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OPERATIONALISING AN ARTIFICIAL INTELLIGENCE MATURITY MODEL IN THE PUBLIC SECTOR

Design Science Approach

[Master's thesis]

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AVALIKU SEKTORI TEHISINTELLEKTI KÜPSUSMUDELI RAKENDAMINE

Disainiteaduslik lähenemine

Magistritöö

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Author's declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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Abstract

Artificial Intelligence Maturity Models (AIMM-s) are used to assess AI capabilities in the organisation. There is no fully developed AIMM for the public sector which could be deployed to public organisations for self-assessment. The aim of this thesis is to develop a complete toolkit for the application of an AIMM prototype in practice and evaluate their validity. An existing AIMM recently developed for the public sector is used as the starting point, in addition to which a Self-Assessment Methodology and a web-based maturity assessment tool are designed. The research uses Design Science Research methodology and an existing procedure model for developing maturity models for approaching the task of designing and testing the artifacts on a pilot public organisation, Statistics Estonia. The artifacts and the self-assessment process are evaluated against established criteria, the most important of which is usefulness. This research is valuable because it expands the design science knowledge about the piloting of an AIMM in practice.

This research concludes that the usefulness of the AIMM deployment to the public sector needs to be improved and the model requires at least one more iteration of redesign and testing before it can be launched into the wider community of public organisations.

This thesis is written in English and is 76 pages long, including 6 chapters, 9 figures and 5 tables.

Keywords: artificial intelligence, public sector, maturity model, design science research, AI capability

Annotatsioon

Avaliku sektori tehisintellekti küpsusmudeli rakendamine. Disainiteaduslik lähenemine

Tehisintellekti küpsusmudeleid (TIKM) kasutatakse tehisintellekti alase võimekuse hindamiseks organisatsioonides. Seni ei ole ühtegi sellist mudelit avaliku sektori jaoks loodud, mida avalikud organisatsioonid saaksid kasutada enesehindamise otstarbel. Käesoleva magistritöö eesmärgiks on töötada välja terviklik komplekt tööriistadest, mis võimaldaksid rakendada TIKM-i prototüüpi päriselus ja hinnata nende tööriistade toimivust. Töö aluseks võeti olemasolev TIKM, mis töötati välja hiljuti avaliku sektori tarbeks. Lisaks töötatakse välja enesehindamise metoodika ja veebipõhine küpsushindamise tööriist. Uurimustöös kasutatakse disainiteaduslikku uurimismetoodikat ning olemasolevat protseduurimudelit küpsusmudelite väljatöötamiseks. Selle mudeli abil disainitakse ja testitakse artefakte ühes avaliku sektori pilootorganisatsioonis, Statistikaametis. Artefakte ja enesehindamise protsessi hinnatakse eelnevalt paika pandud kriteeriumide alusel, millest tähtsaim on kasutatavus. Antud uurimistöö on väärtuslik, kuna ta laiendab disainiteaduse teadmusbaasi selle kohta, kuidas piloteerida TIKM-i päriselus.

Uurimuses järeldatakse, et TIKM-i rakendamise kasulikkust avaliku sektori jaoks tuleb tõsta ja mudel nõuab vähemalt ühte iteratsiooni ümberkujundamisest ja testimisest enne seda, kui seda saab kasutusele võtta avalikus sektoris laiemalt.

Võtmesõnad: tehisintellekt, avalik sektor, küpsusmudel, disainiteadus, AI võimekus

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 76 leheküljel, 6 peatükki, 9 joonist, 5 tabelit.

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List of abbreviations and terms

AI	Artificial Intelligence
MM	Maturity Model
CAF	Common Assessment Framework
I(C)T	Information (and Communication) Technology
AIMM	Artificial Intelligence Maturity Model
IS	Information system
DS	Design science
DSR	Design science research
JRC	Joint Research Council of the European Commission
EC	European Commission
The Tool	Web-Based Tool for carrying out AI maturity self-assessment
The Methodology	Self-Assessment Methodology in support to AI maturity self-assessment by public organisations
RBT	Resource-based theory
ISO	International Standards Organisation
DOI	Diffusion of Innovation
MEAC	Ministry of Economic Affairs and Communications
SE	Statistics Estonia
MAT	Maturity assessment tool
PVP	Public value perspective

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1 Introduction

Artificial Intelligence (AI) is the latest set of technologies that takes the World by storm. AI is considered a disruptive technology that changes the conventional manner of working in an organisation sustainably and radically (Gentsch, 2018). In 2021, 87% of technology and service providers aimed to adopt AI technologies, and 33% of them stated they would spend $ 1 million or more on these technologies in the following two years (Rimol, 2021). Using AI is growing and brings benefits to public and private organisations alike in sectors such as finance, consumer products, automotive, machinery, transport, energy, healthcare, and environmental protection to name just a few – everywhere where data is generated in large – and usually growing – volumes.

However, since AI technologies, such as Machine Learning, Natural Language Processing, Computer Vision, Knowledge Representation, etc. (Samoili et al., 2021)[1] are still considered immature (Ransbotham, 2017), AI-investing organisations struggle to make full use of it or progress slower than expected (Rimol, 2021). At one end of the spectrum are firms which pursue strategic AI programmes while at the other end are the firms that still ignore AI (Lichtenthaler, 2020). While there are many reasons for not pursuing AI technologies yet, a study by Boston Consulting Group and MIT Management Review (Ransbotham et al., 2018) identified that the most common ones among firms are lack of leadership support, technological capabilities, and an articulated business case. Some have argued that the key challenge for the future use of AI [in business] is to develop suitable application scenarios, to convert these into prototypes and to develop operationally usable applications that can then be operated productively and continuously evolved (Fukas, 2022).

[1] For definitions and a full list of AI taxonomy see, Samoili et al., 2021.

1.1 AI and public sector

Like in business, AI's role in government is to support digital transformation. While the use of AI in the public sector is increasing, there are many public organisations where productive applications remain rare (Oxford Insights, 2020). Oxford Insights (2023) which produces the annual Government AI Readiness Index concluded in its 2023 report that 'Understanding how to ensure that AI is adopted effectively for the public good remains a challenge'. Nevertheless, the European Union (EU) AI Watch initiative reported 686 use cases of AI across the 27 EU Member States' and some other European countries' public sectors, of which a third were found to be implemented and used in daily operations, while many were still in the pilot or development phase (Tangi et al., 2022). In Estonia, the Ministry of Economy and Communications (MEAC), which keeps an account of AI application cases in public administration, suggests that there are about 120 of them from 60 state institutions[1] (MEAC, 2024). Nevertheless, the actual diffusion of AI in public sector practice remains low, particularly compared to private companies (Mikalef et al. 2021). Even those state institutions which apply AI aim at 'point solutions' which do not translate into greater systematic capabilities (Ransbotham, 2018). Besides organisation-level challenges, the public sector organisations face unique challenges characteristic of public sector: (i) a lack of technical staff to introduce and assess new technologies, (ii) the risk of potential erroneous use of AI (e.g. security risks, privacy concerns), (iii) the need to guarantee transparency in the context of AI, (iv) moral dilemmas such as when to use AI, and (v) ethical considerations (e.g. non-discrimination of citizens) (Margetts and Dorobantu, 2019). Therefore, policymakers and researchers alike are interested in understanding the factors contributing to and hampering the adoption of AI, preferably at a scale which would make a difference in the way the public value is created (Fatima et al., 2022). However, only a handful of empirical studies exist on determinants of successful AI adoption within public organisations (Neumann, Guirguis, and Steiner, 2024; van Noordt, 2019).

[1] Hereafter, 'public organisation' and 'public sector' are used interchangeably.

1.2 Maturity Models and Artificial Intelligence Maturity Models

One way to support organisations in pursuing AI is to help them understand what is required of them to build the AI capability. For that, diagnosing their level of development is assisted by applying maturity assessments. Interest towards maturity models (MM-s) lies in the need for a structured and standardised approach to initiate or continue organisational development or change. MM-s are widely used in Total Quality Management (ISO, n.d.; EIPA, n.d.), Business Process Management (Tarhan, Turetken, and Reijers 2016), IT management (Becker, Knackstedt, and Pöppelbuß, 2009), digital transformation (Gökalp and Martinez, 2021), software engineering (Wendler, 2012), e-government (Layne and Lee, 2001), and more recently AI (Sadiq et al., 2021). MM-s have in common that they provide a framework to assist organisations by providing extensive guidance and offering a roadmap for improvement (Gökalp and Martinez, 2021). More specifically, Becker, Knackstedt, and Pöppelbuß (2009) define MM as "a conceptual model consisting of a sequence of discrete maturity levels for a class of processes and represents a desired evolutionary path for these processes". Maturity is thus expressed through maturity dimensions and maturity levels.

It is evident that IT support for business processes has become indispensable (Fukas, 2022) and the responsibility for effective and efficient design and use of IT lies with the organisation's IT management (Becker, Knackstedt, and Pöppelbuß, 2009). AI technologies can partially be covered by IT management, but because of AI's nature of being a set of tools and technologies that represent a complex technical system for which both technological and organisational elements need to be considered (Alsheiabni, Cheung and Messom, 2019), it can be argued to merit its own management arrangement and hence maturity model which captures the organisation-wide factors to make effective implementation of AI possible (Seger, Miailhe and Mueller, 2019). Without considering the complexity of the socio-technical interactions of AI and the organisation in which it operates, there is a risk of missing out on identifying the capabilities relevant to the successful application of those technologies (Weber et al., 2022). As Postulated by Mikalef and Gupta (2021), applying AI technologies by themselves is not sufficient for delivering expected outcomes, but organisations require a unique blend of physical, human, and organisational resources to create an AI capability, which will deliver value to its operations, users, or society at large. This is the premise on which all the AIMM-s have been built.

1.3 Research Gap

Already in 2012, there were 237 articles on MM-s from more than 20 domains (Wendler, 2012). MM-s vary in how the model is conceptualised, particularly the dimensions, but also the maturity levels, depending on the objectives of developing the MM. Although the number of MMs has increased, the validation and usefulness of these models is scarce (Tarhan, Turetken, and Reijers, 2016). A literature review by Sadique et al. (2021) reveals that out of the initially selected 83 articles on AIMM-s, 15 met their rigorous research questions (e.g. the information on design approach, typology, architecture, purpose of use, and components is not provided) and selection criteria (e.g. focus on AI in organisation, not narrowing to a particular aspect of AI, such as machine learning). Similarly, when Becker, Knackstedt, and Pöppelbuß (2009) postulated requirements for constructing an MM, out of the studied 51 MMs only 9 complied with those requirements. This implies that there are still relatively few AIMM-s that qualify as academically sound, but also useful for organisations to use them for diagnosing their AI capability.

Moreover, virtually all the AIMM-s covered in the academic literature are developed for business environments where AI is a tool to gain competitive advantage (Mikalef and Gupta, 2021) and therefore are not entirely congruent with the public sector operating environment. In the public sector, the race is not about creating more innovative products and services that would better satisfy customer needs, instead, AI can be seen as a tool for delivering higher public value (Fatima et al., 2022). In public administration, additional considerations, such as equity, data sharing regulations, or explainability of the algorithms, are relevant for the adoption of AI. As such, while some challenges of using AI may be comparable to both the private and the public sector, because of different contextual characteristics the findings from the private sector may not be directly transferrable to the public sector (van Noordt and Tangi, 2023). Zuiderwijk, Chen and Salem (2021) conclude that public sector-specific frameworks for AI deployment are limited.

1.4 Problem definition

The problem to be addressed by this master's thesis is that there is no academic research conducted on developing an AIMM specifically designed for the public sector, which also would have been used for carrying out a maturity assessment. In real life, it manifests itself in not having proper supporting tools for public organisations that they could use to assess their AI maturity level, thus limiting their understanding of what activities and initiatives to launch to contribute to their AI capability, or how they compare to other public organisations in that regard.

The author is aware of only two recent efforts to develop an AIMM specifically for the public sector. Noymanee, Iewwongcharoen, and Theeramunkong (2022) developed an AIMM based on a literature review. Their model consists of four dimensions (strategy, organisation, information, and technology) and five maturity levels, but was not validated (*ibid.*). Dreyling et al. (2024) designed an AIMM also based on the literature review of existing AIMM-s, comprising eight dimensions and five maturity levels. Author of this thesis contributed to this research by expanding the maturity level descriptions. The authors validated the model with experts. It is theoretically grounded but has not been put through empirical validation. This model was taken as the starting point for the current work.

There are few research articles on AIMM-s designed for business entities which would have been validated based on feedback through practice. Most of the AIMM-s developed for research purposes are either conceptual (e.g. Lichtenthaler, 2020) and information on their validity testing is lacking (e.g. Lee, 2020; Schuster, Waidelich, and Voltz, 2021), or they go through the testing with experts (1st phase of feedback) which allows testing their completeness, consistency, and coherence but the model is not applied full-on in practice (2nd phase of feedback), therefore their utility and usability criteria are not tested. As noted by Fatima et al. (2022), existing AI frameworks are not tools that can be readily deployed by public sector practitioners. Figure 1 provides an overview of the research space where the current master's thesis intends to fit. Quadrant I is where most of the research articles fit, while quadrants II and III are sparsely covered. Quadrant IV, with only two articles on the development of AIMM for the public sector – but no evidence on their testing - is where this master's thesis aims. This lack of research on the utility and usability of designated AIMM-s for public organisations is what makes the problem relevant and motivates to undertake current research.

	For Private Sector	For Public Sector
AIMM is developed and validated	I	II
AIMM is ready to be deployed for self-assessment	III	IV

Figure 1. Research gap in studying public sector AIMM-s

1.5 Thesis Objectives

Since the author intends to develop a practically applicable self-assessment tool for public sector AI maturity assessment, there will be a need to test the AIMM in public organisations as a maturity assessment. To narrow the scope of this work for the master's thesis, the focus will be on developing further the AIMM designed by Dreyling et al. (2024) by developing a Self-Assessment Methodology (hereafter the Methodology) for the application of the AIMM in public organisations along with the Web-Based Tool (hereafter the Tool) for collecting information required for the assessment. As noted by Schuster, Waidelich, and Voltz (2021), developing a concrete and easy to use methodology for AIMM assessment [so that companies can measure current state and developments] is an important step.

The objective of this thesis is hence to develop a complete toolkit for the application of AIMM prototype in practice and evaluate its validity. The updated AIMM originally developed by Dreyling et al. (2024), the Methodology and the Tool will all be tested through this exercise either by the experts and/or by the staff of a public organisation who go through the self-assessment exercise as a pilot. This will allow to evaluate the problem adequacy, comprehensiveness and consistency of the AIMM, usability of the Tool and usefulness of the Methodology, based on which all three components may need to be refined (on evaluation, see Chapter 4), or validated. Figure 2 captures the elements of this study where solid arrows indicate who provides feedback for which component[1].

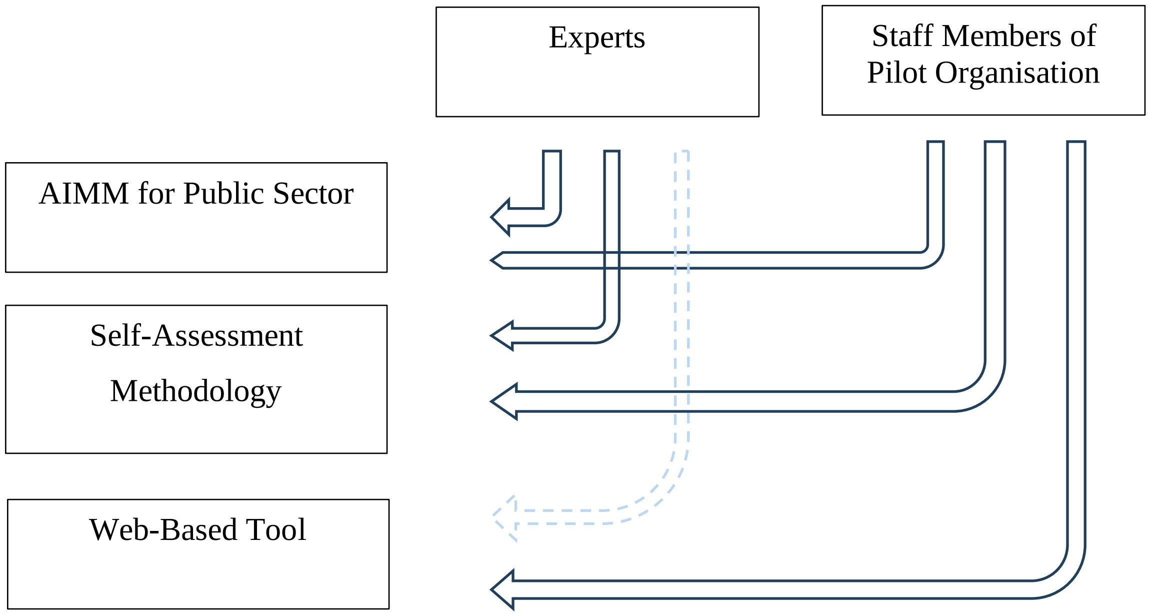

Figure 2. Assessing the Artificial Intelligence Maturity Model

1.6 Research Questions

Based on the research gap, problem definition, and the objectives of the study, the research question (RQ) is:

> **RQ**: How to create an AIMM for public organisations that they can use for self-assessing their AI capabilities?

To answer this question, three research sub-questions (RSQs) were formulated:

> **RSQ-1:** How to design the tools for facilitating the application of the AIMM?

> **RSQ-2:** How useful will be the AI maturity assessment to the public organisations, based on experience from using the AIMM prototype as a self-assessment tool?

[1] The blue dashed line indicates that experts also use the Tool, but no feedback is solicited on its usability.

RSQ-3: What is the contribution of testing the AIMM prototype to DSR?

The methodology to be applied to answer these questions is explained in Chapter 3.

1.7 Thesis Structure

The remaining parts of this thesis will be as follows: Chapter 2 establishes the theoretical background of the research starting from the definition of AI and presents key theoretical frameworks relevant for the study; Chapter 3 presents the research methodology, based on Design Science Research and relying on the procedure of Becker, Knackstedt, and Pöppelbuß (2009) on developing the MM-s; Chapter 4 is about designing and testing the AIMM and other artefacts with experts and a public organisation Statistics Estonia. Chapter 5 focuses on the results considering the research questions and acknowledges the limitations of this research. Lastly, Chapter 6 concludes this research and discusses future research opportunities.

2 Theoretical Background

This chapter will look more closely at the literature relevant to current research. It presents theoretical underpinnings that are relevant for understanding why the adoption of AI in the public sector is difficult and what would be the role of the AIMM in facilitating the development of organisational AI capability. Moreover, it is important to understand what the benefits of the AIMM are and how it should be designed and presented to public organisations to make it useful for them. Finally, it is relevant to look at how can the diffusion of this instrument in the public sector be supported.

2.1 Defining AI

To understand what the application domain of the AIMM is, there is a need to define AI. Tangi et al. (2022) define AI as "a special form of IT systems, applications or software that can perform tasks that normally need human intelligence". Kaplan and Haenlein add the element of purposefulness by defining AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019).

AI as a term is not universally agreed upon either in literature or in practice (Collins et al, 2021; Lemmik and Lauk, 2024) because the term 'intelligence' changes over time. For example, it is suggested that because of a much-improved understanding of non-specified information processing methods, there is a good chance that these will soon be considered non-AI and rather statistics or probability theory (MinnaLearn and University of Helsinki, 2024). In 2023, OECD countries jointly refined the definition of 'AI system' that they had agreed on in 2018, which now reads (subtractions with strikethrough, additions in bold) (Grobelnik, Perset and Russell, 2024):

> *An AI system is a machine-based system that ~~can~~, for ~~a given set of human-defined~~* ***explicit or implicit*** *objectives,* ***infers, from the input it receives, how to generate outputs such as*** *~~makes~~ predictions,* ***content****, recommendations, or decisions* ***that can*** *influenc~~eing~~* ***physical*** *~~real~~ or virtual environments.* ***Different*** *AI systems ~~are~~*

~~designed to operate with~~ varying~~ing~~ ***in their*** *levels of autonomy* ***and adaptiveness after deployment****.*

According to the proposed EC AI Act (Regulation 2021/0106), "Artificial intelligence system means software that is developed with one or more of the techniques and approaches listed in Annex I and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing environments that they interact with". Annex I enlists the following techniques and approaches: Machine learning, logic- and knowledge-based approaches, and statistical approaches (*ibid.)*. The JRC (Samoili et al., 2021) provides an AI taxonomy that is universal for the public sector and private sector alike, consisting of four main categories: learning, communication, reasoning, and perception. This framework will be useful for public organisations when they categorise their IT-tools either as AI or not.

AI Classification	**AI Classification Subdomain**
Learning	Machine learning
Communication	Natural language processing
Reasoning	Automated reasoning, knowledge presentation
Perception	Computer vision, audio processing, connected and automated, optimisation, planning and scheduling, robotics and automation, searching

Table 1. AI taxonomy (Samoili et al., 2021)

One of the crucial differences between AI and non-AI technology is that the former learns to make decisions based on incoming data, rather than being based on an explicitly defined set of rules (Crowston and Bolici, 2019). This self-adaptive property allows AI to learn from user behaviour, react to its environment, and make complex decisions automatically (Pumplun, Tauchert, and Heidt, 2019). Similarly to this and the renewed OECD definition referred to above, Elements of AI course suggests two criteria which are required for AI: a) autonomy which is seen as a capability to solve tasks in a complex environment without constant supervision from a user, and b) adaptability, which is an ability to improve performance through learning from experience (MinnaLearn and University of Helsinki, 2024). This elusive nature of AI makes it difficult to be certain if an application a public organisation has developed or is developing belongs to the category of AI, but the combination of recognition of domains and the criteria of autonomy and adaptability help in making that judgement. The elusive nature of AI also implies that no AIMM can exist without the need to be revised over time, based on the evolving understanding of AI.

2.2 Setting the Context for Studying AI in Organisations

There is a lack of theoretical foundation and documentation in most of the AIMM-s and the relations between an AIMM and organisational capability is unclear (Andrews et al., 2019). As Alsheiabni, Cheung and Messom (2019) state, to their knowledge, no fully developed and theoretically derived AIMM currently exists.

2.2.1 Technological-Organisational-Environmental Framework

One helpful framework to study specific characteristics of AI initiatives is the technological-organisational-environmental (TOE) framework designed by Pumplun, Tauchert, and Heidt (2019). TOE framework has been around for much longer than AI and it has been applied to studying technology adoption for a long time (e.g. Tornatzky, Fleischer, and Chakrabarti, 1990). According to DePietro, Wiarda, and Fleischer (1990) it comprises three elements that influence the adoption process of technological innovations: a) the technological context describing the internal and external relevant technologies available, b) the organisational context that depends on internal structures and processes measured by various factors such as company size and free resources, and c) the environmental context, which describes the business-related field of action, taking into account industry, competitors, government, and suppliers. An analysis of these contexts helps to identify both constraints and opportunities for the adoption of a technological innovation and is therefore relevant for the assessment of readiness to adopt a new technology. The TOE framework has been applied in several domains and disciplines, including IS research, proving its theoretical significance in the analysis of readiness, adoption and innovation deployment (Hoti, 2015). The following table by Hoti (*ibid.*) provides an overview of the fundamental factors that influence technological innovation adoption in small and medium enterprises based on the literature review.

Technological	
1. Relative advantage	The degree to which an innovation is perceived as being better than the idea it supersedes
2. Compatibility	The degree to which an innovation is perceived as consistent with existing values, past experiences and adopter needs
3. Complexity	The degree to which an innovation is perceived as relatively difficult to understand and use
Organisational	
1. Top management support	Support of the top management (CIO) to the IS adoption initiative
2. Organisational readiness (size) cost/financial and technical resources	Compared to large businesses, small businesses face resource poverty and thus difficulties in innovation adoption. Resource poverty manifests itself also in financial constraints and lack of professional expertise
3. Information intensity and product characteristics	The degree to which information is present in product or service of a business, reflects the level of information intensity of that product or service
4. Managerial time	Time required to plan and implement the new IS
Environmental	

1. Industry pressure (competition)	Competition and high rivalry increase the likelihood of innovation adoption to gain competitive advantage
2. Government pressure/support	Government strategies or initiatives that encourage SMEs to adopt new IS.
3. Consumer readiness	Lack of consumer readiness influences the adoption process and is an inhibitor towards IS use

Table 2. Identified elements of the TOE framework (Source: Hoti, 2015)

For developing an AIMM, technological and organisational factors are very relevant for considering the design of the model, while the environmental factors may play less of a role as external to the organisation factors. Pumplun, Tauchert, and Heidt (2019) took a general TOE framework and tested it with experts to create an AI-specific TOE framework. Their result was an extended and deepened framework for AI adoption. Several new factors were added, or existing ones detailed to take into account AI-specific context. The updated TOE framework is presented below.

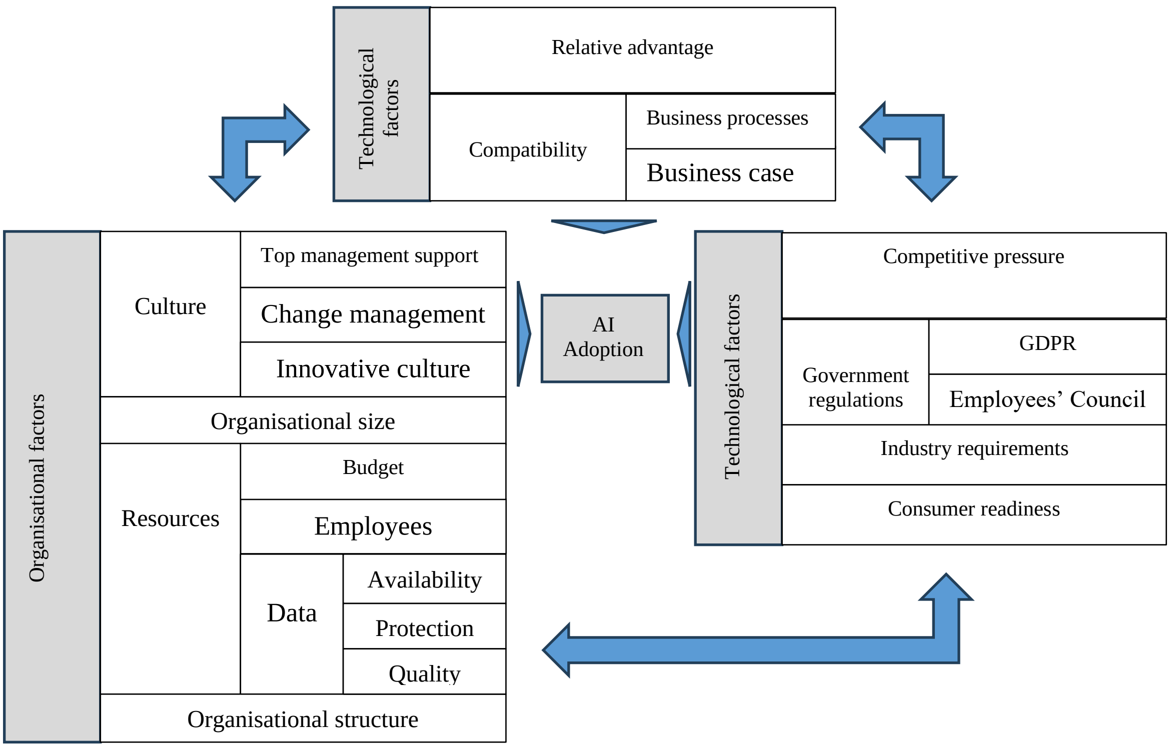

Figure 3. Extended and deepened framework for AI adoption (Pumplun et al., 2019)

The authors, based on the analysis of interviews, came up with 12 propositions, mapping out the effect of factors (either positive or negative) on AI adoption. All five propositions postulated under the technological and organisational factors appear relevant also for the public sector (Pumplun, Tauchert, and Heidt, 2019):

- A dedicated AI budget, which does not entail any obligations to meet performance targets, will have a positive impact on the adoption of AI in companies.
- The availability of data scientists and developers with appropriate expertise, domain knowledge as well as the willingness of users to train AI systems over time will have a positive impact on the adoption of AI in companies.
- The availability of extensive, meaningful, and high-quality data will have a positive impact on the adoption of AI in companies.
- Departments who keep relevant data to themselves, an overreliance on status quo as well as slow and bureaucratically shaped corporate structures will have a negative impact on the adoption of AI in companies.
- Compatibility between AI technology and business processes (e.g., agile forms of work) as well as the development of business case will have a positive impact on the adoption of AI in companies.

First three propositions can be easily detected in the AIMM model developed by Dreyling et al. (2024) as they involve a resource dimension. The other two are not so straightforward and would have to be built into the model through the design of maturity level descriptions.

Environmental factors are less directly applicable because of different contexts of the operating environment of private and public sectors, but also there are elements (such as the proposition "Strict laws regarding the processing of personal data will hamper the training of intelligent machines /…/ and inhibit the introduction of new technologies, which will have a negative effect on the adoption of AI in companies" (Pumplun, Tauchert, and Heidt, 2019)) which apply to public organisations. Overall, the study was intended as a starting point to test the power of factors which enable or impede AI adoption in general, and future studies could investigate or compare specific industries (*ibid.*), or sectors.

Neumann, Guirguis, and Steiner (2019) used this framework to study specifically what technological, organisational, and environmental factors facilitate or hamper the adoption of projects involving AI technologies in public organisations through a multiple case study design and assigned maturity levels to specific AI initiatives. Their theoretical contribution was an expanded TOE framework specific to the public sector AI adoption context, and their practical contribution was a more nuanced insight by capturing shifts in the importance of various factors of the TOE framework across different levels of experience with AI technology in public organisations (*ibid.*).

While the TOE framework provides a useful starting point for constructing an AIMM based on the mapping of relevant antecedents for AI adoption, its fundamental flaw is a difference in the application context–AIMM is not intended to be applied to organisations which are seeking to deploy their first AI solution but on those which are seeking for a balanced approach to AI capacity building. Hence, some factors, such as top management support, availability of qualified staff or innovation supportive organisation culture – all critical for initiating a first AI project – overlap between novice and experienced organisations, but an AI maturing organisation needs to look beyond those factors. For example, Janssen and Kuk (2016) discussed the limitations and challenges of AI in governance, arguing that autonomous algorithms lead to issues with accountability, bias, and discrimination. Kernaghan (2014) recommended the development of an ethics regime for robot applications in public organisations and suggested the need for regulation. These and other factors come into play when the organisation has launched its first AI solution and needs to increasingly think of governance issues that help to mitigate risks and put the development of AI solutions on a more systematic, transparent, and sustainable path.

2.2.2 Resource-Based Theory Used for Constructing AI Capability

Another theoretical framework for explaining how the resources that an organisation owns or has under its control can lead to differences in performance in the same industry (Barney, 2001) is the resource-based theory (RBT). Resources can be defined as tradable and non-specific firm assets, and capabilities as non-tradable firm-specific abilities to integrate, deploy, and utilize resources within the firm (Amit and Schoemaker, 1993). Resources represent the input to the production process, while a capability is the potential to use these resources to improve performance outcomes (Mikalef et al., 2020). The theory assumes that there is a dependency relationship between the firm's resources and its capabilities. In the knowledge-based view of the firm, it is important how organisations can use, combine, and integrate those resources as organisational capabilities to achieve certain outcomes (Dosi, Nelson and Winter, 2000). How to combine these resources is subject to a series of strategic management-level decisions. While the initial theory related both resources and capabilities to the external environment (such as market competition and rent-seeking), the dependency relationship itself is internal to the firm. Therefore, the theory applies also to public organisations.

The RBT has been a central theoretical perspective in researching how ICT investments produce value and enable firms to attain performance gains (Wade and Hulland, 2004). They suggest that the RBT can provide benefits to the IS community as, 1) the RBT provides the foundation for specifying firm-level resources, 2) it allows for distinctions between cross-functional, as well as technical and non-technical firm-level resources, and 3) it enables researchers to systematically test the relationship between the aggregate of resources into capabilities, with key performance outcomes (*ibid.*). Mikalef and Gupta (2021) apply this framework to a study of AI capabilities by identifying the necessary organisational resources that will enable firms to develop these capabilities. They define AI capability as a firm's ability to structure, bundle, and leverage its AI-based resources (*ibid.*). They apply the typology of resources by Grant (1991) who distinguishes between tangible (such as physical and financial resources), human skills (such as knowledge and competencies of employees) and intangible resources (such as cooperation, partnerships, synergy) (Mikalef and Gupta, 2021). The authors then constructed sub-domains of each of these three categories (presented in the table below), based on literature on digital capabilities, business reports and expert interviews, and identified a large list of factors relevant for AI capability, of which important ones emerged (*ibid.*).

Resource Type	Tangible	Human skills	Intangible
Category	Data, technology, basic resources	Technical skills, business skills	Inter-departmental co-ordination, organisational

			change capacity, risk proclivity
Example statements	The AI initiatives are adequately funded We have the capability to share our data across business units and organisational boundaries	We hire data scientists who have the AI skills needed Our managers have a good sense of where to apply AI	We recognise the need to manage change We have a strong proclivity for high-risk projects

Table 3. Categories of AI resources and what they mean. From Mikalef and Gupta (2021)

The authors tested this theoretical construct empirically having C-level technology managers responding to their survey, to explain what resources organisations need to develop to realize business value form their AI investments.

Tapping into the RBT, in another study, Weber et al. (2022) looked at specific capabilities that organisations should develop for AI implementation but arrived at a very different view compared to Mikalef and Gupta (2021). They identified the research gap in a lack of understanding of how certain capabilities facilitate AI implementation by coping with AI's unique characteristics, explaining why those capabilities are needed in the context of AI (*ibid.*). In IS research, there is a twofold relationship between the IT and organisational capabilities: IT use enables organisational capabilities, such as big data analytics capability (Günther et al., 2017). On the other hand, organisational capabilities are needed to make the best use of IT, such as IS development capability (Ravichandran, Lertwongsatien, and Lertwongsatien, 2015). Weber et al. (2022) look at the latter relationship. They mapped relevant organisational capabilities identified in IS research, such as IS development, IS planning and change management, data analytics and data management and organisational resources as organisational factors for AI implementation (*ibid.*). They created three categories of organisational resources, broadly similar to Mikalef and Gupta (2021), and provided descriptions of each resource, resulting in the table below:

Category	Resource	Description
Human Resources	Technical AI skills	Technical skills to develop, deploy and operate AI systems.
	Domain AI skills	Domain skills to support use case selection, AI systems evaluation, and business translation.
	Workforce AI skills	Skills to work with and maintain AI systems in productive use.
IT resources	Data	Data in enough quantity and quality for AI development.
	AI-specific infrastructure	Availability of AI-specific infrastructure (e.g., tools, frameworks, AI engines).
	IT infrastructure	Compatibility of existing IT infrastructure with AI systems.
Intangible resources	AI-business relationship	The relationship between business and AI departments.
	Sourcing relationship	The relationship with external AI solutions and service providers.
	Culture	Collaborative, experimental, and data-driven culture.

Table 4. Organisational resources as organisational factors for AI implementation (Weber et al., 2022)

Through 25 explorative interviews with experts on AI implementation, the authors identified four organisational capabilities that facilitate AI implementation: AI Project Planning, Co-Development of AI systems, Data Management, and AI Model Lifecycle Management (Weber et al., 2022). The authors went on to describe the manifestations of organisational capability in practice, which help to draw out the essence of each of the mentioned capabilities.

This study is pertinent to the development of AIMM in two ways. First, it helps to understand what are the key factors that practitioners highlighted as critical to successful implementation of AI. Through that lens, various familiar concepts from the AIMM-s emerged, most notably data management, and AI model lifecycle management, seen as the ability to manage the evolution of AI models through its various stages, such as development, deployment, and maintenance. Capability such as AI project planning relates to the need to identify suitable use cases that are feasible and deliver added value to the business, which if conceptualised as AI project management is also part of the AIMM-s. As a somewhat new topic, co-development of AI systems highlights the ability to communicate with and integrate stakeholders into AI implementation (Weber et al., 2022). This refers to the need to integrate diverse expertise into AI implementation, such as data scientists, AI experts, domain experts, IT security, end users, and ethics experts, but also the involvement of workforce into the AI development from the very beginning to increase buy-in and decrease resistance (change management). Second, the study is also important for helping to recognise that not all categories of capabilities can be neatly classified into one or the other AIMM dimension or codified into a maturity progression. “Developing an understanding of AI” as part of the AI project planning capability or “Operating AI systems in productive use” as part of the AI model lifecycle management are examples of manifestations in practice that transcend typical AIMM dimension borders. Overall, this study provides some valuable insights without giving a blueprint to constructing an AIMM.

These two studies illustrate that RBT can be used as a theoretical framework for constructing capability frameworks. For the context of constructing an AIMM, it systematically covers resources required for leveraging AI capabilities and allows for the construction of non-tangible resource dimensions, which usually are the key for creating competitive advantage to companies. However, for the purpose of constructing an AIMM, the intangibles, such as data protection and ethics that should be considered in an AIMM (Schuster, Waidelich, and Voltz, 2021), are difficult to construct as resources, because they rather become part of the AI governance framework. Therefore, the RBT can only partially account for the factors that contribute to a comprehensive AIMM.

Second limitation of the RBT in the context of developing AIMM is that the model does not distinguish between the quality of resources that build up AI capability. This is particularly relevant for understanding maturity stages in which the organisations apply AI and, therefore, what are the qualitative differences in the combination of resources that lead to these different maturity levels. Using a public sector analogue, van Noordt and Tangi (2023) concluded through their research that there is an apparent distinction between the AI capability to develop and the AI capability to implement AI technologies. A more nuanced view on what distinguishes an organisation at two adjacent maturity levels regarding any of the resource-related dimensions of an AIMM (such as Data, Technology, or Organisation) will need to be established otherwise.

What can be concluded from the study of the two theories above, the TOE framework and RBT is that they both allow for mapping out contributing factors to the successful implementation of AI. Perhaps the least conceptually developed of the resources in RBT, particularly for the public sector, is the category of non-tangible assets. For example, van Noordt and Tangi (2023) mention co-creation between domain experts and data scientists, internal cooperation between the IT and business departments, external collaboration for data sharing and summing computational resources, and post-development collaboration as critical AI capabilities. Hence, the TOE framework and RBT fall short of allowing to grasp a full landscape of factors which will support not just the launch of successful AI initiatives, but the successful implementation and governing of AI systems.

2.3 Constructing AIMM for the Public Sector from the Public Value Perspective

A complementary theoretical framework helping to construct an AIMM for public sector organisations lies in the public value perspective (PVP). Moore (1995) created an organisational value model that sees the government as an active shaper of the public sphere. He highlights three elements of value (the so-called strategic triangle): the operational capabilities which are supported by legitimacy and support to the organisation from its environment which lead to the creation of public value – the benefits and outcomes delivered to the users or the society at large (*ibid.*). The model is widely applied in the public sphere context, both to public and non-governmental organisations.

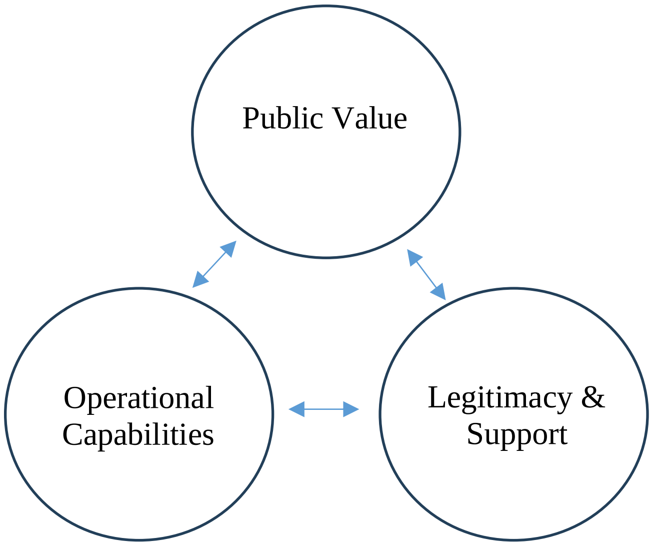

Figure 4. The Strategic Triangle (Moore, 1995)

PVP provides a conceptual framework within which competing values and interests can be expressed and debated, in a deliberative democratic process, by which the question of what constitutes value is established dialectically (Benington, 2011). In other words, public value is what emerges through discussions in the public, but 'the public' is not given but actively shaped by the organisation. Consequently, an important element of the PVP is that rather than passively following the dictates of elected officials and meeting the given responsibilities dictated by legislation and policies, public managers need to use their ingenuity, creativity and expertise (Williams and Shearer, 2011) in exploring new opportunities in public-value creation (Pang, Lee, and DeLone, 2014).

This empowerment of public managers translates also into the organisational capability. According to Benington and Moore (2011), operational capabilities relate to the harnessing and mobilising resources both within and outside the organisation. This is similar to how the relationship between resources and capabilities is constructed in the RBT. In innovation capability perspective, the organisational capability relates to how to spot, develop, test, use and integrate innovations into the organisation (Bekkers, Edelenbos and Steijn, 2011). Pang, Lee, and DeLone (2014) have explored how public sector IT resources are turned into public sector organisational capabilities, which in turn lead to value creation, however itself always pluralistic in nature – competing values, such as ensuring public safety or national security vs individual liberty or privacy.

Finally, legitimacy and support are about creating an 'authorising environment' that builds a coalition of stakeholders from the public sector (such as political leadership), the private sector, and the community whose support is needed to sustain action (Bromell, 2012). According to Madan and Ashok (2023), legitimacy and support for AI come from the political leadership and central governments pursuing digital transformation agendas. Indeed, the governments consider AI as a crucial component of digital transformation, leading to AI strategies in at least 26 European countries (van Noordt, Medaglia, and Tangi, 2023).

The strategic triangle indicates that each of the elements support each other. For example, when managers firm up the legitimacy and support perspective, they make it easier to get resources for their organisation.

What is relevant from this theoretical perspective for the construction and evaluation of AIMM for the public sector is the notion of what constitutes legitimacy for a public organisation engaged in the development and implementation of AI. Molinari et al. (2021) identify three types of challenges to government legitimacy by AI adoption:

1. Challenges to input legitimacy. AI systems require developers to make political choices that may be difficult to detect or correct at a later stage (Mulligan and Bamberger, 2019). For example, it is widely acknowledged that marginalised groups risk being insufficiently involved or represented in digital transformation processes, leading to biases and false conclusions (Giest and Samuels, 2020).

2. Challenges to throughput legitimacy. This happens when government decisions become increasingly more difficult to scrutinize or explain (Burrell, 2016). It can greatly diminish citizen trust in public administration (Molinari et al., 2021). There is a risk that during the development or the deployment of AI, some laws get broken due to data collection practices, unwarranted data sharing or the infringement of citizens privacy rights (Meijer and Thaens, 2020). Furthermore,

unforeseen security risks, such as leaking of personal information due to insufficient security measures in the information systems also belong here (*ibid.*).

3. Challenges to output legitimacy. It may happen when the AI systems do not function as good as expected. This may be due to bias in data, or a vastly more complex social settings compared to controlled testing environments (Bailey and Barley, 2019). A risk is also that the AI systems may not vastly improve predictive accuracy compared to less complex and more transparent techniques, such as regression analysis with a few variables (Salganik et al., 2020). Finally, the development and governance of AI systems may require significant organisational resources which may significantly reduce the effectiveness initially expected when performing the cost-benefit calculation (Molinari et al., 2021).

A common thread to these challenges is the issue of ethics. AI may pose risks to individuals, organisations, and society as a whole by infringing core public values, such as transparency, fairness, and equity (e.g. Mergel et al., 2023). Furthermore, AI can result in undesirable and ethically problematic specific consequences, such as breaches of privacy and security and biases and discrimination in public service delivery, which may result for example in a lack of access to public services by vulnerable and marginalised communities (Stahl, 2021).

As Morley et al. (2020) state, the AI scholars need to translate the largely agreed AI principles to the ‘what’ and ‘how’ of implementation. The challenging aspects have to be captured through the AIMM for public organisations ensuring that proper attention is paid to progressively more demanding requirements through the description of maturity stages. Since maturity models work as a strategic management instrument which help to make strategic level decisions on what kind of changes are required to advance the organisation in producing greater value, operationalising these aspects in an instrumental manner is crucial, particularly from the descriptive and prescriptive point of view. According to Pöppelbuß and Röglinger (2011), there are three kinds of MMs: descriptive (examining the status of capabilities through current characteristics), prescriptive (providing guidelines and measures) and comparative models (providing organisations with the opportunities to benchmark). Sadiq et al. (2021) provide the following explanation of the three models. The descriptive approach is used to evaluate the current situation of a domain as it is, such as in the case of self-assessing an organisation. The prescriptive approach is used to give a roadmap or vision to improve the AI in an organization, which is the case when improvement areas are identified as a result of self-assessment. Finally, the comparative approach provides a comparison within the same organization over time or among a series of organisations when assessment results are made available outside of the organisation (*ibid.*).

The RBT and the TOE frameworks serve as ground theories helpful for understanding the link between AI-based resources and AI capabilities, while the PVP proves useful for explaining the factors relevant for the AIMM for public organisations that relate to the linkages between operational capabilities, legitimacy and support, and the public value created. These theories get exploited relatively frequently in AI capability context and will be helpful in understanding what dimensions of an AIMM can be postulated through resource perspective and which relate to legitimacy aspects crucial for operating in the public domain.

2.4 Diffusing the AIMM in the public sector

Diffusion of innovations is a concept developed by Rogers in 1962 that explains the process in which people or organisations react to innovation by adopting it over time (Rogers, 2003). Innovations can be defined as "the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations (OECD and Eurostat, 2005). From a e-governance policy perspective, AIMM can be considered an innovation which aims to improve the functioning of public organisations, but in order to do that, it needs to be recognised, endorsed and diffused in the public sector. In Becker's, Knackstedt's, and Pöppelbuß's (2009) DSR model, it belongs to Step 5 where different transfer media are used to make it happen (see Section 3.3).

The stages by which an organisation adopts an innovation, and whereby diffusion is accomplished, include awareness of the need for an innovation, decision to adopt the innovation, initial use of the innovation to test it, and continued use of the innovation (LaMorte, n.d.). The DOI theory suggests that potential adopters might not adopt innovation directly until it gains momentum and then diffuses through the population over time (Elmghaamez et al., 2022. Rogers (2003) suggests that the diffusion of innovation process often looks like a normal distribution curve divided into five stages.

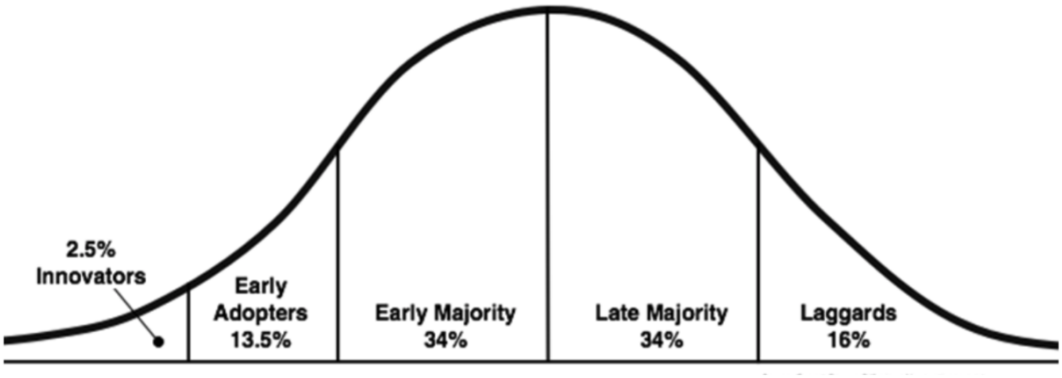

Figure 5. Distribution of adopters of innovation based on the time of adoption. Source: Rogers, 2003.

The innovators are the ones to adopt the innovation due to excitement and novelty. The second group, the early adopters, are keen on utilising the innovation's perceived benefits. Early and late majorities are distinguished by the former requiring evidence that the innovation works before joining in while the latter are naturally sceptical of change and will only adopt the innovation after the majority has tried it. Finally, the laggards are both sceptical of change, but also bound by conservatism. According to Rogers (2003), five main factors influence the adoption of an innovation, and each of these factors is at play to a different extent in the five adopter categories: 1) relative advantage denotes the degree to which an innovation is seen as better than the idea, programme or product that it replaces; 2) compatibility is about how consistent the innovation is with the values, experiences and needs of potential adopters; 3) complexity refers to the difficulty of the innovation to understand or use; 4) triability relates to the extent to which the innovation can be tested or experimented with before a commitment to adopt is made; and 5) observability relates to the extent to which the innovation provides tangible results. These factors will be analysed in the context of the use of AIMM for public organisations in Chapter 4. Note that Hoti (2015) has used three first factors in his TOE framework, hence combining the two theories (Table 3 above).

The essence of DOI theory in the context of AIMM for public organisations is that to spread the use of the model, there are two consecutive strategies. First, by identifying the natural innovators to try out the model on their own organisation allows to gain valuable experience from testing the model and finetuning or upgrading it to represent the best fit considering the experiences of public organisations. Second, after sufficient testing, the MEAC of Estonia could make it part of their policy toolkit and present it as one of the possibilities to consolidate the AI development efforts in public agencies. In the context of the Estonian public sector where the number of AI users is approximately 60 (MEAC, 2024), this is the 'market' for this tool to be promoted as part of the Ministry's continuous support to state agencies for their development of AI solutions.

3 Research Methodology

3.1 Design Science Research

Based on the objective of developing a self-assessment methodology (the Methodology) and the web-based tool in the context of designing and evaluating an AIMM, design science-oriented research methodology has been selected for this master's thesis. Design science research methodology is widely used in information systems research (Recker, 2012; Baskerville et al., 2018). Design science is of importance in a discipline oriented to the creation of successful artifacts (Peffers et al., 2014). Design – the purposeful organisation of resources to accomplish a goal (Boland, 2002) – is both a process (set of activities) and a product (artifact) (Walls et al., 1992). It seeks to create innovations that define the ideas, practices, technical capabilities, and products through which the analysis, design, implementation, management and use of information systems can be effectively and efficiently accomplished (Denning 1997). Artifacts to be created for this master's thesis are the self-assessment methodology and the web-based tool, relying on the AIMM by Dreyling et al. (2024).

AIMM is an artifact of information systems (ISs) because the realm of IS research is at the confluence of people, organisations, and technology (Davis and Olson 1985; Hevner, 2007). Extending it from there, also the artifacts to be created, the Methodology and the web-based tool, are part of the same process of designing and applying an AIMM. They share the goal of providing public organisations a toolset for assessing their AI capability.

According to Hevner et al. (2004), IT artifacts are broadly defined as constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems). The artifacts to be created by this design fall into the category of methods, but also contribute an instantiation in the form of applied AIMM. Instantiations show that constructs, models, or methods can be implemented in a working system. They demonstrate feasibility, enabling concrete assessment of an artifact's suitability to its intended purpose (*ibid*.).

Working system in this case is a public organisation setting. Evaluation of all the three artifacts as presented on Figure 2 is an important component of the research.

3.2 Design Science Research Framework

Hevner (2007) constructed three cycles of activities embodying the design science research. The Relevance Cycle identifies a problem, or opportunity, that is identified in an environment such as an organisation, consisting of people and organisational and technical systems. For this research, the problem was identified as a lack of a self-assessment tool for public organisations to learn about an organisation's AI capabilities and the areas in need for improvement. Relevance Cycle initiates design science research to address the problem or respond to an opportunity. It also defines acceptance criteria for the ultimate evaluation of the research results, i.e., how does the design artifact improve the environment and how can we measure it (*ibid.*). This cycle is relevant for RSQ-1 related to the design of the tools for facilitating the application of the AIMM as well as for RSQ-2 related to the criterion of usefulness of the AI maturity assessment based on the proposed AIMM. The Rigour Cycle provides grounding theories and methods along with domain experience and expertise from the foundations knowledge base (KB) and adds the new knowledge generated by the research to that KB (*ibid.).* What Hevner et al. (2004) consider important is the fact that designs produced are also research contributions and not routine designs based upon the application of well-known processes (otherwise they would not be design science but just the practice of building IT artifacts (Iivari, 2007)). This cycle triggers RSQ-3 about the contribution that testing of the AIMM prototype may have to the DSR. Finally, during the performance of the Design Cycle it is important to maintain a balance between the efforts spent in constructing and evaluating the evolving design artifact (Hevner, 2007). This is what prototyping and testing is about: rapid design and evaluation in a cycle where a design will be changed based on learning from feedback (Penny, 2020). As Iivari (2007) notes, if information systems as design science overemphasizes scientific evaluation of artifacts, it risks being led to reactive research instead of building new artifacts. Keeping the need for the balancing act in mind, this cycle relates to all the evaluation episodes throughout the process of creating the AIMM prototype and the supporting tools, each episode contributing to the improvement through structured feedback.

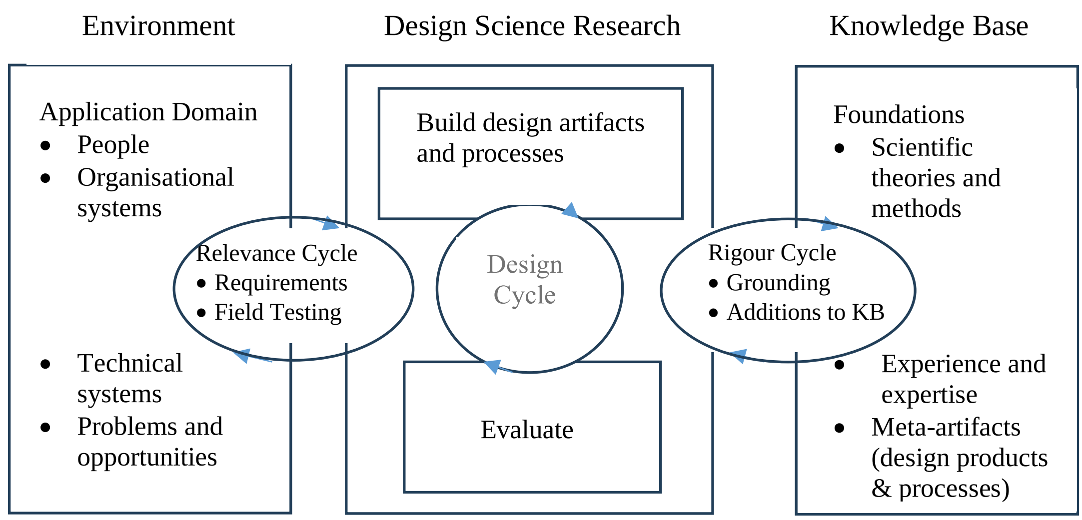

Figure 6. Design Science Research Cycles (Hevner, 2007)

This framework will be returned to in Part 4 of the thesis when interpreting results.

3.3 Procedure Model to Developing Maturity Models

Following the DSR paradigm, Becker, Knackstedt, and Pöppelbuß (2009) describe a procedure for the development of the MMs. The authors are relying on design science research guidelines developed by Hevner et al. (2004). These guidelines can be seen as the foundation of creating the artifacts and to developing a model with a sound theoretical foundation (Alsheiabni, Cheung and Messom, 2019).

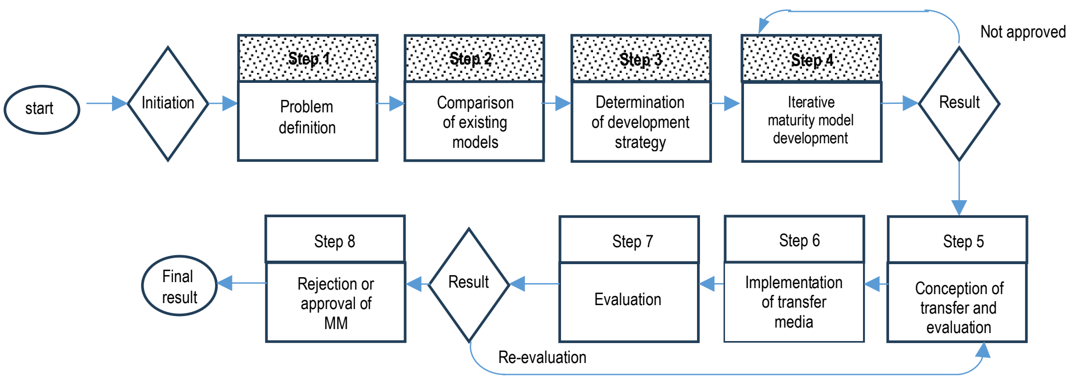

Figure 7. Procedure model for developing maturity models. Modified from Alsheiabni et al., 2019

Steps 1- 3 relate to the development of the AIMM as an artifact. Steps 1-3 are not to be covered in this master's theses as the AIMM by Dreyling et al. (2024) is used as the artifact which has been through these three phases. Parts of step 4 which are also part of Dreyling et al.'s work, are covered next.

Step 4 – Iterative MM development. This phase consists of four sub-stages, relying on Becker's, Knackstedt's, and Pöppelbuß's (2009) four sub-characteristic structures of the proposed new maturity model: design level, model approach, model selection and assessment. Prior to this author becoming engaged in this work, the AIMM for the public sector looked like on Figure 8, extended with initial descriptions of maturity levels. This author participated in the work of Dreyling et al. (2024) in sub-stages three and four, extending the initial descriptions of maturity levels at the cross-section of maturity levels and dimensions into more detailed descriptions of maturity levels used in the Tool for the self-assessment. Also, these initial descriptions were reviewed by experts before opening the Tool for the public organisation going through the self-assessment.

Step 5 – Conception of transfer and evaluation. In this phase, the different forms of result transfer for the academic and user communities need to be determined. In the context of current research, the self-assessment methodology and the web-based tool serve as the transfer media for the AIMM. Evaluation of the problem solution will be incorporated into the transfer design by collecting feedback from the users to all the three artifacts (see Figure 2). User groups will be differentiated by either being experts or members of a public organisation going through the assessment. If there were more than one organisation in the case study, members would also be differentiated by either belonging to a public organisation at a more advanced level of AI maturity or at a lesser level of AI maturity.

Step 6 – Implementation of transfer media. The purpose of this phase it to make the AIMM accessible in the planned fashion for all defined user groups (Becker, Knackstedt, and Pöppelbuß, 2009). Becker, Knackstedt, and Pöppelbuß (*ibid.*) also instruct that the presentation of the maturity model must be targeted with regard to the conditions of its application and the needs of its users (*ibid.*). Self-assessment questionnaire and reports would serve as transfer media (*ibid.)*. At this stage, the AIMM for public sector organisations will be made accessible by invitation. One such organisations goes through the self-assessment.

Step 7 – Evaluation. The purpose of evaluation is to establish whether the MM provides the projected benefits and an improved solution for the defined problem (*ibid.*). Case study whereby public organisations apply the AIMM in practice serve that purpose. Evaluation criteria for the AIMM proposed by Becker, Knackstedt, and Pöppelbuß (*ibid.*) are comprehensiveness, consistency and problem adequacy. Evaluation criteria for the other two artifacts are their usefulness and usability, the latter defined as "perceived usefulness by the users and perceived ease of use" (Jackson, 2020). Perceived usefulness, in turn, is defined as "the degree to which a person believes that using a system would enhance his or her job performance" (Davis, 1989). Finally, the entire process of operationalising the AIMM as a holistic experience is important, therefore the usefulness aspect of the self-assessment exercise will also be evaluated. This concurs with what Mettler and Rohner (2009) recognise in MM-s as they being "some-how in-between" models and methods as they combine state descriptions (*i.e., models* of distinct maturity levels) with activities (i.e., *methods* for conducting assessments, recognising need for action, and selecting improvement measures).

Step 8 - Decision on the rejection, refinement or approval of the AIMM. The outcome of the evaluation may lead to an approval of any of the three artifacts (the AIMM, the Methodology and the web-based tool), a reiteration of the design process, or rejection of any of the three or all the three together.

3.4 Data Collection

Data collection follows the research design laid out in previous section. First, a thorough literature review was carried out to establish the problem and its theoretical context, as well as the scientific and methodological approach to its solution. Second, semi-structured interviews with experts to validate the AIMM, the Methodology are aimed at. Experts with various backgrounds were approached to obtain multiple views from key stakeholders (for the list of expert profiles, see Appendix 2).

Experts were asked to answer five questions (see Appendix 3) related to the AIMM for public organisations. One expert responded in writing instead of an interview. The purpose of this activity was to evaluate the consistency, completeness, and coherence of the AIMM for validation purposes and to obtain suggestions for improving the Methodology prior to their deployment to a pilot public organisation.

Next, it was discussed and agreed with the director of the public organisation who participates in the pilot self-assessment, Statistics Estonia, which roles in the organisation would be most appropriate to engage (for the list of roles, see Appendix 4). Altogether, six individuals were identified to be included in the self-assessment. The web-based maturity assessment tool (MAT), which consists of a set of questions in each of the eight categories of the AIMM, accompanied with explanations from the Methodology, is asked to be used to carry out the individual self-assessment where besides choosing the best description associated with a level of maturity in the AIMM, supporting evidence is also asked for. After collecting, analysing, and synthesizing the information thus collected, a survey questionnaire to the participants who went through the exercise of self-assessment was sent out to collect qualitative feedback on the exercise, particularly on its usefulness, and usability of the AIMM, the Methodology and the web-based Tool. Questionnaire used is available in Appendix 5 and the Methodology in Appendix 6.

4 Designing and Testing the AIMM And Other Artifacts

Following the design layout from the previous chapter, as well as the evaluation scheme from Figure 2, this chapter is about presenting the process and the results against the set criteria.

4.1 Analysis of More Advanced AIMM-s

Dreyling et al. (2024) created the AIMM for the public sector which consists of eight dimensions and five maturity levels. For each of the levels, an initial statement of maturity level called ‘definition of level’ was developed (*ibid.)*. These statements allow to identify progress from lower to higher maturity levels along each dimension, but they are schematic in nature and do not provide sufficient level of detail for organisations to carry out self-assessment. The model at this stage is presented on Figure 8 below.

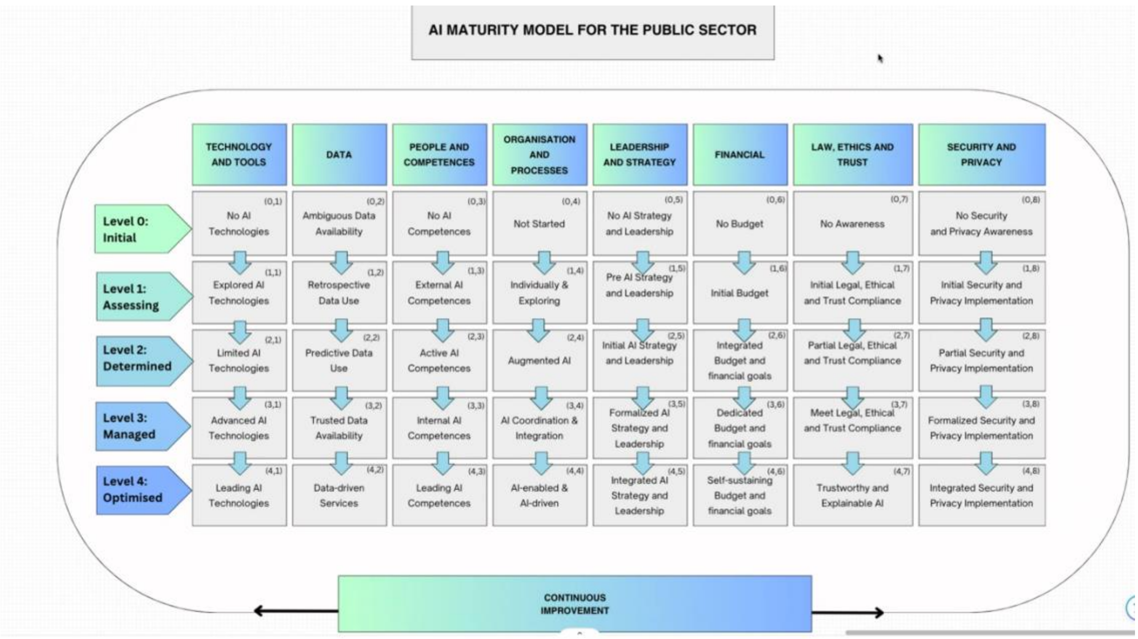

Figure 8. AI Maturity Model for the public sector (Dreyling et al., 2024)

This is where most AIMM-s available in academic literature stop. As Fukas et al. (2023) acknowledge, MMs mostly represent abstract systems that are difficult to apply directly in business practice. Notable exceptions are two models developed by Noymanee, Iewwongcharoen, and Theeramunkong (2022) for the public sector and Saari, Kuusisto, and Pirttikangas (2019) for businesses.

Noymanee, Iewwongcharoen, and Theeramunkong (2022) developed an AIMM for the public sector with four dimensions and five maturity levels. They have used literature review to draw up the model, although the literature is not public sector specific. Their contribution to the field is their attempt to describe in more detail an increasingly demanding and inclusive items at each maturity level under each dimension. These maturity statements in length go beyond those on Figure 8 above but seem inconsistent and insufficient to cover the most relevant aspects under each dimension at every maturity level. No information is provided as to how these statements were constructed, nor on if they were tested and validated. It can be concluded that the AIMM without further instructions is insufficient to guide organisations in self-assessment. Furthermore, the model does not exude pertinence to the public sector context despite its title.

Saari, Kuusisto, and Pirttikangas (2019) developed an AIMM with six dimensions and divided each dimension into two questions with five response alternatives, representing a progression of maturity levels where previous maturity level is a prerequisite for the next level. These prewritten responses are turned into response options in the web-based tool used for completing the self-assessment exercise. They also suggest that the self-assessment is followed with a report where the responses are translated into numerical values on the scale of 0-4 for each dimension which are then compared to the reference group and all organisations' averages. The authors suggest that this report is then used for identifying some preliminary development areas, followed by an AI maturity workshop resulting in a better and joint understanding of what development projects should be planned (*ibid.*). No supportive guidelines are provided to understand better the maturity level response options, nor is it explained how to undertake the self-assessment exercise in terms of the team composition, technical preparation for it or communication. Finally, no information is provided if and how the model was tested and validated before its launch in the public.

Like Noymanee, Iewwongcharoen, and Theeramunkong (2022), Dreyling et al. (2024) had created initial descriptions of maturity levels. The authors had experts validating the

AIMM at this point. Next, the MAT and the Methodology needed to be created, discussed in the sections below.

4.2 Designing the Maturity Assessment Tool

At least two web-based tools (one of them as a prototype), called by Fukas et al. (2023) Maturity Assessment Tools (MATs), have been designed for data collection for conducting organisational maturity self-assessment. Krivograd and Fettke (2012) have developed a list of requirements which a tool must fulfil for the application of maturity models. However, since in the current research the MAT itself is not a main artifact and it is used as a secondary artifact to test out the usefulness of the AIMM and the self-assessment process on one public organisation only, there is no need for a full set of requirements (e.g. user administration, management of versions, generation of reports, comparison between organisations).

Therefore, SurveySparrow tool, a web-based generic survey management instrument, was used for creating the assessment form. It consists of 25 questions, three under each dimension of the AIMM: 1) selection of the most suitable maturity level, presented in the order from the least mature on top to the most mature on the bottom, 2) request to add any evidence (such as decisions, initiatives, or documents) supporting the answer, and 3) request to upload any documents as supporting evidence, if available and applicable.

4.3 Developing the Methodological Guideline for Self-Assessment

As part of the thinking behind designing a usable AIMM for public organisations had usability at its forefront, the author decided to develop a Methodology to assist the participants in self-assessment. The purpose of the Methodology is to explain the AIMM, its dimensions and maturity progression logic, and the implementation of the AIMM process. The latter comprises three steps: 1) decide about the self-assessment and commit the resources, 2) carry out AI maturity self-assessment, and 3) devise an AI capability improvement plan. Intention was to keep the Methodology brief so that it would not discourage participants in the self-assessment exercise from consulting it.

There were no particular examples that served as the model for the Methodology, although two notable materials were of use: “The MITRE AI Maturity Model and

Organisational Assessment Tool Guide" (Bloedorn et al., 2023) that served as an inspiration for explaining the AIMM, and "CAF. The European model for improving public organisations through self-assessment" (EIPA, n.d.) that served as an inspiration for the process description. In addition, the author has participated throughout his professional career in creating numerous guidelines which helped to come up with a usable Methodology.

According to the definition by Becker, Knackstedt, and Pöppelbuß (2009), the Methodology at this stage also served as a transfer media for the AIMM since no face-to-face contact was likely to occur with the public organisation participating in the pilot self-assessment.

4.4 Extending the Maturity Level Descriptions

As discussed above, there is no agreed definition of, nor approach to developing maturity level descriptions that would be usable for the self-assessment. Also, the vocabulary for describing the elements relevant for these descriptions is non-standardised. Fraser, Moultrie and Gregory (2002) offer a useful take on what elements an MM consists of. In their terms, each maturity level description consists of a number of elements or activities for each dimension and possibly a description of each activity as it might be performed at each maturity level (*ibid.*). This is the set of components aimed at for a usable self-assessment tool, also visible in the model of Saari, Kuusisto, and Pirttikangas (2019) analysed above.

A useful example of an AIMM equipped with descriptions of items expected from an organisation at each maturity level, is offered in an organisational assessment tool guide developed by Bloedorn et al. (2022) for commercial purposes. The guide offers generic descriptions of each element as requirement for reaching the minimum threshold at each maturity level. Since their model comprises five MM maturity levels and covers six pillars (in other MM-s called dimensions), each with 3-4 dimensions as a sub-structure of pillars, the entire model covers in more detail the eight dimensions of the AIMM by Dreyling et al. (2024), although not all the elements are aligned between the two models. For example, 'Security and Privacy' is covered under 'Data' while in the model under development this is a separate dimension (Bloedorn et al, 2022). Nevertheless, analogous descriptions were created for the AIMM by Dreyling et al. (2024). Only one dimension, called 'Funding' in the latter model, had to be tailored for the use in the public sector where the funding principles, as well as the decision-making criteria over new investments are somewhat different from the private sector where return on investment is the key criterion (*ibid.*). An overview of the maturity level descriptions is provided in Appendix 7.

4.5 Testing the AIMM with Experts

The AIMM together with the MAT and the Methodology was then tested with four experts who have experience both in AI and the public sector, representing policy perspective, AI implementation perspective, and consultancy perspective (see Appendix 2 for the list of expert profiles). The experts were asked to use the MAT, after consulting the Methodology, for conducting a mock self-assessment based on the AIMM for public organisations. They were requested to pay attention to the ease of using the AIMM, particularly its dimensions and maturity level descriptions. After the use of the toolkit, the experts were requested to point out imminent deficiencies that would have to be eliminated before the deployment of the tools to the pilot public organisation. In addition, experts were requested to provide suggestions on the improvement possibilities of the AIMM. Three experts were contacted over the phone, one answered in writing. 60-minute interviews allowed for a reasonably thorough coverage to bring out most important points.

Feedback from the experts highlighted several useful points. First, the descriptions of maturity levels are quite long and therefore difficult to compare. Also, there is a possibility of dubious areas which require more guidance to deal with, such as in case when some data are labelled and some are not. Second, the model should capture the need for stakeholder engagement better. Third, the model should capture better AI development and AI maintenance, the latter being critical for a sustained successful application of AI. Forth, there should be more attention paid to the option of off-the-shelf AI solutions, because these are easy and cost-efficient to implement. Fifth, infrastructure should be more emphasized under 'Technology' component. Sixth, aiming at inter-organisational comparison may not work that well due to difficulties of calibrating the measurements with each other.

Since none of the topics was mentioned by more than one expert, nor was any of them considered critical, no changes were made to the model prior to launch in the pilot public organisation.

4.6 AI Maturity Self-Assessment Exercise in Statistics Estonia

4.6.1 Brief Introduction to Statistics Estonia

Statistics Estonia (SE) is a state institution which mission is to "be a reliable home for state data, give the data a meaning and value; help the people to understand and make sense of the world through data" (Statistics Estonia, n.d.). The institution intends to stand for the quality of data in the entire country and offer continuously relevant, trustworthy, and meaningful information (*ibid.*). Out of its 380 employees, ca 100 are involved in data processing, analysis or management (Lee, 2023). There is currently no data architecture yet but describing the data (meta data layer) is an ongoing initiative (*ibid.*).

According to the information on the *kratid.ee* website, SE has been involved in three AI projects: chatbot development with a private partner (2018, finished), creation of an enterprise vitality index and a tool (2022, partnering with the MEAC, ongoing), and designing a prototype for entrepreneur's early warning service (2022, partnering with the MEAC, ongoing) (MEAC, 2024). The Department of Experimental Statistics is the hub for everything AI. The Department uses different statistical methods, such as random forest, neural networks, and regression models in their work (Lee, 2023). They have also trained other departments in writing analysis code in R-language (*ibid.*).

Although SE has its own IT Manager, it gets its ICT support – ICT services development and management– from the IT Centre of the Ministry of Finance (MoF). A recent study looking at the ICT management model within the governance domain of the MoF found that the domain's business architecture management capability is rather low and that there is a lack of ICT competency centre capability (CheckIT, 2023). It means that there is no sufficient development support to the initiatives (such as developing AI models) that might involve anything beyond the existing IS-s.

Even more importantly, the use for the data collected by the state is limited to the purpose by which the right to the state has been granted by law. To use the same data for analysis which has not been specified by law, there is a need to anonymise the data or ask an individual for the consent (both for citizens and companies) (Lee, 2023). Currently, ca 260,000 citizens have agreed to be 'opted in' for the use of their data in such endeavours, but for machine learning purposes this means lack of data for training (*ibid.*).

4.6.2 Self-Evaluation Strategy in Statistics Estonia

When approaching a public organisation with a request to participate in the self-assessment process based on a prototype AIMM, combined with research tasks (such as providing feedback on the process) not relevant for the organisation, the most important consideration was to make it as little burdensome as possible to the organisation while still achieving the objective of obtaining the expected results. Therefore, it was suggested to assemble a small team of staff members of the organisation to cover the key roles relevant for AI application (see the list in Appendix 4). Also, no face-to-face contacts were envisaged due to busy schedules of the SE staff members, which made it more challenging to instruct the participants before the self-assessment exercise. A thorough written instruction was therefore sent via e-mail to all the participants and the Methodology was made available and strongly recommended to be read before conducting the exercise. Unfortunately, SurveySparrow survey instrument used for carrying out the self-evaluation does not allow to integrate hypertext or hover-over text into its surveys to make the access to explanations and use of terms better accessible.

4.6.3 Carrying out AI Maturity Self-Evaluation in Statistics Estonia

Self-evaluation exercise was carried out individually by the assigned staff members between 16 April and 4 May 2024. Out of five persons proposed by the Director General, a product manager turned out not to be engaged in the development of AI for her business needs, therefore this role was replaced with a data governance expert. Nevertheless, the person was interviewed to obtain more information about the

Five responses were received through SurveySparrow survey instrument. Information was transferred into MS Excel file where respondents were anonymised. The file will be used later to inform the Director General of the survey results. Based on the result, a summary figure was drawn up, representing average scores per dimension, as well as minimum and maximum points (corresponding to maturity levels 1-5) to illustrate the spread between the two.

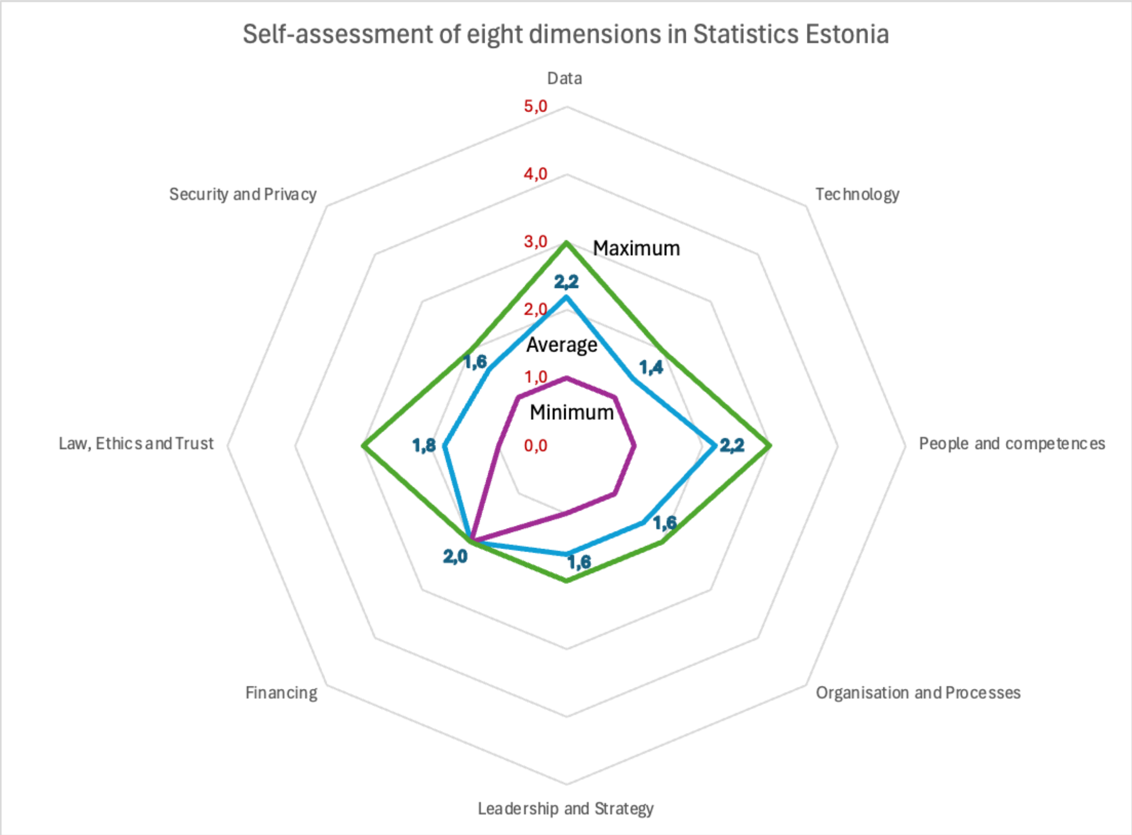

Figure 9. Self-assessment results from Statistics Estonia

As seen on Figure 9, the average scores per dimension varied from 1.4 (‘Technology’) to 2.2 (‘Data’), leading to the eight-dimension average of 1.75. More importantly, the spread between five respondents was never greater than two (‘Data’, ‘People and Competences’, and ‘Law, Ethics and Trust’) while for ‘Financing’ it was zero. For the remaining four dimensions, the spread was one. Besides quantitative information, also qualitative statements were collected to explain the answers.

4.6.4 Evaluation of the Self-Assessment Exercise

To learn about the self-assessment exercise, a short questionnaire through SurveySparrow survey instrument was sent out. The questionnaire can be found from Appendix 5. Out of 5 participants, four filled it in (80%). Although the number of respondents is small, some crude conclusions can be drawn. First, the Methodology was considered quite favourably by those who used it, suggesting that it is a useful tool for assisting in the self-assessment. However, even more useful would have been to incorporate the explanations of terms and examples into the web tool. This is not surprising considering that the AI-related terminology and concepts are relatively new and complex, particularly when used in an

AIMM which stretches across eight dimensions. Second, participants agreed that it was relatively difficult to find the right choice from the list of maturity levels presented in the AIMM. This corroborates the expert opinion that it was difficult to find the right option from lengthy descriptions of maturity levels. This is perhaps one key finding which requires the AIMM to be redesigned to a significant extent. Third, the eight dimensions of the AIMM were considered favourably by all the participants. Fourth, participants rated relatively favourably all the eight dimensions of assessment from the perspective of their own confidence in having sufficient knowledge of their functioning in Statistics Estonia. Most favourably were rated 'Technology', 'Leadership and Strategy, 'Financing' and 'Data', least favourably 'Law, Ethics and Trust' and 'Security'. Finally, when asked about the usefulness of the self-evaluation exercise in identifying the strengths and areas for improvement in AI capacity development, this obtained an average rating of 2.5 on the 1-5 Likert scale. This is a significant finding which has to be investigated further. One interpretation is that the organisation did not reap any benefits by the time of the evaluation, but also that no tangible benefits are in sight. This is understandable because the way the self-assessment exercise was carried out does not bring about a high-value analytical report that could be used for identifying clear areas for improvement.

5 Discussion

This chapter discusses the findings from the evaluation considering the established evaluation framework suggested in Section 3.3. The overall objective of this research was to develop a complete toolkit for the application of AIMM prototype through a pilot study and evaluate its validity. This chapter addresses the main research question "How to create an AIMM for public organisations that they can use for self-assessing their AI capabilities?

The study operationalises a newly developed AIMM for the public sector by Dreyling et al. (2024) through a pilot self-assessment in a public organisation, relying on the procedure model for developing MM-s by Alsheiabni, Cheung and Messom (2019). Two additional artifacts, the MAT for conducting the web-based self-assessment and the Methodology for guiding the assessors were created to support the self-assessment process. Having a public sector specific AIMM tested and validated would solve an important gap in the landscape of supporting tools that could be deployed in support of public organisations in their pursuit of enhancing AI capabilities needed to successfully deploy AI initiatives and manage them through their entire life cycle. Having tested the AIMM and the self-assessment process in a pilot public organisation Statistics Estonia and evaluated the process and the artifacts according to the DSR framework provided valuable insights into the usefulness of the tools and the process.

The evaluation framework covers a range of evaluands and criteria from section 3.3, summarized in the table below. It also responds to the research sub-question one by outlining the criteria to which the developed tools have to correspond.

RSQ-1: How to design the tools for facilitating the application of the AIMM?

Evaluand	Criteria
AIMM for the public sector	Comprehensiveness Consistency Problem adequacy
The Methodology	Usefulness

The MAT	Usability
The self-evaluation process	Usefulness

Table 5. Evaluands and the evaluation criteria used in the thesis

From the evaluation carried out, it can be concluded that the AIMM satisfies the criterion of comprehensiveness to a significant degree, being mindful of an opportunity to integrate stakeholder engagement better into the model. A high level of consistency of the AIMM in terms of application of the self-assessment framework in the same manner was verified through low variation in responses to determining the maturity level on each of the eight dimensions. Consistency in terms of language and logic of descriptions of maturity when progressing from a lower level to a higher level of maturity was evaluated by experts when asked to detect any defects, but none were identified. It is not the most reliable method of ensuring consistency, but it provides some level of assurance that no obvious defects are present. The criterion of problem adequacy was satisfied with the creation of the three artifacts: the extended AIMM for public organisations equipped with proper maturity level descriptions, the Methodology and the MAT which together allow for any public organisation to carry out self-assessment of their AI capabilities.

The Methodology was regarded highly, hence validating the need for such an instrument and its usefulness. The web-based tool as a secondary artifact was not directly evaluated by the participants due to its limited functionalities at this stage. It was not meant to serve as an instrument beyond the immediate need for carrying out the pilot self-assessment. However, the respondents indicated that they would like to see the MAT improved by incorporating informative elements (such as explanations of terminology and examples) from the Methodology into it to facilitate its use. Therefore, it can be concluded that it is of limited usability in its current form.

Another research question will be answered through collected feedback.

> **RSQ-2:** How useful will be the AI maturity assessment to the public organisations, based on experience from using the AIMM prototype as a self-assessment tool?

Finally, feedback from Statistics Estonia indicated limited usefulness of the self-assessment exercise in its pilot format. However, this raises a conceptual question. It is obvious that the application of the AIMM omitted two crucial steps which are essential to bringing value to the participating organisation: the analysis report that serves as the basis for discussion at a consensus meeting of relative strengths and potential areas for improvement in the participating organisation and allows for developing a subsequent roadmap for identifying improvement projects. Therefore, it may be that going through the full exercise would have ended in a more favourable assessment, hence denying the need for substantial revision of the tools. However, more research would be needed to identify the reasons behind such an evaluation result. At this point, no clear decision can be taken whether to reject the self-assessment process as the artifact or refine it by testing it fully in another public organisation, as required by Step 8 from Alsheiabni, Cheung and Messom (2019).

It would be useful to improve the presentation of the descriptions of the maturity levels to respond to the feedback received both from the experts and the assessors before addressing any other public organisation.

5.1 Knowledge contribution to the Knowledge Base

Because the DSR's context includes research goals, evaluation in DSR has a broader purpose than in the 'ordinary' practice of design (Venable et al, 2016). Therefore, it is not sufficient to evaluate the utility of the artifacts. In a design science project, evaluation must also regard the design and the artifact in the context of the knowledge it contributes to the knowledge base (Hevner et al., 2004).

The following paragraphs answer the research sub-question number 3.

RSQ-3: What is the contribution of testing the AIMM prototype to DSR?

This research has made one notable contributions to the field of AIMM development. It is the first effort to bring to life a complete toolkit that would allow for a practical self-assessment using the AIMM in public organisations. Two emphases are relevant: there has been no previously elaborated AIMM for the public sector to be taken that far, nor has there been a set of tools designed as a complete package for conducting self-assessment. As discussed in section 4.1, Saari, Kuusisto, and Pirttikangas (2019) developed one of the rare extended descriptions of maturity levels but did not provide any guidelines for helping the interested organisations to understand better each of these characteristics. For the public sector, the only AIMM designed specifically for this context does not go beyond the statements for each maturity level that are not sufficient for undertaking self-assessment. This contribution is a valuable piece of research which allows for completing the AIMM for public organisations by reiterating the design process of dimensions and corresponding descriptions of maturity characteristics, and the Methodology and the Tool to reflect these changes.

5.2 Research Limitations

There are several limitations to this research that must be acknowledged. First, since the process of self-assessment using the AIMM developed for the public sector was in the prototyping phase, the stage related to drawing up an analytical report which would have had to be discussed among the participants for consensus-building was omitted. Such as in the CAF process (EIPA, n.d.), based on that consensus-building meeting, an improvement plan is designed. Lack of these steps rendered the research incomplete and most likely affected the perception of utility of the participants of the entire exercise. This would be relevant for public organisations involved because they need to get real benefits from the time and energy invested into this exercise.

Second, the size of sample organisations in the case study could have been larger to get a better insight into the functioning of the AIMM in different organisational contexts. One could argue that Statistics Estonia is a reasonably AI capable organisation (score of 1.75) in the Estonian public administration but testing the model on a more mature organisation could have revealed how well the maturity descriptions work for these higher levels. As noted by Wilson and Broomfield, the social and structural differences among organisations may be bigger than differences among sectors. From the other side, Statistics Estonia is a capable organisation building their own AI models, which many organisations in the Estonian public administration cannot do due to their small size or different core business where data is not in the centre of everything. Such organisations would likely score lower, but it could also reveal that their intention is not to build their own AI solutions but use instead off-the-shelf solutions or co-operate with other state institutions to build solutions to common problems. One such example is from supervisory agencies in Estonia which shared their experiences with each other on suitable AI solutions for risk assessment of their subjects – how to identify with the use of AI high risk subjects based on their behaviour to deploy audit resources specifically on them instead of doing it based on more conventional risk assessment methods.

Third, due to a small number of participants in the self-evaluation exercise, there is not enough information on how broadly the AI is integrated into the organisation and how well is its use known throughout the organisation. Since the participants were appointed by the management based on prescribed profiles by the author leading to five possible respondents, each by their function expected to be well aware of the AI developments (see Appendix 4), the results were rather consistent throughout the responses. Having had a broader spectrum of participants could have revealed higher variety in responses, potentially indicating the need to communicate better the AI developments, policies, and rules across the organisation, but also more divergent viewpoints on the suitability of the model and related artefacts.

Finally, DSR has its inherent limitations in guiding the creation of deployable AIMM and related artifacts to public organisations. This is because apart from the creation of the AIMM, there is relatively limited theory that can be applied to guide through the steps 5-9, envisaged by Becker, Knackstedt, and Pöppelbuß (2009). Grey literature from consultancies and expert organisations may have an advantage here, because it is based on practical knowledge and testing by experts working in the field. Another DSR limitation is that since the full process of deploying an AIMM is very resource-intense, it is difficult to research an entire process until the end as part of the same research, even if an existing AIMM is used as the starting point.

6 Conclusions

This research in the frame of this thesis was an effort to establish a practical set of tools for carrying out AI maturity self-assessment in public organisations, relying on the AIMM developed by Dreyling et al. (2024). It applied the DSR methodology and a procedure model for developing MM-s by Alsheiabni, Cheung and Messom (2019) for approaching the task of designing and testing the artifacts on a pilot public organisation, Statistics Estonia. Besides that methodological framework, the author explored four theories relevant to the topic of developing AIMM-s to a varying degree, considering the RBT and the TOE frameworks as ground theories which are helpful for understanding link between the resources and AI capabilities, while the PVP proved useful for explaining factors relevant for the AIMM for public organisations that relate to the linkages between operational capabilities, legitimacy and support, and the public value created. Finally, diffusion of innovations theory can be utilized in devising a strategy of spreading the use of the AIMM for public organisations.

This research proposes that the AIMM for the public sector requires at least one more iteration of redesign and testing of maturity level descriptions before it could be launched to the wider community of public organisations.

Based on the conducted research and the findings presented in Chapters 4 and 5, several practical propositions can be formulated.

Proposition 1. The usefulness of the assessment exercise can be increased by enhancing the process. One option is to carry out the exercise in full: add the missing elements of analytical report and the consensus meeting to have the participating organisation sharing experiences among its staff members. This will add the element of learning that was absent from the current pilot exercise which is very important for any self-assessment to prove valuable.

Another option is to change the methodological approach from self-assessment to assessment with the involvement of an expert to guide the organisation from the very beginning through the entire exercise.

Third option is to improve the communication with the organisation by having a series of interactive meetings to inform the participants better of the entire exercise and allow for timely questions and other feedback. This could consist of a face-to-face meeting with the General Director by introducing the approach and agree the timeframe and steps of the exercise. Second, a kick-off meeting with the assessment team to introduce the model, the Methodology and the Tool would be potentially useful to clarify what is expected of the participants and what are the steps on that path. Examples from other organisations – once they become available – could be a useful means to suggest how this exercise could benefit both the participants, as well as the entire organisation.

Proposition 2. The usefulness can be enhanced by improving the descriptions of the maturity levels. The assessment methodology has to be upgraded so that the composite descriptions of maturity levels at each intersection between a dimension and a maturity level are easier to grasp. As the feedback from Statistics Estonia shows, the relative ease with which the participants thought they found the right choice from the list of maturity level descriptions was 2 on the 5-point Likert scale.

This requires more thorough follow-up than was possible during the preparation of this master’s thesis, based on the feedback received both from the participants in the self-assessment exercise, as well as the experts. Interactive workshops where experts have a possibility to actively engage in shaping the descriptions might be the best way forward to ensure that the descriptions are as easy to understand as possible. More testing on other experts not part of this design exercise will be needed.

As part of the improvement effort, the Methodology also could be integrated into the self-assessment web-based tool, particularly considering that not every person is equally familiar with all the dimensions. This requires applying a different survey instrument as the idea is not new to the author but the used survey instrument SurveySparrow did not allow for such integration.

Proposition 3. The AIMM will be improved by upgrading the dimensions of the model. The feedback from the participants and the experts demonstrates that the existing dimensions work relatively well, although there will always be personal preferences as to how to organise the model. As we have seen in Section 4.1, there are numerous ways of structuring the AIMM. Nevertheless, several suggestions by the experts are worth considering. First, the model should capture the need for stakeholder engagement better. This can be integrated into existing descriptions of maturity levels or accomplished by expanding the model by one more dimension. Second, there should be more attention paid to the option of off-the-shelf AI solutions, because these are easy and cost-efficient to implement.

Proposition 4. The self-assessment exercise would be perceived more useful after the feedback will be provided to the participating organisation. Statistics Estonia had not yet received the feedback from the self-assessment exercise in the form of a report by the time of filling in the feedback form. This means the perception of usefulness of the exercise was limited compared to the situation if the analytical report – however limited – would have been delivered.

6.1 Future Research

There are a few possibilities to take this research further. First, there were several suggestions from experts and participants on upgrading the AIMM (see Section 4.5). Using that feedback to create version 2.0 of the AIMM will require another round of testing and evaluation to validate the artifacts, which would lead to the deployable AIMM for public organisations.

Another possibility, related to former, is to deploy the AIMM into public organisations with different characteristics in terms of their already observed technological and innovation capabilities (see, for example, Lember, Kattel and Tõnurist, 2018 for the Estonian context). This would allow to establish how well the AIMM works for organisations at different level of (AI) maturity and explore the linkages between digital transformation capability from earlier studies and the AI capability.

Yet another possibility is to use a different research framework instead of DS, such as action research. Both Cole et al. (2005) and Järvinen (2007) argue that the similarities in the field of IS research between these approaches are substantial. As action research originates from the concept of the researcher as an active participant in solving practical problems in the course of studying them in organisational contexts (Peffers et al., 2014), it is a possibly a suitable alternative to the DSR in constructing a deployable AIMM and related artifacts.

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7 Appendices

Appendix 1 – Non-exclusive licence for reproduction and publication of a graduation thesis[1]

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Appendix 2. List of experts evaluating the AIMM for the public sector, the MAT and the Methodology:

- Estonian Information System Authority (policy perspective)
- Private Sector expert collaborating with the public sector on AI (AI implementation perspective)
- Public sector product manager experienced with developing AI solutions (AI implementation perspective)
- Public sector management consultant (research and consultancy perspective)

Appendix 3. Evaluation Questions regarding the AIMM and the Methodology to experts

1. Are there any imminent deficiencies in the AIMM that would need to be eliminated before its launch to the pilot public organisation?
2. Is the composition of the self-evaluation team [indicated in Appendix 4 and presented to the experts] adequate? Should all the selected members of the public organisations assess all the eight dimensions?
3. How understandable and realistic in their ambition considering the Estonian public sector organisations' circumstances are the maturity level descriptions? What is missing from the descriptions? How helpful is the Methodology in explaining the self-assessment process and the concepts used in the descriptions?
4. How useful could the self-assessment using the AIMM for public organisations prove to be? What other steps would be necessary to take after the completion of the self-assessment exercise?

Appendix 4. List of roles in Statistics Estonia participating in self-evaluation:

- Senior management representative - provides leadership and commits to self-assessment;
- IT manager –supports the organisation with translating business needs into technological support required to get the job done;
- Data scientist – first-hand experience from working with AI modelling;
- Development manager – initiating or supporting innovations in the organisation, translating business needs into technology needs (technology management);
- Product manager – owner of product or service which (potentially) benefits from the use of AI.
- Added later: Data Governance Expert

Appendix 5. Questionnaire to members of the Statistics Estonia after self-assessment exercise

Please answer on the scale of 1-5 where the scores are used as follows:

1– not at all; 2 – not really; 3 – not decided; 4 – somewhat; 5 – very much

1. On a scale of 1-5, how much did the Methodological Guidelines for Self-Assessment help you in using the web tool for self-assessment?
2. On a scale of 1-5, how much would you have benefitted from having the explanations of terms and some examples integrated into the web tool instead of being in a separate document?

3. On a scale of 1-5, how easy or difficult was it to find the right choice from the list of maturity levels?

4. On a scale 1-5, how well do you think the eight dimensions of the model (Data, Technology, People and Competencies, Organisation and Processes, Leadership and Strategy, Financing, Law, Ethics and Trust, and Security and Privacy) capture all relevant aspects of AI capability?

   Which areas would you add or eliminate from the list?

5. Please indicate on a scale of 1-5, how confident you feel you have sufficient knowledge about the situation in your organisation (Mark with X in suitable box)

	Not confident at all	Not very confident	Undecided	Rather confident	Very confident
Data					
Technology					
People and Competencies					
Organisation and Processes,					
Leadership and Strategy					
Financing					
Law, Ethics and Trust					

Security and Privacy					

6. On a scale of 1-5, how useful do you believe the AI maturity self-evaluation exercise will be to your organisation in identifying the strengths and areas for improvement in AI capability development?

Appendix 6. Methodological Guideline for self-assessment based on the AIMM for public organisations

The Methodological Guideline is available at the following location: https://docs.google.com/document/d/1ZZ0QI5E7ou-tkV6F1OnyCxuqNYoBxueYmFEIuJWIUEA/edit?usp=sharing

Appendix 7. Maturity Level Descriptions of the AIMM for public organisations

The file with maturity level descriptions along with the text for the web tool is available at the following location:

https://docs.google.com/document/d/1ch5akB2YDdCF0YcPAO1SVXMP8s04AQnmmYgNevagAlY/edit?usp=sharing