely agree (7). Linked to each answer is a numerical value to allow for statistical analyses to be performed. The adapted statements are as follows (Babar et al., 2007): Work more Quickly (U1): using the maturity model and tool in my job would enable me to accomplish tasks more quickly; Improve Performance (U2): using the maturity model and tool would improve my job performance; Increase Productivity (U3): using the maturity model and tool in my job would increase my productivity; Effectiveness (U4): using the maturity model and tool would enhance my effectiveness on the job; Makes Job Easier(U5): using the maturity model and tool would make it easier to do my job; Useful (U6): I would find the maturity model and tool useful in my job; Perceived Ease of Use (Ei): Easy to Learn (E1): learning to operate the maturity model and tool would be easy for me; Easy to Perform (E2) I would find it easy to get the maturity model and tool to do what I want it to do; Clear and Understandable (E3): my interaction with the maturity model and tool would be clear and understandable; Easy to become Skilful (E4): I would find the maturity model and tool to be flexible to interact with; Easy to Remember (E5): it would be easy for me to become skillful at using the maturity model and tool; Easy to Use (E6): I would find the maturity model and tool easy to use; Self-predicted future use (Si): Actual Usage (S1): I predict that I will regularly use the maturity model and tool in the future; Use model without tool (S2): I would prefer using the maturity model and tool to paper-based forms for performing inspections.

Table 20, adopted from Farshidi (2020), gives an overview of the performed statistical analyses. Three analyses are visible, all providing different insights about the results, and are explained below. Besides the Likert questions, two open-ended questions were also asked regarding the strengths and weaknesses of the tool. This provides this thesis with interesting improvement points and future research on new use cases of the tool. These statements are discussed after the statistical analyses.

		Descriptive Statistics			Factor Analysis			Summary of Responses						
								1	2	3	4	5	6	7
		Mean	Standard Deviation	Cronback's α	Perceived Usefulness	Perceived Ease of Use	Self-predicted future usage	Extremely disagree	Quite disagree	Slightly disagree	Neither	Slightly agree	Quite agree	Extremely agree
Work more Quickly	U1	4.2	1.49	0.80	-0.07	0.11	0.68	0.00%	12.5%	25%	12.5%	25%	25%	0.00%
Improve Performance	U2	4.5	1.07	0.81	0.38	-0.42	0.53	0.00%	0.00%	25%	12.5%	50%	12.5%	0.00%
Increase Productivity	U3	4.9	0.99	0.80	0.82	-0.09	0.00	0.00%	0.00%	0.00%	50%	12.5%	37.5%	0.00%
Effectiveness	U4	5.5	0.76	0.80	0.06	0.03	-0.39	0.00%	0.00%	0.00%	12.5%	25%	62.5%	0.00%
Makes Job Easier	U5	4.8	0.71	0.80	0.04	0.08	0.23	0.00%	0.00%	0.00%	37.5%	50%	12.5%	0.00%
Useful	U6	5.6	0.92	0.77	0.32	0.69	0.04	0.00%	0.00%	0.00%	0.00%	62.5%	12.5%	25%
Easy to Learn	E1	5.2	1.39	0.80	-0.51	0.78	0.06	0.00%	0.00%	12.5%	12.5%	37.5%	12.5%	25%
Easy to Perform	E2	5	1.69	0.77	-0.08	0.93	0.10	0.00%	12.5%	12.5%	0.00%	25%	37.5%	12.5%
Clear and Understandable	E3	5	1.31	0.74	0.32	0.90	0.18	0.00%	0.00%	12.5%	25%	25%	25%	12.5%
Easy to become Skilful	E4	4.4	1.30	0.77	0.94	0.38	0.05	0.00%	12.5%	12.5%	12.5%	50%	12.5%	0.00%
Easy to Remember	E5	4.8	0.89	0.79	0.52	-0.09	0.44	0.00%	0.00%	0.00%	50%	25%	25%	0.00%
Easy to Use	E6	4.1	1.25	0.77	-0.06	0.98	-0.07	0.00%	0.00%	12.5%	12.5%	37.5%	25%	12.5%
Actual Usage	S1	5.4	0.92	0.78	0.48	-0.02	0.78	0.00%	0.00%	0.00%	12.5%	50%	25%	12.5%
Use model without tool	S2	4.1	0.83	0.76	0.65	0.21	0.78	0.00%	0.00%	25%	37.5%	37.5%	0.00%	0.00%
Perceived Usefulness	Ui	4.92	2.50		1.00	-0.02	0.03							
Perceived Ease of Use	Ei	4.75	3.2		-0.02	1.00	0.41							
Self-predicted future usage	Si	4.75	1.24		0.03	0.41	1.00							

Table 20: Statistical analysis of TAM questionnaire results (adopted from (Farshidi, 2020))

An extensive statistical analysis was performed on the data. Table 20 shows all statements and their code, adopted from Babar et al. (2007), along with the numerical results from the analyses. The statements are also grouped into three factors. The *Descriptive Statistics* section shows the mean values of the responses along with their standard deviation. Cronbach's Alpha denotes the reliability of the results. For most statements, the mean lies between (4) Neither and (5) Slightly agree and (6) Quite agree, indicating a mild optimism towards the tool. The combined mean for the Perceived Usefulness factor is 29.5, which results in an average mean of 4.91 when divided by size. The standard deviation for the statements of this factor is around 1, with an outlier being the standard deviation of statement U1, Work more Quickly, which is 4.92. Checking the heatmap shown in the right part of the table confirms this as there is a large spread of answers ranging between (2) Quite disagree and (6) Quite agree. This can be explained by some participants pondering on whether they would even like the activities of maturity assessments to become part of their workload, as opposed to hiring external auditors to perform the; "*I do not know how much I want to rely on such a tool instead of an external auditor. Do we want to take this responsibility as a team?*". For factor Perceived Ease of Use, the means also lie between (4) Neither and (5) Slightly agree, with the averaged mean being 4.75. Many participants found the information overwhelming, a threat posed by the attempt to provide extensive data reporting capabilities. Participants noted *The UI seems intuitive after some practice, but I think it has a steep learning curve*, and *Improve usability and understanding of how the tool works*. Participants also noted that they would have liked more time with the tool. They furthermore gave improvement suggestions which are discussed in the following section. Looking at the Self-predicted future usage, the mean value of the responses is again slightly positive. For S1, participants indicated that they would like to use the in the future. The heatmap shows that the distribution of the responses is all neutral to positive, so no participant responded negatively to the statement. S2, related to adopting the maturity model without using the tool, received results more skewed to the negative side. All responses are between 3 and 5, indicating that the participants were not against using the maturity model without the tool. This can be explained by some participants already being very positive about the insight that the maturity model itself could provide; *"I now have a much clearer picture of our current maturity, this was not possible before"*. For all results, Cronbach's Alpha was used to indicate the reliability level of the data. High reliability indicates a high degree of collecting the same data if the experiment is run with the same participants and under the same conditions (Laitenberger & Dreyer, 1998). According to Carmines & Zeller (2012), measures with a Cronback's Alpha higher than 0.8 indicates high reliability. For this study, all statements had a Cronbach's Alpha between 0.74 and 0.81, indicating fairly high reliability of the data resulting from the TAM questionnaire.

Factor analysis was also conducted on the statements to report on possible relations between them. This analysis technique clusters all statements and then assigns them to the indicated set of factors. As TAM prescribes three factors, the algorithm that was used was tuned to cluster into three sets. The factor loadings indicate the correlation of statements with a particular factor, where -1 indicates a perfect negative correlation and 1 is a perfect positive correlation. According to Harper et al. (1980), a statement can be confidently assigned to a factor if it has a factor loading of at least 0.7. As TAM defines the set of statements for each factor, one would expect the data to also show this. For factor *Perceived Ease of Use* this is the case. Statements E1 through E6 almost all have a factor loading of ¿ 0.7 for this factor. Statement E4 has a factor loading of 0.34 and statement E5 even has a negative factor loading. (Harper et al., 1980) note that sometimes factor loadings of ¡ 0.7 can also still be considered significant. While this could be the case for statement E4, for E5 this is certainly not the case. For factor *Perceived Usefulness*, the factor loadings are less significant, with only statements U2, U3, and U6 having potentially significant loadings. For factor *Self-predicted future usage* both statements have a significant loading higher than 0.7.

As mentioned before, factors Perceived Usefulness and Perceived Ease of Use are strongly correlated to Self-predicted future usage (Babar et al., 2007). Table 20 reflects this. Of course, all factors have a perfect positive correlation with themselves. However, no correlation is found between factors Perceived Usefulness and Self-predicted future usage. Perceived Ease of Use and Self-predicted future usage does have a positive correlation (0.41), however. Perceived Usefulness and Perceived Ease of Use themselves are shown to be independent of each other, with a negligible negative correlation of -0.02

6.2.3 Tool strengths & weaknesses

This section goes more in-depth on the answers that participants filled in for the open questions. During the case study sessions, participants were also asked to think out loud and notes were taken of this.

Regarding the strong points of the tool, the participants liked the overall functionality of the tool. The ability to see the as-is state of their team's data analytics maturity was new to most participants, and they liked the overview that the tool provided. Most participants were interested in the gathered data to see how specific maturity scores were composed. They noted that using the tool this way gave them a better understanding of where they are now. Furthermore, the ability to see bottlenecks and relevant improvement recommendations was also seen as useful. Multiple participants noted that they liked how the tool helps them identify growth opportunities quickly, and they even expressed the desire to use the tool during a brainstorming session to formulate a new long-term growth plan.

They also liked the automatability of the tool. Automating the data processing and reporting was seen as helpful and easy to maintain. They noted that, due to the low investment needed to use this tool, they no longer face an entry barrier to start using maturity modeling for their working environment. This makes the whole process less daunting to get into. Another strong point that was mentioned relates to the quantitative data and the automation it enables. It was argued that, although some context is lost due to the lack of qualitative data, historical context is quickly gained due to the maturation page. Participants liked to see their progression in the maturation of the Code coverage metrics clearly and visually. This is related to another mentioned benefit of the tool's reporting capabilities: reporting to management. Some participants noted that the tool could help provide visual and transparent overviews of the as-is situation while also helping show the benefits of maturing. They thought this could be used to help them gain the support of management on some of their innovation projects.

The participants also mentioned some use cases where the tool could be applied. Most often mentioned was the potential to make the tool comparative instead of predictive. Extending the tool and underlying database could allow multiple parties to use the automated maturity assessment tool and share their data. This is not extremely hard to do from a technical perspective and would require only a part of the underlying logic to be rewritten. The platform on which the data is stored would need to be changed from Google Sheets to something else. This could be on cloud platforms like AWS or Azure, notebooks, or a local coding environment with an always-up virtual machine. This can then be used for two primary purposes: internal application and external application.

Regarding internal usage, one case study participant noted that the tool could be used by a small organization with only one data analytics team to capture the whole organization through one maturity assessment. However, this is not possible for larger organizations as there may be multiple data analytics teams with their tooling and processes. The proposed tool with extended database functionality could be used to compare the performance of these different teams. Not only the aim is to see which team performs the best but also to see why this is the case and why another team may struggle. Teams' data could be overlapped to see their current maturity levels and goals, and analyses could be done to compare this. Furthermore, management could use this insight into the teams' performance to enforce company standards. For example, an organization may want all its teams to have a DA report uptime of more than 95%. This enforced maturity metric could then be added as an inference engine type so that teams can keep track of their maturity concerning this threshold.

Regarding the external application of the tool with comparative features, organizations could compare their performance to that of competitors. Of course, this is only possible if organizations are willing to publicize this data. They may happen if the maturity model gains recognition with organizations and customers, where customers may request that organization uphold a certain level of maturity over all their processes. The tool can then be used as proof of performance and for performance analyses against competitors. Another fascinating use case of the tool lies in gathering a lot of data on the maturation paths of different organizations. For this purpose, the data would not have to be publicly available, which should boost the adoption rate of the tool. The characteristics of organizations could be collected, as well as data on their maturation paths and historical performance. Analyses like pattern mining and supervised machine learning could then be applied to predict an organization's most optimal or common maturation path based on its characteristics. Finally, another improvement point one case study participant mentioned was creating an app for the tool. Such an application would allow for more mobile insight into the maturity of the data analytics team. This is possible since the tool does not require a lot of user input, so using it on the move is not hard as it only involves reading from graphs.

The participants also mentioned several flaws and improvement points of the current version of the tool. Some are related to the improvement suggestions mentioned above, but most are related to the UI and usability of the team. More than half of the case study participants said the tool could be hard to use initially due to information overload. They wanted a landing page and tutorial overlay to help them learn to use the model. Some participants even gave concrete improvement suggestions to the UI, like inverting a particular axis or changing the spacing of some information. They also indicated that including documentation on the maturity model in the tool would also improve the user experience. Furthermore, showing more clearly the relation between different maturity metrics would make analyzing the team's maturity easier.

7 Discussion

In this chapter, the findings of this research are discussed and used to answer the research questions. First, the sub-questions are answered through a concise overview of the relevant results. Then the main research question is answered.

7.1 Maturity models and components in literature

A significant component of this research is the performed systematic literature review. The literature study is used to answer the first few research questions. The first research question is meant to gather knowledge on the current domain and state-of-the-art maturity models. Insight needs to be collected on what maturity models have already been developed in the field of data analytics. Furthermore, insight into the existence of automated solutions to maturity assessment needs to be gained. This research question results in a large set of relevant research papers containing either the development, validation, or transfer of maturity models or articles containing theoretical reflection on the topic or a similar topic.

After following the SLR steps described in the protocol by Kitchenham (2004), a large set of maturity models was found in a plethora of domains. Even during the screening phase of the literature research, dozens of maturity models were removed from consideration in the domains of healthcare, construction, logistics, and floor management. These maturity models were all *domain-specific* and could, therefore, not be transferred to the data analytics domain. A pool of data analytics-specific and general-purpose maturity models remained. The most commonly used maturity model is *CMM(I)* (S. E. Institute, 2010). This maturity model has five maturity levels (like most) and is applied over a wide range of domains. It is an evolution of the earlier *CMMI.* Another well-known maturity model is *COBIT* (I. G. Institute, 2007), which is also a maturity model of practitioner origin. Regarding the academic maturity model landscape, no common maturity models stand out. Much research has been done on the structure of maturity models, for example, by Steenbergen et al. (2010) and de Bruin et al. (2005), who are cited often. This helps inform this research on how to structure the proposed maturity model. However, no such reuse can be seen when looking at all developed maturity models. These are rarely reused or transferred to another domain except by the same author(s). We, therefore, end up with a set of 32 models in the data analytics domain. This pool of maturity models is later filtered based on their structure for the design of the proposed maturity model. It is important to note that none of these maturity models are proposed alongside an automated maturity assessment process, nor was there any paper found into this research avenue. The overview of currently proposed and used data analytics maturity models in literature answers the first sub-question: "*Which data analytics maturity models exist in literature?*". The dataset collected for this answer forms the basis for answering the next research question.

The second sub-question: "Which features and concepts are common in data analytics maturity models?" relates to the content of the maturity models. By analyzing the dataset of collected and relevant maturity models, insight can be gained into proven structures that can be used to build the proposed maturity model. A clear distinction was found between continuous and staged maturity models (Lahrmann et al., 2011). Staged maturity models are structured to provide one overall maturity level upon performing a maturity assessment. In contrast, continuous models include hierarchy levels so that maturity levels can be given for specific processes. Generally, newer maturity models have a constant structure that allows for more granular data. This also suits itself well for a maturity model that uses quantitative data to automate parts of the maturity assessment process. Quantitative data can be quickly processed to be insightful on multiple levels of detail. Therefore it was chosen to use this structure for the proposed maturity model. Some other maturity models used Likert question-based data that was transformed into numerical data (Hausladen & Schosser, 2020; Gastaldi et al., 2018), however, no research was yet done on the usage of quantitative values retrieved directly from the organizations data sources.

The research was also done on other structure-related maturity model characteristics. A list of characteristics was extracted from a set of *procedure models* (Steenbergen et al., 2010; Caiado et al., 2021), which are methods that describe how to create maturity models. It should be noted that no procedure model mentioned using quantitative data for automation, nor was creating a maturity model capable of supporting automation. The list of extracted characteristics was used to analyze the collected pool of maturity models and determine the best characteristics for the proposed model. Ultimately, it was chosen to design a prescriptive, continuous maturity model with a numerical inference engine named QDAMM and an implementation tool supporting automation (AutoMAT). Besides being part of the answer to sub-question 2, these design choices also directly inform sub-question 4: "*How can a new data analytics maturity model be designed to support automatic maturity assessment?*".

Furthermore, since the collected papers also mention maturity model limitations that the author tries to mitigate and implementation barriers, these are collected as well. By combining these limitations with the structural characteristics of the collected maturity models, an analysis can be done on the correctness of current maturity models. Significant performance gaps can be identified, and possible ways to use automation to mitigate these can be identified. For example, the limitation of maturity models not allowing for continuous maturity assessments can be mitigated through automated data collection, processing, and reporting. Other often mentioned limitations relate to the empirical validation of the maturity models and a poor grounding in literature. This research tries to mitigate these threats through a thorough research design, combining multiple research methods. Further limitations relate to potential bias and ambiguity, which are threats to can be partially mitigated through the usage of quantitative data and automation (Schmitz et al., 2021; Muller & Hart, 2016). A lack of visualization (Al-Sai et al., 2019), difficulty updating the maturity model, and maturity items being too vague high-level are also limitations that a maturity assessment tool could fix. Lastly, an often-mentioned limitation is the absence of automation in maturity models.

Other research has proposed ways to classify the overall maturity level of an organization (Lismont et al., 2017). A limitation is this method is that it does not replace manual steps in an automated way. This method furthermore restricts the resulting maturity level to only the highest level of detail, with no option to drill down and analyze the as-is situation further. Research by Shrestha et al. (2020) also features a partly automated solution by proposing a tool that automated the data collection, processing, and reporting steps. However, they argue that their data collection automation is not actually automated as the data is still collected through surveys and this still is a manual task.

Besides analyzing the maturity model structure, characteristics, and limitations, the papers and models were also analyzed to find common maturity items relevant to the data analytics domain. The pool of collected maturity models was first filtered on a list of context characteristics to ensure that incomplete or unavailable models were removed from the analysis. The content of the remaining maturity models was then extracted and analyzed through frequency analysis. The maturity items were collected along with their definition and level of detail. Common maturity dimensions include *Data*, which is related to all data-related activities that an organization performs. *Technology* is related to the IT systems and tooling an organization uses daily. *Strategy* is related to the decision-making and short and long-term goal and plans of an organization. *Governance* is related to activities on the management and security side. *Organization* is another common maturity dimension related to a company's internal and external environment and culture. Frequent capabilities and KPIs were also extracted and placed under the frequent maturity dimensions top-down if the extracted definition allowed for this. This process is also the basis for answering sub-question 4, related to the design of an automation-supporting data analytics maturity model. All collected and analyzed data help answer sub-question two on which maturity concepts and features are common. This data informs sub-questions three and four, related to the maturity model design.

7.2 Maturity model design

As mentioned, a set of procedure models was collected to answer sub-question one. Procedure models by Caiado et al. (2021); Steenbergen et al. (2010) were adapted to include automation support through quantitative metrics in the design steps.

Although automated methods of maturity model elicitation also exist, like a method proposed by Raber et al. (2012) that uses the Rasch method together with data collected from Likert questions to automatically assign importance weights to maturity items, these were not used for this study. Such methods were poorly validated, however, and would make the design process less transparent so it was chosen not to adopt them. Furthermore, the methods do not allow for easily taking into consideration previously published maturity models, something that greatly improves a model's validity (Brooks et al., 2015).

Following this newly designed adapted procedure model, a new maturity model is proposed. The scoping phase of the design was already performed for sub-question 1, and populating the maturity model with items can be done using the analyzed dataset from research question 2. Using a top-down approach, the list of frequent maturity dimensions is populated with capabilities and KPIs. According to a new step in the procedure model, the KPIs are now populated with maturity metrics, data points that can be directly extracted from quantitative datasets. Using such low-level granularity for the composition of the maturity levels allows for more drill-down and analysis potential than classification based on machine learning (Lismont et al., 2017; Limpeeticharoenchot et al., 2022). Creating data connections to these data sources can allow for continuous and real-time extraction of the data points to inform the inference engine and calculate maturity levels. These datasets differ for each organization; some may not even have them readily available. However, the processes that the maturity metrics relate to should be as universal as possible. This way, all organizations can use the maturity model. To ensure this, the proposed maturity model is validated by experts to ensure that it is complete, accurate, and relevant.

Sub-question 3 is "*How can a data analytics maturity model's performance and effectiveness be evaluated?*" and is related to validating a maturity model's performance and effectiveness. In the analyzed literature, some sources were found on the expert evaluation of maturity models. A paper by Salah et al. (2014) presents a template for the expert evaluation of maturity models. This template was combined with data on how the collected maturity models were introduced. Of the 32 models, only 20 were empirically validated, while seven were completely untested, further confirming a lack of empirical validation as an often-occurring maturity model limitation. This data was used to create the expert interview protocol to validate the proposed maturity model. It consisted of two rounds. The first round consisted of semi-structured exploratory research on the automation possibilities of maturity modeling. Some questions were also tailored to collecting domain-relevant maturity items, which could be included in the maturity model. The second round of interviews involved providing interviewees with the maturity model and expert evaluation template and asking for their feedback. This protocol for conducting the expert interviews for validating the maturity models answers the third research question.

Sub-question four can be answered using the procedure model and frequent maturity item analysis mentioned before, alongside the created interview protocol. The steps were performed to develop a maturity model containing quantitative maturity metrics, which have the potential to be automated through a data connection to a data source used by the implementing organization. The maturity model comprises a maturity model, mentioning all maturity areas and components, and an assessment method in the form of a tool built in Tableau and Excel. The UI was designed alongside a UX expert and later validated as part of answering sub-question 5. The tool automates the maturity assessment process by completely automating the data processing and reporting steps. The data collection step which comes prior can be automated after an effort is made to identify the available data sources and connect to them using data connections. The tool then gives insight into the current maturity (as-is) of the organization, as well as insight into a possible to-be situation and a roadmap to achieve this maturity. The tool can be implemented in a smaller organization to capture its context. However, implementing the tool at a larger organization would need it to be limited to a single data analytics department or team, as aggregating and averaging the data over multiple entities lessens its insights. However, the tool can be extended to allow for a comparative component allowing larger organizations to keep track of the maturation progress of multiple entities and teams. Different from other work, this tool does not use machine learning for automation. Methods designed by Peña et al. (2019) and Limpeeticharoenchot et al. (2022) use machine learning to estimate maturity levels based on input data. While this does automate the data processing activity Shrestha et al. (2020), it turns the process into a black box. The inference engine that uses the decision calculus to convert the data to maturity levels suffers from a lack of transparency and interpretability. During the expert semi-exploratory interview round the experts stressed the assurance aspect of maturity models, stating that results need to be interpretable by stakeholders like managers.

To conclude, the designed maturity model (QDAMM) and tool (AutoMAT) form this research's main contribution and answer the sub-question related to creating a maturity model that supports the automation of all three phases of the maturity assessment process. The tool can be improved upon easily as the baseline has been created, offering excellent avenues for future research.

7.3 Maturity model implementation

In an attempt to answer sub-question 5: "*Do the proposed maturity model and tool help in attaining a higher maturity level?*", related to the usefulness of the proposed maturity model and tool in helping organizations reach higher maturity levels, a single *within*-case study was conducted at InTraffic. Input data were gathered to provide the inference engine with data for all maturity metrics. The output data was then reported to the case study participants through the data reporting functionality of the tool. The participants were then asked twelve 7-point Likert questions and two open questions to formulate their thoughts and opinions on the maturity model and tool. A discussion of the results from this case study can be found in the previous chapter. The data from the case study help answer sub-question 5: early results indicate that the maturity model and tool help organizations and teams mature inexpensively cost and time-wise. However, future research should validate the tool more by collecting more current and historical data from many organizations to check the generalizability of the maturity model.

7.4 Answering the main research questions

Through answering all sub-questions, an effort is ultimately made to answer the main research question: "*How can a data analytics maturity model be developed and validated that automatically quantifies KPIs to support decision-makers at data-intensive organizations?*". This question is answered in a decomposed manner throughout the sub-questions. First, insight was gained into common components and characteristics of non-automated data analytics maturity models. Types of datatypes and inference engines were then analyzed to determine whether including quantitative data and creating a tool for data processing and visualization will allow maturity models to support automation. A design method was then adapted to allow for automation to be included in the design process, and this was executed to propose a new maturity model. The maturity model, supported by a tool, was validated by experts and through a case study. Case study participants noted that the tool helped greatly in giving them gain insight into the current maturity, as well as helping them to create an improvement roadmap based on the recommendations that the tools offered. This forms the answer to the main research question.

8 Evaluation and Limitations

This chapter covers the evaluation of this research. First, threats to validity are discussed, and choices related to this are explained. Afterward, some limitations of this research are presented. The chapter concludes with a section on possible future research. This covers both research topics on the continuation of this study and some topics that are less related.

8.1 Threats to validity

The validity of this research needs to be assessed to guarantee its scientific contribution and value. Zhou et al. (2016) researched threats to validity and categorized these into four groups of threats: construct, internal, external, and conclusion validity (see table 21). How these validity types and possible threats are relevant to this research is discussed below.

Category	Definition
Construct Validity	Identify correct operational measures for the concepts being studied.
Internal Validity	Seek to establish a causal relationship, whereby certain conditions are believed to lead to other conditions, as distinguished from spurious relationships
External Validity	Define the domain to which a study's findings can be generalized.
Conclusion Validity	Demonstrate that the operations of a study, such as the data collection procedure, can be repeated with the same results.

Table 21: Validity categories (adopted from (Zhou et al., 2016))

8.1.1 Construct Validity

Construct validity refers to the extent to which a measure or study accurately reflects the theoretical concept it represents (Zhou et al., 2016). Poor construct validity harms the research's reproducibility as the definitions used can be interpreted in multiple ways by researchers. This research refers to the extent to which concepts retrieved through the SLR keep the same meaning they had in the original work. These concepts are used throughout the research in the proposed model, the expert evaluation rounds, and even the case study. Therefore, if the concepts are poorly defined, research participants may assign different meanings to what is presented, leading to poor input. Another threat is related to the inclusion and exclusion of research papers based on the domain knowledge of the researcher. An effort was made to mitigate this by carefully documenting the definitions of found concepts and coding used in research papers according to a categorization scheme adapted from Wendler (2012). A changelog was also kept to track and explain changes in the dataset.

The proposed maturity model's design and structure are also prone to construct validity threats. Such a model consists of plenty of concepts related to the model's hierarchy and construction and its content in the form of processes, maturity levels, and thresholds. Several sets of maturity items were grouped based on their definitions and names. Some errors could have been made during this process, however, as the research may have misinterpreted the use and meaning of said maturity items. This can be related to the maturity items' significance and level of abstraction. For example, some maturity items occurred on multiple abstraction levels (also defined as part of this research) and were then placed on a single level. Mistakes could have been made during this process. Using the definition list and the changelog is meant to mitigate this. Furthermore, it allows for the results to be transparent and explainable.

During the interviews and case study, the experience of participants with the DA domain and maturity models (or lack of them) also influenced their input. During the first exploratory round, it was made sure that all experts were familiar with maturity models, while familiarity with DA was less of a concern. During the second round of expert interviews, where the maturity model was validated, knowledge of the DA domain was necessary. Definitions of all maturity items in the maturity model and a thorough description of the research were provided to the participants to ensure that their interpretations were non-ambiguous. However, a problem with the addition of the definitions was that some maturity items found in papers did not have an accompanying definition. These, therefore, needed to be created by the author, which presents yet another threat to this validity. The definitions were reviewed during the before-mentioned expert evaluation round; however, some experts remarked on the definition and scope of some maturity items. Besides these mitigating factors, this risk has to be accepted as part of this research, and the focus should be on the transparency of the results and definitions.

8.1.2 Internal Validity

Threats to the internal validity of this project are a possible bias of the researcher when conducting the SLR. All choices have been documented to counteract this, and a strict research protocol was followed. Also relevant are threats related to the expert interviews and case studies. The interviews should be carefully planned and communicated, and an interview plan should be drafted to validate the proposed model effectively. The case study should also be designed carefully, and the scientific value of the research should be protected from corporate interests. Its results then need to be accurately reported and without bias. This is all done to ensure that the results of research such as this align with the views of the research participants.

A threat relevant to this validity type is related to gathering data during the expert evaluation phase. The 11 interviewees were asked to give feedback on an already constructed maturity model based on the SLR. Due to this prior research into the maturity model, some design choices were already made. This limited the scope of feedback for the interviewees as it is much easier to comment on things included in the proposed maturity model than items excluded. To counteract this, the interviews were performed in two rounds, where the first round was exploratory to produce new findings. The second round used an academically-reviewed evaluation form to validate the proposed maturity model.

The sample size of the interviews round was 11. While the participants were all experts in maturity modeling and data analytics, a wider audience could have been reached using the Delphi method. It was chosen not to employ this method as this research aimed to reuse already existing maturity models instead of creating one from scratch. Using this method to validate the model would have taken significantly more time and effort than validating through interviews. The interviews also allowed for more exploratory data to be gathered. Furthermore, the interviewees may not have understood all capabilities in the proposed maturity model. This would lead to incomplete feedback sets. Some interviewees did note this in the comment section of the expert evaluation template by Salah et al. (2014). However, due to the number of interviewees, other experts could cover these gaps. To further increase the relevancy of all maturity items in the proposed model, frequency restrictions were imposed on all maturity items found in the SLR. This meant they were only included in the model if they were common enough. Regarding the proposed automated maturity assessment tool, this has only undergone one round of feedback. Therefore, it could be argued that this tool is not yet validated enough. Furthermore, insufficient historical data was gathered to validate the tool to its fullest potential. This research would therefore lend itself well to a follow-up study.

Furthermore, Zhou et al. (2016) mention incomplete results from the SLR as another significant threat to internal validity. This study is valid as the SLR was performed relatively early in the research process, at a stage where the researcher did not have much in-depth knowledge of the domain. This could have caused the SLR to have been performed in the wrong direction and with incomplete search terms. To counteract this, a systematic process was followed during the entire SLR, including several 'orientation' steps, like gathering research-relevant papers from which the search terms were generated through frequent term analysis. Another aspect of this validity threat is the exclusion of gray literature, which contains a lot of practitioner-made maturity models. It was chosen to omit these to guarantee the academic validity of all featured sources. The potential lack of maturity items caused was mitigated through the rounds of expert evaluation of the maturity model.

8.1.3 External Validity

The external validity concerns the generalizability of the research. The ability to transfer the study and its results to other applications in the same or similar domains greatly influences its usefulness. Furthermore, the research needs to properly understand and represent the domains that it is situated in.

This research aims to design a valuable data analytics model for all organizations. Generalizability is very important for this. Mainly as the maturity model uses quantitative maturity metrics, a method of data collection and representation that offers less context and specificity than assessing maturity through qualitative maturity models. The SLR was used to propose a model consisting of only the most frequent maturity items. For example, even a capability like *machine learning* was removed during the evaluation phase as not all organizations employ it and because those that do all use it under vastly different circumstances.

Regarding the interviews, it is essential that the group of interviewees properly represent the overall population. This ensures that feedback is given on all aspects of the maturity model. An expert may not have proficiency with all incorporated DA capabilities, but they did not have to provide feedback on this aspect to cope with this. However, It was ensured that the total spread of experts covered all parts. Multiple experts also had to agree on a maturity item being rightly or wrongly incorporated in the maturity model for a corrective change to occur. The same is true for including formerly missing maturity items.

Of course, the setting of the case study also affects the external validity. As is mentioned in the *Threats to validity* section, the limited scope of the case study, i.e., a single within-case study, threatens the generalizability of the research. While experts have reviewed the maturity model during the interview phase, the implementation of this model and the automated maturity assessment tool has not been rigorously examined. As a case study object, the data analytics team within InTraffic presents a generic team with no apparent outlier characteristics. They perform all processes mentioned in the maturity model, some more documented and mature than others. InTraffic being situated in the public transport domain, a less common domain, is irrelevant to the generalizability of the case study results, as the domain of the processed data does not impact the processes that handle the data themselves. Furthermore, the team has a spread of maturity levels over all their processes, while their average maturity is around level three. Therefore, they do not represent an edge case of being very immature or mature, possibly skewing the data and making it less valuable. However, having done case studies at other companies and teams would have increased the generalizability of the results. These further rounds of validation and implementation are good topics for future research. Additional implementation rounds of the data analytics team of InTraffic would also yield valuable data regarding the maturation over time of the team. This progression of time is currently represented using mock data, as no historical data was collected. However, this data was not gathered due to the same reason that no other organizations were used as case study units.

8.1.4 Conclusion Validity

Conclusion Validity concerns the conclusions drawn from the results of the study. Data and clear and logical reasoning should substantiate the claimed results to ensure a high conclusion validity. Furthermore, statistical tests should be correctly applied, and their conclusions must be valid.

To substantiate the correctness of the proposed maturity model, frequency analysis was used to process the results of the SLR. In contrast, the expert evaluation used the number of experts agreeing or disagreeing to steer the design choices. This meant that some measure of quantitative data was used in the design process, allowing for inclusion and exclusion rules to be set. These have indeed been used and led to the proposed maturity being based on as much quantitative data as possible. Regarding the implementation and validation of the automated maturity assessment tool, TAM was used to collect quantitative data. Statistical analyses were applied to the collected data. Descriptive statistics show the main and standard deviation, which are mildly positive across the board. All questions had a related Cronbach's Alpha of around 0.80, indicating that the results can be considered significant Babar et al. (2007). Furthermore, factor analysis was performed over the data, and while not all TAM questions were clustered in the correct manner, the results are still fairly significant across the board, proving the correctness of the TAM questions.

8.2 Study limitations

Several limitations of this research have been identified. Most of these limitations are related to the scope of the study and therefore present themselves as interesting points for future research. Other limitations are related to the design of the maturity model. The limitations are discussed below.

First, the limited number of interviewees during the rounds of expert evaluation poses a limitation to this research. A total of 11 experts participated, but this could have been even more. While there was no noticeable gap in the expertise and domain coverage with the current expert pool, some data gathered through the exploratory expert interviews were relatively sparse. This could have been negated through an increase in the number of interviewees. The same can be said for the second round of interviews regarding evaluating the maturity model. The proposed model could be improved through multiple iterations of design and validation.

Furthermore, using interviews to evaluate the maturity model allows for in-depth reviewing of the model, but it is time-intensive. Data gathering techniques like the Delphi method would also have been beneficial. This method would allow for more diverse and extensive data to be gathered quickly for a large sample size of experts. This method was not employed as this research has an exploratory component, but it could be helpful for the future evaluate of the maturity model and its components.

Like with the expert evaluation of the maturity model, it could also be argued that the case study setup had a small sample size. As only one case study was performed, the validation data is not very comprehensive or even representative of the overall population, as only one sample was assessed. Furthermore, only one round of data gathering was performed at the organization due to scheduling choices. This means that no historical data was gathered but instead mocked. This is a limitation of the study, as the progress in the maturation of the DA team was not tracked. Therefore, the case study participants did not have extensive experience with the automated maturity assessment tool they could report on. And as is the case with the maturity model, the tool itself would also benefit significantly from multiple design iterations to improve its functionality.

A last consideration is related to the SLR. The exclusion of gray literature could be seen as a limitation. This choice meant that maturity models used by practitioners were more often excluded from the research, even though these may contain valuable maturity items. This choice was deliberate, however, as this possible gap in the data was covered through the expert interviews.

8.3 Future Research

Naturally, this research presents avenues for future research projects. The study was exploratory and therefore presented several topics to be further researched. Some of these topics relate to continuing this research, while others are more long-term or situated in slightly differing domains. These are discussed below.

First off, this research could be continued in a new study. The data that was gathered, as well as the designed artifacts, could be extended upon. The SLR could be expanded to include even more sources and maybe even gray literature. A possible overlap of the DA domain and its maturity model with other domains like data governance and security could be researched to see how different models could be used together or combined. The extensiveness of the literature research in the DA domain could also be increased to include even more maturity models. Research could also be done to create more systematically derived definitions of the maturity items in the maturity model. Furthermore, more research could be done on the structure of the maturity model. For example, the model currently does not assign weights to the different maturity items or indicate dependencies or relations between the additional maturity items. These can be derived through the usage of the Delphi method. Another exciting research topic could be the application of process mining over organizations' maturation paths to see if a common maturation path could be found. These findings could be incorporated into this research's maturity model and tool. The model is partly quantitative and has an extensive inference engine that could be extended further.

Besides adding to the presented artifacts, future research could also perform a more extensive validation of the presented findings of this study. The small sample size of the case study was mentioned in the previous section as a limitation. Multiple iterations of design and validation could be performed to improve the effectiveness of the maturity model and the tool. This would also provide data on the usefulness of the artifacts as it is used to mature organizations. The data the tool provides becomes richer and more informative as more maturity assessments are performed with it. More historical data will become available to organizations using it, making the analyses that can be performed more in-depth.

Several interviewees and case study participants also saw potential in using the tool for comparative analyses. Research could be done on creating a database with maturation data of multiple organizations or even data on various teams within one larger organization. The inference engine could be extended by providing insight into performance gaps relative to other teams or competitors. The improvement suggestions could also be fine-tuned and developed with a best practice repository to improve the coverage and specificity of the recommendations so that they better suit a specific organization or team.

The automation capabilities of the tool could also be improved upon. Applying NLP techniques to process qualitative data automatically could significantly speed up data collection. Automating quantitative data collection could also be extended by automatic data source identification or by creating built-in connectors for the most popular data sources. The improvement suggestions could also be generated through a pre-trained language model, or built into the tool using IF-THEN logic (Lukhmanov et al., 2022).

9 Conclusions

Maturity modeling can help organizations gain insight into their current maturity, i.e., as-is performance. Organizations continue to try and implement innovations in data analytics, sometimes successfully or sometimes not, to improve their capability to generate value from data. However, organizations often struggle with creating insight into their current performance, let alone developing insight into possible paths of maturation. Maturity assessments can be performed to gather and synthesize data on the organization's performance to determine its maturity. This is currently done through interviews that collect and then assess qualitative data. This process is criticized as being slow and costly. Some research has indicated the need to automate the maturity assessment process. To this end, this research posed the main research question:"*How can a data analytics maturity model be developed and validated that automatically quantifies KPIs to support decision-makers at data-intensive organizations?*".

Although this research question covers many points, an effort was made to answer it by decomposing the question into five sub-questions. While answering these sub-questions, a knowledge base was created consisting of common maturity models published in data analytics or a similar domain. This knowledge base was created through the execution of a Systematic Literature Review according to a protocol by Kitchenham (2004). A set of common maturity models was examined in-depth, while all maturity models were analyzed to determine their structure, composition, and their maturity levels. This dataset helps to answer the first research question, and by extending it further, sub-question two could also be answered to. By performing frequency analysis on the maturity items of which maturity models were composed, insight was gained into what processes and capabilities are most important in data analytics. A list of maturity model limitations helped enforce the requirements created for the proposed maturity model. This is also the main contribution of these two sub-questions, to create a dataset from which a new maturity model (QDAMM) could be designed. As part of the design science methodology by A. Hevner & Chatterjee (2010), this process later informed the creation and validation of the maturity model.

Automation of the maturity model is also part of the main research question. The collected maturity models were analyzed on whether they support (a part of) an automated maturity assessment process. Quantitative data points were created based on the collected maturity metrics. These data points can be collected from organizations' datasets through their day-to-day activities. The maturity metrics were linked to the KPI mentioned in the maturity model, along with an inference engine capable of determining the maturity level of the maturity metric. This is done through logic which compares the quantitative input data to the set of maturity levels and thresholds for that maturity metric. This new maturity model was created according to an adapted procedure model, which indicates the steps to follow to produce a model capable of supporting automatic maturity assessments by including quantitative data. This procedure model partly answers sub-questions 3 and 4. Another factor in this is the collected set of maturity model requirements that was composed based on an analysis of the collected data of the systematic literature review. This data was used to propose a maturity model consisting of maturity dimensions decomposed into capabilities that are further decomposed into KPIs. These KPIs can then be automatically quantified using quantitative maturity metrics. Next, as part of answering sub-question 4, the proposed maturity model is validated through two rounds of expert interviews. The first round served exploratory means, while the second round used an expert evaluation template for maturity models by Salah et al. (2014) to refine the maturity model further,

Then, a tool was created to prepare for answering sub-question five through the implementation and validation of the maturity model using a single *within*-case study. This tool, partly built in Tableau and partly in Excel, allows the data processing and reporting steps to be completely automated. The data collection step can be automated after an effort is made to determine which data sources the organization has available. Data connections can then be made to automate the data collection, allowing for continuous maturity assessments if desired. The maturity model and tool were then validated through the case study, where participants commented on the input and output data of the tool. They also answered questions according to the Technology Acceptance Model (Davis, 1989) and commented on the strengths and weaknesses of the tool. The case study participants noted the usefulness and potential of the tool in helping them assess their maturity in a (partly) automated way, thus answering sub-question five and, thereby, the main research question.

Future research could look at validating the maturity model and tool further. While threats to validity have been mitigated as best as possible, there is still room to improve the external validity by increasing the sample size of both the expert interviews and the case study. Case studies could be conducted at organizations of different sized and domains. The tool could be extended in various ways to improve its ease of use, automation, capabilities, and comparative features. Refactoring the internal logic and using a dedicated data storage solution could extend the tool to allow for comparative maturity assessments. This can provide insight into the data analytics maturity of an organization both internally across multiple teams or externally by comparing maturity to competitors. Research could also be done using NLP techniques and innovations to process qualitative data from interviews automatically. Furthermore, if enough data is gathered through the tool's adoption, process mining could be applied to the maturation paths of organizations. Combined with a supervised machine learning classifier, this could be used to estimate the best maturation path for an organization, given its characteristics.

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Appendices

A SLR Data

All data that was gathered as part of the Systematic Literature Review can be found at: *https://docs.google.com/spreadsheets/d/1Rnix85bb_QeUSXhGjxz4z4fB3Sr3rFjAznuOFuRHn4Y/edit?usp=sharing*

B Maturity model characteristics

Procedure model paper	**Appl. scale**	**Availability**	**Def. of maturity**	**Descr. of domain**	**Design doc.**	**MM knowledge**	**Origin**	**Reliability**
Understanding the main phases of developing a maturity assessment model	X				X		X	X
Maturity models in business process management	X		X	X	X	X	X	X
What makes a useful maturity model? A framework of general design principles for maturity models and its demonstration in business process management	X		X	X	X	X	X	X
Business Intelligence Maturity: Development and Evaluation of a Theoretical Model								
The Design of Focus Area Maturity Models						X		
A framework for developing a domain specific business intelligence maturity model: Application to healthcare					X	X		
Towards a Business Intelligence Maturity Model for Healthcare					X			
Towards Developing Strategic Assessment Model for Big Data Implementation: A Systematic Literature Review					X			
Assessment Methodology for a Maturity Model for Interorganizational Systems – The Search for an Assessment Procedure					X			
Assessment of Industry 4.0 Maturity Models by Design Principles								
Designing and Evaluating Prescriptive Maturity Models: A Design Science-Oriented Approach					X		X	X
Closing the Loop: Evaluating a Measurement Instrument for Maturity Model Design				X				
Holistic Guidelines for Selecting and Adapting BPM Maturity Models (BPM MMs)					X		X	
Evaluating a process for developing a capability maturity model								
Methods and techniques for maturity assessment		X						
Assessing Organizational Capabilities: Reviewing and Guiding the Development of Maturity Grids								
Development of an Intelligent Maturity Model-Tool for Business Process Management		X	X					
Developing dashboards for SMEs to improve performance of productive equipment and processes		X	X					
Evolution of project based organization: A case study				X				
A Design Science Research Perspective on Maturity Models in Information Systems	X							
A hybrid deep learning and ontology-driven approach to perform business process capability assessment								
Total count:	4	3	4	4	9	4	5	4

Characteristic abbreviations: Appl. scale (char 1. Application scale, Availability (char .6) Def. of maturity (char 9. Definition of underlying notion of maturity), Descr. of domain (char 10 Description of domain & components), Design doc. (char 11. Design process documentation), MM knowledge (char 16. Knowledge from older MMs), Origin (char .23), Reliability (char .25).

Table 22: *Context* maturity model characteristics.

Procedure model paper	**Assess. data type**	**Assess. met.**	**Assess. tool**	**Automation**	**Cap. areas**	**Inference engine**	**Focus**	**Granularity**	**Implem. guide**	**Improv. measures**	**Matur. paths**	**Maturity concept**	**Maturity levels**	**MM type**	**Maturity principle**	**Evaluat. method**	**Purpose**	**Respondents**	**Target group**	**Visualization**
Understanding the main phases of developing a maturity assessment model	X			X		X		X	X				X		X	X			X	
Maturity models in business process management	X			X		X	X	X	X	X	X		X		X	X		X		
What makes a useful maturity model? A framework of general design principles for maturity models and its demonstration in business process management	X			X		X	X	X	X	X	X		X		X			X		
Business Intelligence Maturity: Development and Evaluation of a Theoretical Model	X					X						X	X	X						
The Design of Focus Area Maturity Models	X					X							X	X						
A framework for developing a domain specific business intelligence maturity model: Application to healthcare	X		X			X							X				X			
Towards a Business Intelligence Maturity Model for Healthcare											X	X	X							
Towards Developing Strategic Assessment Model for Big Data Implementation: A Systematic Literature Review	X	X	X			X							X							
Assessment Methodology for a Maturity Model for Interorganizational Systems – The Search for an Assessment Procedure	X			X									X	X			X			
Assessment of Industry 4.0 Maturity Models by Design Principles	X		X													X				
Designing and Evaluating Prescriptive Maturity Models: A Design Science-Oriented Approach	X				X	X	X					X	X				X		X	
Closing the Loop: Evaluating a Measurement Instrument for Maturity Model Design							X													
Holistic Guidelines for Selecting and Adapting BPM Maturity Models (BPM MMs)	X			X		X										X	X		X	
Evaluating a process for developing a capability maturity model	X			X									X							
Methods and techniques for maturity assessment																	X			
Assessing Organizational Capabilities: Reviewing and Guiding the Development of Maturity Grids					X	X							X	X	X		X			
Development of an Intelligent Maturity Model-Tool for Business Process Management	X		X										X							X
Developing dashboards for SMEs to improve performance of productive equipment and processes	X		X																	X
Evolution of project based organization: A case study	X		X							X	X		X		X					
A Design Science Research Perspective on Maturity Models in Information Systems				X	X	X	X	X				X		X	X	X		X	X	
A hybrid deep learning and ontology-driven approach to perform business process capability assessment	X	X																		
Total count:	16	2	6	7	3	11	5	4	3	3	4	4	14	4	6	5	6	3	4	2

Characteristic abbreviations: Assess. data type (char 2.), Assess. Met (char 3. Assessment methodology), Assess. tool (char 4. Assessment tool), Automation (char 5.), Cap. areas (char 7. Capability areas), Inference engine (char 8.) Focus (char 12. Focus of model), Granularity (char 13. Granularity mentioned), Implem. Guide (char 14. Implementation guide), Improv. Measures (char 15. Improvement measures), Matur. paths (char 17. Maturation paths), Maturity concept (char 18.), Maturity levels (char 19.), MM type (char 20. Maturity model type), Maturity principle (char 21. maturity principle), Evaluat. method (char 22. Method of evaluation), Purpose (char 24.), Respondents (char 26.), Target group (char .27), Visualization (char 28.).

Table 23: *Structure* maturity model characteristics.

C Proposed Reference Model

Dimension	Capability	KPI	Metric
Data	Data Analytics	DA use case coverage	Use case coverage
			DA request completion speed
			Ad-hoc DA request count
		Types of analyses	Data analysis type
			Aggregation level
			Time to create DA report
			DA report relevancy
		Data integration	Code testing coverage
			Script execution success rate
		Machine Learning	Accuracy
			Prediction speed
	Data Management	Data usage	Data accessibility
			Transparency on data requirements
		Data quality	Data quality management
			Dataset documentation
			Data quality controls implemented
			Data consistency
		Formal data management process	Process definitions
			Data archiving duplication
			Data archiving retention span
	Data Sources	Availability of external data sources	Availability of external data sources
		Provisioning/frequency of data	Data retrieval frequency
			Overdue data deliveries
		Richness of available data sources	Richness of available data sources
		Transparency on available data	Transparency on available data
	Data Reporting	Distribution	Digitalization of distribution
			Interface
			Frequency of provisioning
		Impact	Impact on culture
			User satisfaction
			Revenue
		Quality	Analysis type
			Alerting
			User profiling
			Templating
		Usage	Usage by users
			Availability
Governance		DA organizational structure	DA team structure
			DA dedicated FTE
		Data access	DA solution access
			Data access
Organization	People	Team Diversity	Diversity consideration in hiring
			Organization competency awareness
			Team skills diversity
		Training plans	Amount of trainings
			Training encouragement
		User capabilities	User capabilities
	Culture	Executive sponsorship	Executive sponsorship
		Recognition of importance of DA	Recognition of importance of DA
Strategy		Budget	Budget
		Data analytics strategy	Data analytics strategy
		Innovation Processes	Innovation Processes
		Partner / supplier coordination	Partner/ supplier coordination
Technology		Data storage architecture	Data storage architecture
		DA architecture	Structure
			Robustness
			Up-to-date tooling
		Flexibility to add new data sources	Flexibility to add new data sources
			Capabilities to handle unstructured data

Table 24: Proposed Reference Model.

D Reference Model Documentation

Figure D shows the reference model of the Automated Data Analytics maturity model. It follows the hierarchy of maturity components that are depicted in figure ??. The maturity metrics for each KPI are described in the tables below. The KPIs are described in descending order, as shown in the figure below.

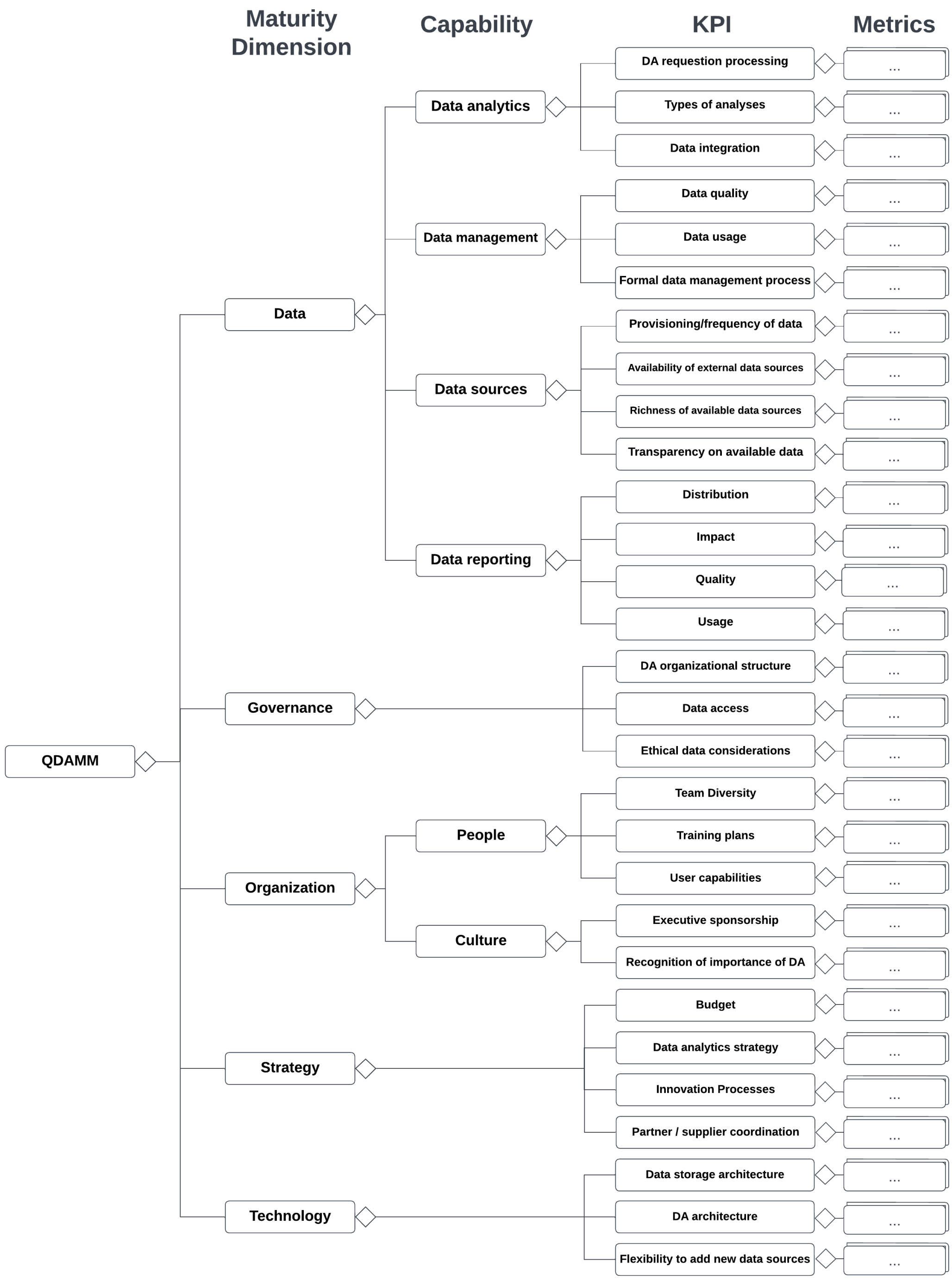


Figure 12: Reference model of the Automated Data Analytics maturity model.

Dimension	Capability	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Data	Data Analytics	DA request processing	DA request completion speed (hr)	New DA requests cannot be completed in 32 working hours.	New DA requests are completed in 32 working hours.	New DA requests are completed in 24 working hours.	New DA requests are completed in 16 working hours.	New DA requests are completed in 8 working hours.	While often dependent on SLAs, the speed with which a request for a new ad-hoc DA report can be fulfilled should be minimized.
			Ad-hoc DA request count (# in month)	The ratio: [key stakeholders] / [ad-hoc DA requests per month] is equal to or larger than 3	The ratio: [key stakeholders] / [ad-hoc DA requests per month] is smaller than 3	The ratio: [key stakeholders] / [ad-hoc DA requests per month] is smaller than 2	The ratio: [key stakeholders] / [ad-hoc DA requests per month] is smaller than 1	The ratio: [key stakeholders] / [ad-hoc DA requests per month] is smaller than 0.5	Number of ad-hoc DA requests. Indicating a potential lack of current DA report coverage. Related to KPI User capabilities as self-service DA reduces this amount.
		Types of analyses	Data analysis type	Descriptive analytics.	Diagnostic analytics.	Predictive analytics.	Prescriptive analytics.	Self-learning analytics.	Analysis types, showing a progression to more advanced analytics types.
			Aggregation level	Data cannot be aggregated	The data can be aggregated on time	The data can be aggregated on region, scale and time.	All needed data aggregation levels are present in less than 50% of currently available datasets.	All needed data aggregation levels are present in all available datasets.	The possible aggregation levels of data analysis. Showing the possible levels of detail in analyses.
			DA report relevancy (%)	Less than 50% of DA reports are actively used; viewed at least once per month.	50% of DA reports are actively used; viewed at least once per month.	75% of DA reports are actively used; viewed at least once per month.	90% of DA reports are actively used; viewed at least once per month.	100% of DA reports are actively used; viewed at least once per month.	The relevancy of available DA reports. All should serve a purpose and be regularly used. The use case and relevant stakeholders must be documented.
		Data integration	Code testing coverage (%)	0% of code is unit-tested.	25% of code is unit-tested.	50% of code is unit-tested.	75% of code is unit-tested.	100% of code is unit-tested.	Percentage of code/scripts which are covered by unit tests. The extensiveness is not relevant in this equation.
			Script execution success rate (%)	Less than 75% of all data transformation scripts run without failure.	75% or more of all data transformation scripts run without failure.	More than 90% of all data transformation scripts run without failure.	More than 95% of all data transformation scripts run without failure.	More than 99% of all data transformation scripts run without failure.	Amount of times a DA script completes vs. the amount of times failed, expressed as a percentage.

Table 25: Reference model: maturity dimension *Data* (1/4).

Dimension	Capability	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Data	Data Management	Data usage	Data accessibility	Data is stored only locally without access from network or other devices	Data are stored in some sort of central repository, but majority is stored locally without access to the rest of the organization	All data are centrally stored and available across the organization	All data are centrally stored and available across the organization and integrated with relevant external stakeholders	Complete virtual data organization to access data universally (with individual usage permissions)	The accessibility of the datasources used for DA reports. Indicates how easy it is to get data for self-service DA.
			Transparency on data requirements (%)	0% transparency and documentation on data usage.	25% transparency and documentation on data usage.	50% transparency and documentation on data usage.	75% transparency and documentation on data usage.	100% transparency and documentation on data usage.	Percentage of data flows, from data source to DA reports which are documented w.r.t. its content and uses.
		Data quality	Data quality management	There is a feeling about data being of good or bad quality.	It is clearly stated which aspects are part of data quality and need to be measured in terms of assessing data quality.	Data quality is defined regarding the requirements of different stakeholders.	Data quality is measured objectively and for each data source it is known which quality it has.	The data quality assessment is conducted regularly for data source.	The role and extensiveness of data quality assessments in the DA team and organization.
			Dataset documentation (%)	0% of datasets are documentated.	25% of datasets are documented.	50% of datasets are documented.	75% of datasets are documented.	100% of datasets are documented.	Percentage of datasets which have documentation
			Data quality controls implemented (%)	0% of DA scripts include automated data quality controls over input/output.	25% of DA scripts include automated data quality controls over input/output.	50% of DA scripts include automated data quality controls over input/output.	75% of DA scripts include automated data quality controls over input/output.	100% of DA scripts include automated data quality controls over input/output.	Percentage of transformation scripts with automated input/output quality controls
			Data consistency (%)	Datasets are less than 80% consistent in terms of content and notation.	Datasets are messy and are 80% consistent in terms of content and notation.	Datasets are 95% consistent, so a bit faulty in terms of content and notation.	Datasets are 99% consistent and contain almost no faults.	Datasets are 100% consistent and contain no faults.	Percentage of rows in all datasets which contain faulty data
		Formal data management process	Process definitions	No data management process or related policies in place	Data management and related policies are siloed and not formally defined	Decisions are made on a current-need-base about which data should be acquired and stored	Sporadical reviews are performed to check the usefulness of the data currently stored in relation to their usage and acquire data according to estimated data needs	Data sources and types and data policies are periodically reviewed to assess their usefulness and actual usage - also a periodical review of data limitations, e.g., what data are missing, and opportunities for the future	The way in which DA processes are formally defined and assessed on their usefulness.
			Data archiving duplication (#)	No data is archived. So there are 0 copies of the data	Data is archived but duplicated 0 times.	Data is archived and duplicated 1 time.	Data is archived and duplicated 2 times.	Data is archived and duplicated at least 3 times.	Number of duplicates which are stored (so not original)
			Data archiving retention span (# years)	No data is archived. So the retention span is 0 years.	Data is archived 0.25 years. Sensitive data is not processed with special care.	Data is archived for 0.5 years. Sensitive data is not processed with special care.	Data is archived for 1 year. Sensitive data is processed with special care.	Data is archived for 3 years. Sensitive data is processed with special care.	Retention length in years

Table 26: Reference model: maturity dimension *Data* (2/4).

Dimension	Capability	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Data	Data Sources	Availability of external data sources	Availability of external data sources (%)	Less than 50% of external data sources are documented	More than 50% of external data sources are documented	More than 75% of external data sources are documented	More than 85% of external data sources are documented	More than 95% of external data sources are documented	Percentage of data extraction scripts runs which succeed
		Provisioning/frequency of data	Data retrieval frequency	Data is retrieved on an ad-hoc basis.	Data is retrieved monthly.	Data is retrieved daily.	Data is retrieved hourly.	Data is retrieved in real-time.	Frequency with which data is retrieved from the data sources.
			Overdue data deliveries (%)	Data is delivered on time in less than 60% of all cases. Or no data deliveries occur	Data is delivered on time in 60% of all cases.	Data is delivered on time in 75% of all cases.	Data is delivered on time in 90% of all cases.	Data is delivered on time in 100% of all cases.	Percentage of on-time data deliveries
		Richness of available data sources	Richness of available data sources (%)	Less than 60% of all information needs can be satisfied with either internal or external data	More than 60% of all information needs can be satisfied with either internal or external data	75% of all information needs can be satisfied with either internal or external data	Large selection of internal and external data sources available to satisfy at least 90% of information needs with best possible data.	Large selection of internal and external data sources available to satisfy 100% of information needs with the best possible data.	Percentage of DA reports-related desires which can be fulfilled by current datasets
		Transparency on available data	Transparency on available data (%)	0% of data-sources are documented.	25% of data sources are documented.	50% of data sources are documented.	75% of data sources are documented.	100% of data sources are documented.	Percentage of external data sources which have documentation

Table 27: Reference model: maturity dimension *Data* (3/4).

Dimension	Capability	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Data	Data Reporting	Distribution	Digitalization of distribution (%)	0% of DA reports are digital. All are paper-based.	50% of all DA reports are digitally distributed.	75% of all DA reports are digitally distributed.	90% of all DA reports are digitally distributed.	100% of all DA reports are digitally distributed.	Percentage of DA reports which are digitally distributed as opposed to paper-based
			Interface	No real DA solutions in the organization	The DA solution has a client-server interface only accessible through a specific device	The DA solution has a client-server interface accessible through a few select devices	The DA solution is web-based and is accessible through all the desktop devices	The DA solution has advanced RIA interface, accessible through all the mobile devices	Interface of the DA solution, an indication the flexibility in using the platform on different devices.
			Frequency of provisioning	DA reports are paper-based	DA reports are adhoc and not updated after creation	DA reports are updated daily	DA reports are updated on an hourly basis	DA reports are real-time and continuously updated.	Frequency with which DA reports are updated.
		Impact	Impact on culture	No reliability	DA gains in importance	Promotion of and demand for the use of DA	DA as a corporate asset	DA as the basis for all decisions; critical impact of DA on organizational performance	Impact of the DA reports on decision-making and culture.
			User satisfaction (1-5)	Users are very unsatisfied with the DA reports and give it an average score of less than 3, or this is not tracked.	Users are not satisfied with the DA reports and give it an average score of above 3	Users are satisfied with the DA reports and give an average score of 3.5	Users are very satisfied with the DA reports and give an average score of 4	Users are extremely satisfied with the DA reports and give an average score of 4.5 or higher	Expressed by including a 1-5 rating system and collecting and averaging scores
			Revenue	The DA practices do not provide net revenue and this is also not desired.	The DA practices do not provide net revenue but this is tolerated.	The DA practices break-even in terms of revenue.	The DA practices provide sufficient revenue:	The DA practices provide a lot of revenue.	Expressed as % of revenue against costs
		Quality	Analysis type	No graphical data	Static reports with text/tables	Reports include static reports with graphical data	DA solutions supports dynamic data navigation	Dynamic statistical analysis	Content and extensiveness of the DA reports.
			Alerting (%)	0% of all digital DA reports have alerted procedures set, or there are no digital DA reports	Only 25% has automated alerting set.	Only 50% has automated alerting set.	More than 75% of relevant DA reports have automated alerting methods.	100% of relevant DA reports have automated alerting methods that are checked regularly.	Found by checking all DA reports' existing alerting rules/procedures.
			User profiling	There is no DA solution	The DA solution does not support user profiling	The DA solution only supports macro-area profiling	The DA solution supports single user profiling	The DA solution supports context-based profiling	The support of the DA solution in filtering content based on the logged-in user.
			Templating (%)	0% of processes use templating is used.	25% of processes have associated templates which are periodically reviewed and updated.	50% of processes have associated templates which are periodically reviewed and updated.	75% of processes have associated templates which are periodically reviewed and updated.	100% of processes have associated templates which are periodically reviewed and updated.	Calculated by comparing all DA processes against those which have documented templates.
		Usage	Usage by users (%)	Less than 50% of key stakeholders check the DA reports or this is not checked	More than 50% of key stakeholders check the DA reports	75% of key stakeholders check the DA reports	90% of key stakeholders check the DA reports	100% of key stakeholders check the DA reports	The % of stakeholders with access who also check the reports.
			Availability (%)	The up-time of the DA reports is less than 75%. Or there are no digitally available DA reports.	The up-time of the DA reports is more than 75%.	The up-time of the DA reports is more than 855%.	Reports are digitally available with an up-time of 95%	Reports are digitally available with an up-time of more than 99%	Expressed as % up-time.

Table 28: Reference model: maturity dimension *Data* (4/4).

Dimension	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Governance	DA organizational structure	DA team structure	No defined roles and organizational units for DA	Internal, formalized standards but no roles	Internal, formalized standards with defined roles	Rudimentary DA competence center (DA CC)	DA CC with a comprehensive spectrum of tasks and competences	Structure and formalization of roles in the DA team.
		DA dedicated FTE (%)	There is not enough FTE (less than 75%) to execute a large set of DA processes which hinders performance.	There is a lack of FTE (75%). A small set of DA processes cannot be performed in time which hinders performance.	There is enough FTE to manage the status quo of the DA processes (only 90%). There is no capacity for technical debt or other improvements.	There is enough FTE for performing all DA processes and managing technical debt (100%)	There is a lot of FTE dedicated to DA processes (more than 110% with relation to all tasks and innovation processes)	Available FTE vs. desired FTE number. Then expressed as %-part of that desired number.
	Data access	DA solution access (%)	There is no DA solution to which key stakeholders can get access so 0% have access.	40% of key stakeholders have access to the DA solution and reports.	60% of key stakeholders have access to the DA solution and reports.	80% of key stakeholders have access to the DA solution and reports.	100% of key stakeholders have access to the DA solution and reports.	% of stakeholders with access to DA reports that are relevant to them
		Data access (%)	Data is not available so 0% of stakeholders have access.	Only 40% of all stakeholders have access or the data is only shared on request.	60% of key stakeholders have access to all relevant datasets.	80% of key stakeholders have access to all relevant datasets.	100% of key stakeholders have access to all relevant datasets.	% of stakeholders with access to datasets that are relevant to them
	Ethical data considerations	Ethical data considerations	No thought is given to ethical aspects of data processing and reporting.	The organization has done ad-hoc research into which data could potentially be under ethical scrutiny if processed but does not yet act on it.	The company does not process data which could have unethical implications. There are no safeguards in place to protect this process and new datasources are not investigated until another ad-hoc research.	Yearly assessments are done on ethical aspects of data processing. There is a complete insight into where sensitive data is used and safeguards are in place. There is not yet extensive documentation on the topic.	Assessments are done multiple times per year on ethical aspects of data processing. There is a complete insight into where sensitive data is used and safeguards are in place. Everything is carefully documented and complies with the relevant QA standards.	How the organization tackles ethical considerations in relation to collecting, processing and reporting sensitive data.

Table 29: Reference model: maturity dimension Governance.

Dimension	Capability	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Organization	People	Team Diversity	Diversity consideration in hiring	Employee competencies are not tracked	Employee competencies are tracked. Diversification of team capabilities is not a priority.	The diversification of team competencies is considered during the recruitment process. This is limited to the current situation and competency requirements.	The diversification of team competencies is considered during the recruitment process. Efforts are made to fill possible future gaps in competencies.	Besides consideration of talent and diversification in the recruitment process, hiring/working with outside talent on a short basis is also considered	Consideration of required DA competencies and diversification in the hiring process.
			Organization competency awareness	Diversification of team capabilities is not a priority.	The organization keeps track of the team's competencies but does not know which competencies should be aimed for.	The organization has once performed an assessment to evaluate the team's DA competencies against those that are required.	The organization performs sporadic assessments to evaluate the team's DA competencies against those that are required.	The organization continuously assesses the required DA skills for its practices and checks these against the employee competencies.	Awareness of the organization and DA team of the required DA teams for their DA processes.
			Team skills diversity (%)	The team lacks the required competencies to adequately tackle DA problems (less than 50%).	The team lacks the required competencies to adequately tackle DA problems though they struggle (50%).	The DA team has most of the required capabilities to tackle the current DA challenges (75%).	DA teams are diversified enough in terms of their expertise and technical knowledge to tackle the current DA challenges (90%). Future tasks cannot be completed	The team has all required competencies (100%), is constantly training and improving, and are future-proof w.r.t. possible new DA challenges and tooling.	Expressed as % coverage of required competencies. Can be retrieved from an internal CV tool.
		Training plans	Amount of courses/training sessions (#)	Employees attend 0 courses/training sessions a year.	Employees attend 1 training a year.	Employees attend 2 courses/training sessions a year.	Employees attend 3 courses/training sessions a year.	Employees attend >3 courses/training sessions a year.	Can be retrieved from an internal CV or training plan tool.
			Training encouragement	There are no training programs to improve the DA competencies of the employees	The DA training programs are mainly focused on highlighting DA importance	There are ad-hoc DA training programs focusing on specific issues	Employees are encouraged to choose their own training programs for personal development	Continuous DA training programs	Encouragement of organization to employees to follow a training plan.
		User capabilities	User capabilities	No stakeholders have DA expertise, and therefore cannot interpret reports	Most stakeholders do not possess DA expertise (e.g. analysis and interpretation of the reports), some can manage static reports	Most stakeholders are only able to interpret static reports, some understand sophisticated reports	Most stakeholders have the competencies to manage sophisticated reports, but only few can perform self-service DA /DA	All stakeholders have the competencies to manage sophisticated reports and perform self-service DA /DA	Capabilities of DA solution users with regards to DA concepts and practices.
	Culture	Executive sponsorship	Executive sponsorship	Executive management is unaware about DA	No executive sponsorship for DA	DA is sponsored informally by middle-management but without executive attention	There is at least one executive sponsor of DA	DA is sponsored unequivocally by top management	Support for DA practices from executive management.
		Recognition of importance of DA	Recognition of importance of DA	The relevance of DA is not part of the values of the organization	There are conflicting messages/rumors about the importance of DA for the enterprise	DA technology and potential still cause confusion, but there is political will to succeed with it	The importance of evidence-based operations and decision making is stressed at all levels	The importance of DA is an organizational value that all should know and embrace	Recognition of DA by the organization and its incorporation into the culture.

Table 30: Reference model: maturity dimension *Organization*.

Dimension	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Strategy	Budget	Budget (%)	A negligible amount is spent on DA initiatives	Average annual spending on DA is less than 1% of the ICT operational expenditure	Average annual spending on DA is between 1% and 3% of the ICT operational expenditure	Average annual spending on DA is between 3% and 7% of the ICT operational expenditure	Average annual spending on DA is more than 7% of the ICT operational expenditure	Average annual spending on DA as %-part of the ICT operational expenditure
	Data analytics strategy	Data analytics strategy	There is no DA strategy defined in the organization	There is an informal DA strategy on team basis	The DA strategy is defined in terms of local strategies in units or department level, and are only partially aligned with the corporate strategy	The DA strategy is defined in the corporate level and is aligned with the business strategy	The DA solution leads the change management within the organization	Extensiveness of the DA strategy defined in the organization.
	Innovation Processes	Innovation Processes	There are no explicitly defined DA innovation processes in place.	DA innovation processes are implemented on an ad-hoc basis and not yet documented.	DA innovation processes are explicitly defined and documented. Decision criteria are based on the transactional value a DA project could generate.	DA innovation processes are explicitly defined and documented. Decision criteria are based on the informational, strategic, transformational, transactional, and infrastructural value a DA project could generate. Innovation processes are executed with expertise and aligned with other processes.	DA innovation processes are explicitly defined and in place to improve and redesign processes throughout the company and develop best-class-service operations. The innovation processes are constantly evaluated and improved.	Existence and documentation of DA innovation processes.
	Partner/supplier coordination	Partner/supplier coordination	There are no coordination and regulatory mechanisms with DA suppliers	There is intermittent communication with stakeholders to gather requirements	Service level agreements limited to ICT topics	Service level agreements for continuous update and improvement of the DA	The DA suppliers provide performance management and KPIs for the DA solution	Method of coordination and partnership between the DA organization and its customers/partners.

Table 31: Reference model: maturity dimension *Strategy*.

Dimension	KPI	Metric	1 - Initial	2 - Repeatable	3 - Defined	4 - Managed	5 - Optimizing	Description
Technology	Data storage architecture	Data storage architecture	No dedicated data storage	Data marts	(Dedicated) data warehouse	Data lake	Enterprise data warehouse built on data lake	Architecture of the data storage.
	DA architecture	Structure	There is no real DA architecture as the data collection and analytics are mainly paper based	The DA solution does not support decoupling between transactions and analytics	The DA solution partly supports transactional and analytics decoupling	The DA solution supports transactional and analytics decoupling	The DA solution has a multi-level architecture for analytics	Architecture of the data transformation scripts.
		Robustness (%)	Less than 70% of all deploys succeed, or there is no codebase to deploy into so no deploys are done.	70% or more of deploys and code integrations succeed.	80% or more of deploys and code integrations succeed.	95% or more of deploys and code integrations succeed.	99% or more of deploys and code integrations succeed through the usage of pipelines and extensive testing.	Expressed in success rate. Can be retrieved from logging.
		Up-to-date tooling	DA tools are vastly outdated and updating them is impossible.	DA tools are vastly outdated but can be updated with major effort	DA tools are mostly up-to-date and can be updated with minor effort.	DA tools are up-to-date and can be updated with minor effort.	DA tools are up-to-date and easily maintained and updated.	Usage of up-to-date tooling and ease of keeping these up-to-date through updates and modularity.
	Flexibility to add new data sources	Flexibility to add new data sources (min)	No new datasources can be added as the usage of datasources is on a singular basis for ad-hoc DA reports therefore adding new datasources required a lot of work and takes more than 600 minutes	Only a limited set of datatypes like CSV can be added therefore adding a new datasource takes more than 300 minutes	Adding a new datasource of any kind is a manual task that requires >60 minutes.	Adding a new datasource is a semi-automatic task that requires <30 minutes.	Adding a new datasource is done in <10 minutes through templating and automation.	Can be retrieved by tracking ticket 'In progress' time
		Capabilities to handle unstructured data	Unstructured data (text, video, audio) cannot be processed by IT systems	Semi-structured data structures like JSON can be processed	Capability to process textual forms of unstructured data (e.g., text analysis)	Capability to image-based processing	Capability to process all types of unstructured data (text, audio, video, etc.)	Capabilities of the DA solution to handle unstructured data.

Table 32: Reference model: maturity dimension *Technology*.

E Expert Interview Protocol

The interviews were conducted according to the protocol described in this appendix. A set of experts was first collected before sending out invitations. This list is not included in this thesis due to privacy reasons. With each participant deemed helpful to this research and willing to participate, a semi-structured interview was conducted that lasted about 45 minutes. These were often online and always recorded. The questions in Table 33 were asked, and the responses were noted. After the interviewees gave their thoughts on matters like important maturity components, all other interviewees' responses were also shown. This was discussed so that each interviewee could give their opinion. Opportunities for automation were also discussed.

Afterward, the interviewees were shown the proposed reference model and were asked to give opinions on it according to an expert evaluation template for maturity models, described by Salah et al. (2014). However, often there was no time for this, and the reference model and the evaluation template were sent to the interviewees after the interview. Unfortunately, not all interviewees then returned a filled-in review form.

	Step	**Content**
	1.	A brief description of the project and the main goal of the interview
	2.	Introductory questions
10 min		How long have you been working in the field of Data Analytics (or similar field)? Are you familiar with the concept of maturity models? Does your organization currently use maturity assessment methods or other audit techniques? Do you think that using/introducing maturity models for maturity assessments is beneficial for your organization? Do you know of any maturity models? (in the DA domain or others which are general)
	3.	Maturity modeling
15 min		Do you currently have insight into the performance of your Data Analytics processes? How do you perform maturity assessments? How often / how much time does it take? What is the output of these assessments? (visually/ prescriptive or descriptive) Which factors/KPIs do you believe are important for assessing the maturity of Data Analytics Would it be possible to automate the maturity assessments? What are useful KPIs/data sources for such automation?
	4.	Maturity model draft evaluation
25 min		Considering the maturity model characteristics we have gathered in the SLR, which ones would you say are the most important? Considering the proposed architecture, is this depiction accurate/complete? Considering the maturity levels included in the DA MM draft, do you think these are fitting? Considering factors/KPIs that we have included in the DA MM draft, which ones would you say are the most important? Are any factors/KPIs missing? Are any factors/KPIs obsolete? How could (KPIs of) this model be automated?
	5.	Closing
5 min		What do you think about our work? Would you consider using a maturity model like the one that was shown for assessing your Data analytics maturity? Do you think that automating this model is useful? May we contact you later for the evaluation of the altered MM using a set of questions in template form? Can we use the name of your company in the scientific paper or do you prefer an anonymous name? Do you have any questions or additional feedback?

Table 33: Expert interview protocol

F Reference Model Evaluation Form

The reference model evaluation form sent to the interviewees contains three sheets. An introduction sheet with an explanation, a sheet containing the evaluation template with questions, and the reference model itself. The reference model can be found in Appendix C (note that this version has been slightly updated to reflect the feedback). The introduction sheet text is stated below, after which the evaluation form, adapted from Salah et al. (2014), is displayed.

Introduction
Thank you for reviewing the draft of the Data analytics maturity model. This page briefly explains this document's content. The maturity model is built for the Data Analytics domain, with the aim of supporting as much automation as possible. Automation is possible in 3 aspects: 1. Data collection, 2. Data processing, 3. Data reporting.

Data processing and Data reporting will be automated using a Tool. This is not relevant to this evaluation. What matters for this evaluation is the maturity model that prescribes what data needs to be collected to perform a maturity assessment, and whether this data collection can be automated. Where possible, the maturity model consists of quantifiable KPIs and includes automation tips.

The purpose of this evaluation is twofold: 1. Is the maturity model with all dimensions and capabilities comprehensive enough and is its coverage adequate? 2. Are the KPIs, metrics, and their thresholds (maturity level values) logical, and are the automation options realistic?

Document content
Sheet 2. *Evaluation Template* contains an assessment form that should be filled in. Read through the questions and then go to Sheet 3. *Data Analytics Maturity Model Draft.* This sheet contains the actual maturity model. Pay attention to the header row to see what each column is.

The table is structured as follows: Left: Reference model with 4 columns - Dimension, Capability, KPI, Metric. Middle: Maturity levels and Metric thresholds. Right: Description of each Metric and automation option.

The last column is empty and provides space for comments from your side. This is about feedback that does not fit in Sheet 2—evaluation Template, such as tips for other automation options. And again, thank you for taking the time to help with the study!

Evaluation form
Alongside the questions that are stated in Table 34, a set of open questions were also asked. These are as follows:

Q1. Would you add any maturity levels? If so please explain what and why?

Q2. Would you update the maturity level description? If so please explain what and why?

Q3. Would you add any processes or practices? If so please explain what and why?

Q4. Would you remove any of the processes or practices? If so please explain what and why?

Q5. Would you redefine/update any of the processes or practices? If so please explain what and why?

Q6. Would you suggest any updates or improvements related to the scoring scheme? If so please explain what and why?

Q7. Would you suggest any updates or improvements related to the automation possibilities? If so please explain what and why?

Q8. Would you like to elaborate on any of your answers?

Q9. Could the model be made more useful? How?

Q10. Could the model be made more practical? How?

Expert Information					
Date: Name (Optional): Organization/Insitute: Position: Email:					
Criteria	**Strongly Dis-agree**	**Slightly Dis-agree**	**Neither Dis-agree Nor Agree**	**Slightly Agree**	**Strongly Agree**
Maturity Levels The maturity levels are sufficient to represent all maturation stages of the domain (Sufficiency) There is no overlap detected between descriptions of maturity levels (Accuracy)					
Processes and Practices The processes and practices are relevant to the domain (Relevance) Processes and practices cover all aspects impacting/ involved in the domain (Comprehensiveness) Processes and practices are clearly distinct (Mutual Exclusion) The metric levels for each KPI and Capability are correctly assigned to their respective maturity level (Accuracy) The automatability of the metrics is logical (Automatability)					
Maturity Model *Understandability* The maturity levels are understandable The assessment guidelines are understandable The documentation is understandable *Ease of Use* The scoring scheme is easy to use The assessment guidelines are easy to use The documentation is easy to use *Usefulness and Practicality* The maturity model is useful for conducting assessments The maturity model is practical for use in industry					

Table 34: Reference model evaluation form (adopted from Salah et al. (2014))

G Automated Maturity Assessment Tool screenshots

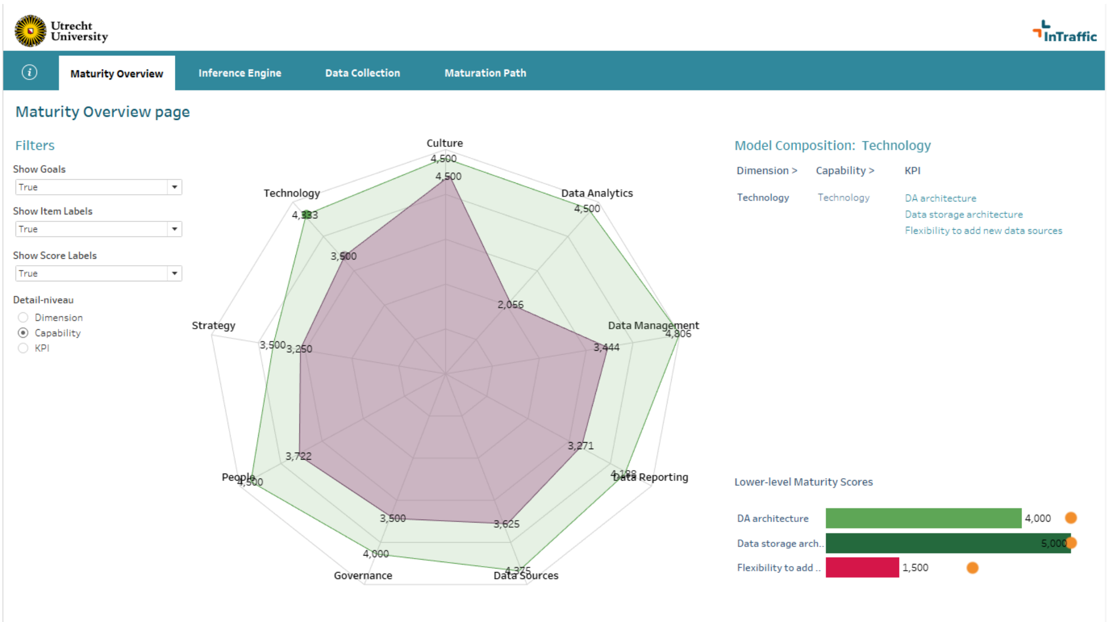


Figure 13: Automated maturity assessment tool: Maturity overview page.

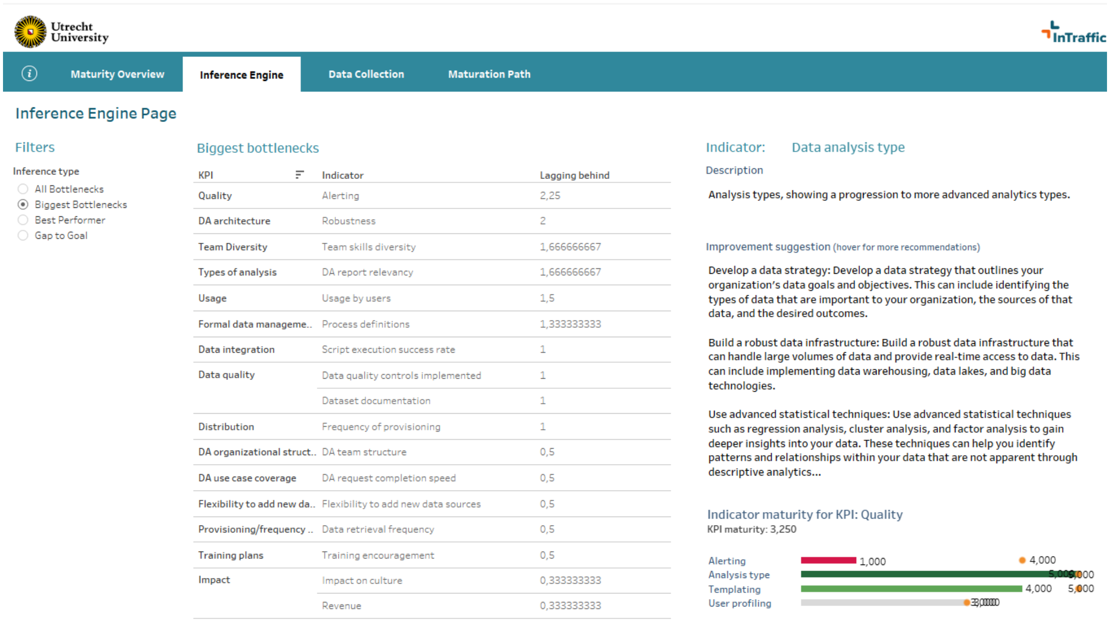


Figure 14: Automated maturity assessment tool: Inference engine page.

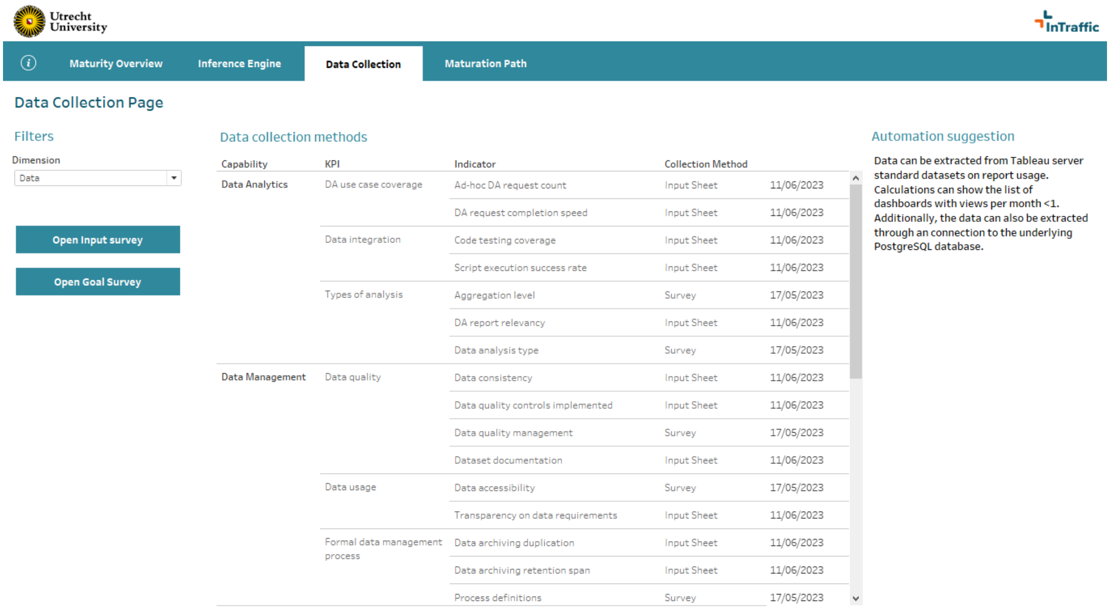


Figure 15: Automated maturity assessment tool: Data collection page.

Figure 16: Automated maturity assessment tool: Maturation path page.

H Case Study Protocol

The case study protocol used to conduct the industrial case study is described below. The last three sections, related to validity, limitations, and reporting, have been incorporated into Chapters *5. Results* and *7. Study limitations*. They are not elaborated upon here.

Background and motivation

The main aim of the case study is to evaluate the proposed maturity model through case study research. The model results from RQ4 and is embedded in an automated maturity assessment tool. In line with RQ5: "Do the proposed maturity model and tool help in attaining a higher maturity level?", the objective is to collect data on the tool's usefulness to test whether it positively impacts an organization's ability to estimate its maturity. This case study protocol is structured according to Wohlin et al. (2012) to achieve this.

For this thesis, it is interesting to be able to collect real-world data to input into the maturity model and automated maturity model assessment tool. This should give insight into the accuracy of the reference model regarding real-world data analytics processes and their maturation paths. The results will help further refine the maturity model to improve its usefulness to organizations. For the case company (described in further detail in the next section), the goal of participating in this study is to create insight into their current data analytics landscape. As their primary business case is related to data analysis, improving in this area means generating more value for internal and external stakeholders. Even more fundamental than insight into maturation paths, the organization also desires insight into the as-is state of the processes. As the data analytics team is currently going through a 'storming' phase, the goal is to use the maturity model and assessment to understand the status quo. The hope is to expand on this knowledge by documenting and streamlining processes to mature. Furthermore, using data and knowledge on the performance of the data analytics team, i.e., maturity levels, to promote the company's services to potential customers is also desired.

Case study unit

The case study is a single within-case case study (Yin, 2009). The object of study is an automated maturity assessment tool based on a design science process. It is built in Tableau and has a Google sheet (as default) as its data source, which can be filled through any desired method. This data source contains data corresponding to the reference model. The quantitative data, which can be gathered through the organization's tools and processes, is collected by the case study participants, while the qualitative data is gathered through a questionnaire. The calculated maturity levels based on the input data, as well as the usefulness of the tool, are desired data.

Selection

The primary case study is at InTraffic, an organization performing data analytics in the public transport sector. This case was chosen due to their workflow and business cases involving data analytics. Furthermore, their willingness to participate and share all data regarding their data analytics processes made them suitable candidates. Inside this company, data analytics team members are used as case study participants. They cover relevant functions like data engineering, analysis, science, product owner, and delivery management.

Procedures and roles

The tasks range from data collection to interviews and training of case study participants. There are two main steps: before data collection to TAM & after data collection to TAM. The input data is based on the performance of the data analytics processes and therefore does not vary between case study participants. Consequently, this data only needs to be collected once. All other case study participants will be shown the whole process but do not need to provide data.

The case study steps are detailed below:

1. Explain the reference model to the case study participant. They should understand which data analytics processes are included and why. This gives them context on why they provide data regarding these processes later.
2. (Only first case study participant) Let the case study participant fill in the quantitative dataset used for the automated maturity assessment. This is done in a Google sheet embedded in the automated maturity assessment tool. Afterward, also let them fill in the Goal-setting questionnaire. Based on this process of having them collect data, an automation guideline can be created for all quantitative maturity metrics.

3. Let case study participants complete the questionnaire for all qualitative measures. The automated maturity assessment tool calculates the maturity levels of the data analytics processes.
4. The assessment results are discussed with the case study participant through a semi-structured interview. The case study participant can use the tool to take in the features. Then, questions are asked to collect data on their beliefs about the accuracy of the assessed maturity levels. The case study participant is shown the most significant bottleneck, and improvement recommendations are offered. Their thoughts are then collected.
5. The Technology Acceptance Model is used to assess the perceived usefulness of the automated maturity assessment tool. Furthermore, thoughts on possible negatives and points for the extension of the tool are collected by asking a set of open questions on the topic. Here, participants can write down their thoughts on the matter.

Some data on the case study participants are shown below. Some data has been removed to anonymize the entries.

Job title	**Degree**	**Experience**
Data Solutions Consultant	Bsc	24
Data-analyst	Msc	5
Data-analyst	Bsc	2
Data Science Analyst	Msc	7
Data-analyst	Msc	5
Data-analyst	Msc	2
Data-analyst	Msc	4
Data Engineer/Analyst	Msc	4

Table 35: Case study participant pool composition

Data collection

The calculated maturity levels based on the input data, as well as the usefulness of the tool, are desired data. The maturity levels are shown in the tool and are stored in tables resulting from embedded calculations in the tool. There is only one dataset for the quantitative measures, as this is data generated through processes and tools. There are multiple datasets for the qualitative data questionnaire and TAM questionnaire, however. These are collected for each case study participant. Furthermore, demographic data is gathered for each case study participant, like their job title. This is shown in the section above.

Analysis

The analysis of the input data is done by the automated maturity assessment tool. The participants' thoughts on the tool's results are qualitative and collected through the interviews. These are then discussed with the respondents and reported in the thesis. The results of the TAM questionnaire are aggregated to see the average responses. Based on all this data, recommendations are given to refine further the maturity model and the tool in future work.

Plan validity

A discussion of validity and threats to it can be found in chapter 7 of this thesis. Validity concerns related to this case study protocol are discussed there.

Study limitations

A discussion of the limitations of this case study protocol can be found in chapter 7 of this thesis.

Reporting

The results of the automated maturity assessment will be reported to the case study participants during the case study itself. The final results and collected data can be found in Chapter *5. Results.* The hope is that other data analytics practitioners and researchers in this domain will find it helpful.

I TAM Questionnaire

The Technology Acceptance Model Questionnaire

The Technology Acceptance Model (TAM) is designed to give you an opportunity to rate this product's usefulness ad ease-of-use.

To as great an extent as possible, think about all the tasks that you do with the product while you answer these questions.

Please read each statement and indicate how stronly you agree or disagree with the statement. Please read the statements carefully, but don't spend a lot of time on each item -- your first impression is fine.

Note that for this questionnaire (TAM), **all items have a positive tone** so greater levels of agreement (to the **right of the scale**) indicate a **better user experience.**

[redacted] Switch accounts

Not shared

* Indicates required question

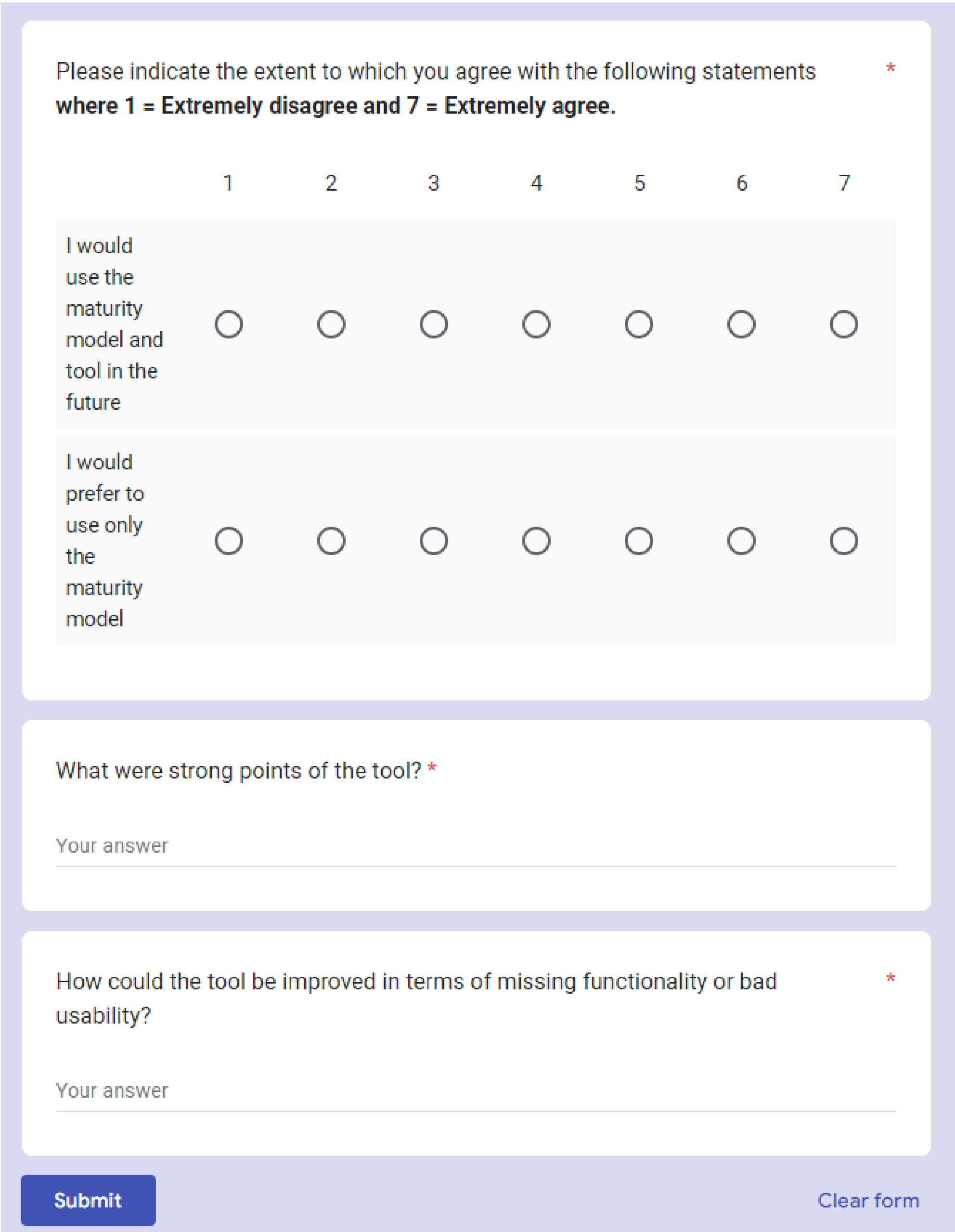
What is your name? *

Your answer

Please indicate the extent to which you agree with the following statements **where 1 = Extremely disagree and 7 = Extremely agree.** *

	1	2	3	4	5	6	7
1. Using this product at work enables me to complete tasks more quickly than other products in its class.	○	○	○	○	○	○	○
2. Using this product improves my job performance.	○	○	○	○	○	○	○
3. Using this product increases my productivity.	○	○	○	○	○	○	○
4. Using this product enhances my effectiveness at work.	○	○	○	○	○	○	○
5. Using this product makes it easier to do my job.	○	○	○	○	○	○	○
6. I would find this product useful at work.	○	○	○	○	○	○	○

7. Learning how to handle the product would be easy for me.	○	○	○	○	○	○	○
8. I would find it easy to let the product do what I want it to.	○	○	○	○	○	○	○
9. My interaction with this product would be clear and smooth.	○	○	○	○	○	○	○
10. I would find this product flexible to work with.	○	○	○	○	○	○	○
11. It would be easy for me to become agile with the product.	○	○	○	○	○	○	○
12. I would find it easy to use.	○	○	○	○	○	○	○



Please indicate the extent to which you agree with the following statements **where 1 = Extremely disagree and 7 = Extremely agree.** *

	1	2	3	4	5	6	7
I would use the maturity model and tool in the future	○	○	○	○	○	○	○
I would prefer to use only the maturity model	○	○	○	○	○	○	○

What were strong points of the tool? *

Your answer

How could the tool be improved in terms of missing functionality or bad usability? *

Your answer

Submit

Clear form

Figure 17: Technology Acceptance Model (TAM) questionnaire (adopted from (Davis, 1989; Babar et al., 2007)

J Maturity model & tool implementation guide

This appendix describes implementing and using the automated maturity assessment tool. First, embedding a maturity model into the tool is explained. Afterward, inputting maturity assessment data is explained, and then the usage of the dashboarding part of the tool is described.

The tool can be downloaded, which grants access to the dashboarding aspect and the data source. The data source is embedded in the Tableau folder and can be retrieved through the application.

Embedding & changing the maturity model

The tool consists of a dashboarding part, made in Tableau, in which a set of Excel datasheets is embedded. This means that changes in these sheets indicate that the data source of the dashboard automatically changes, and the visualized data is updated accordingly. When opening the data source sheets, several hidden sheets for processing need not be opened. Four sheets, namely *Model*, *Grid Model*, *Historical data*, and *Final dataset*, are needed by the dashboard to draw data from and combine and join to produce the required underlying data relations. The *Input Data (Quantitative)* sheet is used for imputing data and is described below. For embedding and altering the reference model shown in the tool, the sheet *Reference model structure* is needed.

This sheet contains data on the structure of the reference model. All other sheets draw data from this place to indicate the form of the maturity items, their maturity level thresholds, and descriptions. Therefore, if the reference model needs to be altered, this sheet is the only place to require changes. This gives the tool flexibility, allowing it to be easily used in other domains and for other purposes.

The first four columns (A to D) indicate the maturity items, from maturity dimensions to maturity metrics. The following five columns (E to I) show the thresholds for the five maturity levels for that maturity metric. Data is extracted from these cells through regexes, meaning that the first number is extracted from the natural language and used as a threshold. This allows the column to contain context in the text while also being used as a quantitative threshold. Columns J, K, and L have data on the definitions, methods of calculating the input data, and automation sources for a particular company. Column K indicates the origin of the data. When more data collection automation occurs, this can be replaced to show how data is extracted. In conclusion, when the embedded reference model needs to be changed or replaced, this sheet can be adjusted according to the user's desires. Changes in the inference engine concerning maturity level calculation are automatically adjusted to reflect changes in the reference model.

Inputting data

When the reference model is correctly represented in the Reference model structure sheet, maturity assessments can be performed by (automatically) inputting data. This is done in three places, depending on the data type.

Quantitative data is added through the set of sheets. Specifically in sheet *Input Data (Quantitative)*. Indicate the day of data retrieval in the first row in the relevant column. This ensures that the application knows the retrieval day for each data point so that historical data is correctly displayed. Then, the input value can be added for each maturity metric. These metrics are shown in column A, and their description and measurement methods are shown in columns B and C, respectively.

Data on qualitative maturity metrics and maturation goals can be added through the *Data collection page*. Here, two buttons enable the showing and hiding of two separate questionnaires, which are also linked to the embedded data source. If a user fills out these questionnaires and refreshes the data source in Tableau, the data is automatically processed and shown in the dashboarding. For the maturation goals, new entries overwrite the previous data so that goals always represent the latest wishes of the users. As for the input data on the maturity metrics, all entries are stored to keep track of historical performance. The dashboards show the most recent entries for all qualitative data. For quantitative data, however, averages over the last month are displayed for some metrics, while the newest entry is shown for some. Code testing coverage, for example, represents progress toward a final state. At the same time, maturity metric DA report availability means the performance in an area that is time-sensitive.

Assessing results through dashboarding

The inputted data and processed data that the inference engine output is displayed in the set of dashboards of the tool. These have been described in detail in section 4.5 of this thesis. Appendix G shows pictures of the four sheets and their underlying visualization. Note that the dashboard is interactive, meaning filtering, zooming, and hovering are possible to change focus and popups. A UX designer with 20+ years of experience in the field has designed the UI. It has been designed to be easy to use, especially for less data-savvy users.

K Case study - Input & output data

Metric	Description	28/05/2023
DA request completion speed (hr)	Average time in hours to complete new DA requests. From data collection to the end of data reporting. Across all domains and DA request sizes.	80 hr
Ad-hoc DA request count (# in month)	The number of ad-hoc (outside of always-up DA reports) DA requests. Expressed as the outcome of formula: [#key stakeholders / #ad-hoc DA requests per sprint].	4
DA report relevancy (%)	The relevancy of available DA reports. Expressed as the percentage of DA reports which is checked at leats once per month.	35
Code testing coverage (%)	Percentage of code/scripts which are covered by unit tests. The extensiveness is not relevant in this equation.	91
Script execution success rate (%)	Amount of times a DA script completes vs. amount of times failed, expressed as percentage	70
Transparency on data requirements (%)	Percentage of data flows, from datasource to DA reports which is documented w.r.t. its content and uses.	75
Dataset documentation (%)	Percentage of datasets which have documentation	20
Data quality controls implemented (%)	Percentage of transformation scripts with automated input/output quality controls	0
Data consistency (%)	Percentage of rows in all datasets which contain faulty data	95
Data archiving duplication (#)	Number of duplicates which are stored (so not original)	3
Data archiving retention span (# years)	Retention length in years	7
Availability of external data sources (%)	Percentage of data extraction scripts runs which succeed	90
Overdue data deliveries (%)	Percentage of on-time data deliveries	90
Richness of available data sources (%)	Percentage of DA reports-related desires which can be fulfilled by current datasets	80 %
Transparency on available data (%)	Percentage of external data sources which have documentation	80
Digitalization of distribution (%)	Percentage of DA reports which are digitally distributed as opposed to paper-based	100
User satisfaction (1-5)	Expressed by including a 1-5 rating system and collecting and averaging scores	4
Alerting (%)	Found by checking the existing alerting rules/procedures over all DA reports.	2
Templating (%)	Calculated by comparing all DA processes against those which have documented templates.	95
Usage by users (%)	The % of stakeholders with access who also check the reports.	35
Availability (%)	Expressed as % uptime.	99
DA dedicated FTE (%)	Available FTE vs. desired FTE number. Then expressed as %-part of that desired number.	100
DA solution access (%)	% of stakeholders with access to DA reports that are relevant to them	80
Data access (%)	% of stakeholders with access to datasets that are relevant to them	80
Team skills diversity (%)	Expressed as % coverage of required competencies. It can be retrieved from an internal CV tool.	70
Amount of training (#)	Can be retrieved from an internal CV or training plan tool.	3
Budget (%)	Average annual spending on DA as %-part of the ICT operational expenditure	5
Robustness (%)	Expressed in success rate. It can be retrieved from logging.	70
Flexibility to add new data sources (min)	Can be retrieved by tracking ticket 'In progress' time	600 minutes

Table 36: Quantitative input data, collected during the first case study interview

Metric	18/05/2023
DA request completion speed	(5) 100% of all new highly relevant DA report requests can consistently be fulfilled in under a day. Less important requests are completed during the sprint length.
Ad-hoc DA request count	(4) The ratio: [#key stakeholders / #ad-hoc DA requests in a month] is smaller than 1.
Data analysis type	(3) Predictive analytics.
Aggregation level	(5) All needed data aggregation levels are present in all available datasets.
Time to create DA report	(4) The creation of new DA reports takes on average <2 hours.
DA report relevancy	(4) There is a digitally available library of DA reports. More than 90% of reports are useful and often checked.
Code testing coverage	(5) 100% of code is tested.
Script execution success rate	(5) >99% of scripts run without failure.
Data accessibility	(5) Complete virtual data organization to access data universally (with individual usage permissions)
Transparency on data requirements	(5) 100% transparency and documentation on data usage.
Data quality management	(5) The data quality assessment is conducted regularly for data sources.
Dataset documentation	(5) 100% of datasets are documented.
Data quality controls implemented	(5) 100% of DA scripts include automated data quality controls over input/output.
Data consistency	(4) Datasets are mostly consistent and are only >0.1% faulty in content and notation.
Process definitions	(4) Sporadical reviews are performed to check the usefulness of the data currently stored concerning their usage and acquire data according to estimated data needs
Data archiving duplication	(5) Data is archived and duplicated at least thrice.
Data archiving retention span	(5) Data is archived for 3 years.
Availability of external data sources	(5) 100% of external data sources are documented and data retrieval methods succeed >99%.
Data retrieval frequency	(3) Data is retrieved daily.
Overdue data deliveries	(4) Data is delivered on time in 90% of all cases.
Richness of available data sources	(4) Sufficient selection of internal and external data sources available to satisfy 100% of information needs with at least one kind of data.
Transparency on available data	(5) 100% of data sources are documented.
Digitalization of distribution	(5) 100% of all DA reports are digitally distributed.
Interface	(4) The DA solution is web-based and is accessible through all the desktop devices
Frequency of provisioning	(3) DA reports are updated daily
Impact on culture	(4) DA as a corporate asset
User satisfaction	(5) Users are extremely satisfied with the DA reports.
Revenue	(3) The DA practices breakeven in terms of revenue.
Analysis type	(5) Dynamic statistical analysis
Alerting	(4) More than 50% of relevant DA reports have automated alerting methods.
User profiling	(3) The DA solution only supports macro-area profiling
Templating	(5) 100% of processes have associated templated which are periodically reviewed and updated.
Usage by users	(4) 90% of key stakeholders check the DA reports
Availability	(5) Reports are directly and constantly available. Downtime limited to <0.1%
DA team structure	(4) Rudimentary DA competence center (DA CC)
DA dedicated FTE	(4) There is enough FTE to perform all DA processes and manage technical debt.
DA solution access	(5) 100% of key stakeholders have access to the DA solution and reports.
Data access	(5) 100% of key stakeholders have access to all relevant datasets.
Diversity consideration in hiring	(5) Besides consideration of talent and diversification in the recruitment process, hiring/working with outside talent on a short basis is also considered
Organization competency awareness	(5) The organization continuously assesses the required DA skills for its practices and checks these against the employee competencies.

Team skills diversity	(5) The team has all required competencies, is constantly training and improving, and are future-proof w.r.t. possible new DA challenges and tooling.
Amount of training	(5) Employees attend >3 trainings a year.
Training encouragement	(4) Employees are encouraged to choose their own training programs for personal development
User capabilities	(4) Most stakeholders have the competencies to manage sophisticated reports, but only a few can perform self-service DA /DA
Executive sponsorship	(5) DA is sponsored unequivocally by top management
Recognition of the importance of DA	(4) The importance of evidence-based operations and decision-making is stressed at all levels
Budget	(4) Average annual spending on DA is between 3% and 7% of the ICT operational expenditure
Data analytics strategy	(3) The DA strategy is defined in terms of local strategies at the units or department level and is only partially aligned with the corporate strategy
Innovation Processes	(3) DA innovation processes are explicitly defined and documented. Decision criteria are based on the transactional value a DA project could generate.
Partner/ supplier coordination	(4) Service level agreements for continuous update and improvement of the DA
Data storage architecture	(5) Enterprise data warehouse built on data lake
Structure	(5) The DA solution has a multi-level architecture for analytics
Robustness	(5) >99% of deploys and code integrations succeed through the usage of pipelines and extensive testing.
Up-to-date tooling	(5) DA tools are up-to-date, easily maintained and updated.
Flexibility to add new data sources	(4) Adding a new data source is a semi-automatic task that requires <30 minutes.
Capabilities to handle unstructured data	(2) Semi-structured data structures like JSON can be processed
Ethical data considerations	(3) The company does not process data which could have unethical implications. There are no safeguards to protect this process and new data sources are not investigated until another ad-hoc research.

Table 38: Goals input data, collected during the first case study interview

Metric	Description	17/05/2023
Data analysis type	Analysis types, showing a progression to more advanced analytics types.	Diagnostic analytics.
Aggregation level	The possible aggregation levels of data analysis. Showing the possible levels of detail in analyses.	All needed data aggregation levels are present in all available datasets.
Data accessibility	The accessibility of the data sources used for DA reports. Indicates how easy it is to get data for self-service DA.	All data are centrally stored and available across the organization and integrated with relevant external stakeholders
Data quality management	The role and extensiveness of data quality assessments in the DA team and organization.	Data quality is defined regarding the requirements of different stakeholders.
Process definitions	The way in which DA processes are formally defined and assessed on their usefulness.	Decisions are made on a current-need-base about which data should be acquired and stored
Data retrieval frequency	Frequency with which data is retrieved from the data sources.	Data is retrieved daily.
Interface	Interface of the DA solution indicates the flexibility in using the platform on different devices.	The DA solution is web-based and is accessible through all the desktop devices
Frequency of provisioning	Frequency with which DA reports are updated.	DA reports are updated daily
Impact on culture	Impact of the DA reports on decision-making and culture.	Promotion of and demand for the use of DA
Analysis type	Content and extensiveness of the DA report.	Dynamic statistical analysis
User profiling	The support of the DA solution in filtering content based on the logged-in user.	The DA solution only supports macro-area profiling
DA team structure	Structure and formalization of roles in the DA team.	Internal, formalized standards with defined roles
Diversity consideration in hiring	Consideration of required DA competencies and diversification in the hiring process.	Besides consideration of talent and diversification in the recruitment process, hiring/working with outside talent on a short basis is also considered
Organization competency awareness	Awareness of the organization and DA team of the required DA teams for their DA processes.	The organization performs sporadic assessments to evaluate the team's DA competencies against those that are required.
Training encouragement	Encouragement of organization to employees to follow a training plan.	Employees are encouraged to choose their own training programs for personal development
User capabilities	Capabilities of DA solution users with regards to DA concepts and practices.	Most stakeholders are only able to interpret static reports; some understand sophisticated reports
Executive sponsorship	Support for DA practices from executive management.	DA is sponsored unequivocally by top management
Recognition of the importance of DA	Recognition of DA by the organization and its incorporation into the culture.	The importance of evidence-based operations and decision-making is stressed at all levels
Data analytics strategy	Extensiveness of the DA strategy defined in the organization.	There is an informal DA strategy on team basis
Innovation Processes	Existence and Documentation of DA innovation processes.	DA innovation processes are explicitly defined and documented. Decision criteria are based on the transactional value a DA project could generate.
Partner/ supplier coordination	Method of coordination and partnership between the DA organization and its customers/partners.	Service level agreements for continuous update and improvement of the DA
Data storage architecture	Architecture of the data storage.	Enterprise data warehouse built on data lake
Structure	Architecture of the data transformation scripts.	The DA solution has a multi-level architecture for analytics
Up-to-date tooling	Usage of up-to-date tooling and ease of keeping these up-to-date through updates and modularity.	DA tools are up-to-date and easily maintained and updated.
Capabilities to handle unstructured data	Capabilities of the DA solution to handle unstructured data.	Semi-structured data structures like JSON can be processed
Ethical data considerations	How the organization tackles ethical considerations in relation to collecting, processing and reporting sensitive data.	The organization has done ad-hoc research into which data could potentially be under ethical scrutiny if processed but does not yet act on it.
Revenue	Expressed as % of revenue against costs	The DA practices breakeven in terms of revenue.

Table 37: Qualitative input data, collected during the first case study interview

Metric	Maturity level	Maturity level Goal
DA request completion speed	1	5
Ad-hoc DA request count	2	4
Data analysis type	2	3
Aggregation level	5	5
DA report relevancy	1	4
Code testing coverage	3	5
Script execution success rate	1	5
Data accessibility	4	5
Transparency on data requirements	4	5
Data quality management	3	5
Dataset documentation	1	5
Data quality controls implemented	1	5
Data consistency	3	4
Process definitions	3	4
Data archiving duplication	5	5
Data archiving retention span	5	5
Availability of external data sources	4	5
Data retrieval frequency	3	3
Overdue data deliveries	4	4
Richness of available data sources	3	4
Transparency on available data	4	5
Digitalization of distribution	5	5
Interface	4	4
Frequency of provisioning	3	3
Impact on culture	3	4
User satisfaction	4	5
Revenue	3	3
Analysis type	5	5
Alerting	1	4
User profiling	3	3
Templating	4	5
Usage by users	1	4
Availability	4	5
DA team structure	3	4
DA dedicated FTE	4	4
DA solution access	4	5
Data access	4	5
Ethical data considerations	3	3
Diversity consideration in hiring	5	5
Organization competency awareness	4	5
Team skills diversity	2	5
Amount of trainings	5	5
Training encouragement	4	4
User capabilities	3	4
Executive sponsorship	5	5
Recognition of importance of DA	4	4
Budget	4	4
Data analytics strategy	2	3
Innovation Processes	3	3
Partner/ supplier coordination	4	4
Data storage architecture	5	5
Structure	5	5
Robustness	2	5
Up-to-date tooling	5	5
Flexibility to add new data sources	1	4
Capabilities to handle unstructured data	2	2

Table 39: Inference engine output, along with the indicated goals for each maturity metric