UNIVERSITY OF TURKU

ABSTRACT

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Title	ORGANISATIONAL READINESS FOR ARTIFICIAL INTELLIGENCE ADOPTION		
Supervisor(s)	Prof. Eija Koskivaara, Prof. Anne-Françoise Rutkowski, Prof. Patrick Rousseau		

There have been major leaps in the artificial intelligence market in recent years, and many organisations have begun to take an interest in artificial intelligence solutions to develop their business. In recent years, the Finnish government has carried out several projects aimed at promoting development related to the utilisation of artificial intelligence and at improving European-wide co-operation in the scientific and business use of artificial intelligence. The purpose of this master's thesis is to explore how large companies perceive their own capabilities in the adoption of artificial intelligence, along with assessing which internal and external elements they consider relevant. To evaluate this topic, this research paper analyses the responses from 13 Finnish organisations through semi-structured interviews.
This study uses the Technology-Organisation-Environment (TOE) theory as the research framework through which these issues are addressed. The TOE framework examines the technology available to an organisation, the external environment, and the internal and external characteristics of the organisation. Based on this research, Finnish organisations raise business case and process understanding, cultural aspects, strategic linking and data-related issues as the most relevant elements that have an impact on the adoption of artificial intelligence.

There are plenty of commercial outlets discussing the concepts around AI for business, however scientific research is still fairly limited. The aim of this master's thesis is to narrow this research gap by approaching the topic in a structured, exploratory manner, hopefully also arousing interest in further research.

Key words	AI adoption, TOE framework theory, technology-environment-organisation, business use case, business needs

TURUN YLIOPISTO

TIIVISTELMÄ

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x	Pro gradu -tutkielma
	Lisensiaatintutkielma
	Väitöskirja

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Tekoälymarkkinoilla on viime vuosina tapahtunut suuria loikkauksia, ja monissa yrityksissä on yhä enenevässä määrin kiinnostuttu tekoälyratkaisuista liiketoiminnan kehittämiseen. Suomen valtio on viime vuosina julkaissut useita hankkeita, joilla on pyritty edistämään tätä tekoälyn hyödyntämiseen liittyvää kehitystä, sekä parantamaan Euroopan-laajuista yhteistyötä tekoälyn saralla niin tieteessä kuin liikemaailmassakin. Tämän Pro Gradu-työn tarkoituksena on selvittää, miten suomalaiset suuryritykset kokevat omat valmiutensa tekoälyn käyttöönotossa, selvittämällä mitä organisaation sisäisiä sekä ulkoisia elementtejä he pitävät relevantteina. Aiheen arvioimiseksi tässä tutkimuksessa analysoidaan 13 suomalaisen organisaation vastauksia teemahaastatteluiden avulla.

Tässä tutkimuksessa käytetään teknologian, organisaation ja liiketoimintaympäristön puitteita (TOE-framework) viitekehyksenä, jonka kautta näitä kysymyksiä tarkastellaan. TOE-viitekehys tarkastelee organisaation käytettävissä olevaa teknologiaa, ulkoista liiketoimintaympäristöä, sekä organisaation sisäisiä ja ulkoisia ominaisuuksia. Tämän tutkimuksen perusteella suomalaiset organisaatiot nostavat liiketoimintalähtöisyyden sekä prosessiymmärtämisen, organisaatiokulttuurin osa-alueet, strategisen linkittämisen sekä dataan liittyvät ongelmat keskeisimmiksi elementeiksi, joilla on vaikutusta tekoälyn käyttöönottoon.

Liiketoiminnan edistämistä tekoälyratkaisujen avulla on käsitelty paljon mm. kaupallisilla artikkeleilla, mutta riippumattomia tieteellisiä tutkimuksia on tällä hetkellä rajoitetusti saatavilla. Tämän Pro Gradu-työn tavoitteena on kaventaa tätä tutkimusaukkoa lähestymällä aihetta jäsennellyllä tavalla, toivottavasti herättäen kiinnostusta myös lisätutkimuksiin aiheesta.

Avainsanat	Tekoäly, AI adoption decisions, use cases, TOE framework, Technology-Organisation-Environment, TOE-viitekehys, liiketoiminnan tarpeet

ORGANISATIONAL READINESS FOR ARTIFICIAL INTELLIGENCE ADOPTION

Case Finnish business domain

Master's Thesis in
International Master's in Management of IT (IMMIT)

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And lastly to my partner in crime Jack, my fiancé, who both kept me sane along the way and pushed me to keep going when I needed it.

The originality of this thesis has been checked in accordance with the University of Turku quality assurance system using the Turnitin OriginalityCheck service.

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LIST OF TERMINOLOGY

AI = Artificial intelligence

TOE = Technology-Organisation-Environment

DOI = Diffusion of Innovation theory

DL = Deep learning

ML = Machine learning

BDA = Big data Analysis

RPA = Robotic process automation

POC = Proof of Concept

DevOps = Development and Operations

GDPR = General Data Protection Regulations

IS = Information Systems (Science)

ROI = Return on Investment

VDA = Virtual Digital Assistant

CoE = Centre of Excellence

BI = Business intelligence

GDP = Gross domestic product

1 INTRODUCTION

1.1 Background

The importance and relevance of artificial intelligence (AI) has been continuously maturing for both business and academia in recent years, and Finland is not an exception (Alapietilä and Lundström, 2019; Ailisto et al., 2019). Consequently, in 2017 the Ministry of Economic Affairs launched a national program with the goal of turning Finland into a leader in AI applications, thus enhancing economic growth and wellbeing (Ministry of Economic Affairs and Employment, 2019). This government-led focus on AI was planned to spur interest within Finnish organisations to adopt AI technologies and tools into their operations, thereby improving performance and creating economic value in a variety of industries such as retail, healthcare, manufacturing, finance and public organisations (Korczak et al., 2018). Through this €160 million investment, significant increases to the Finnish economy are expected, with a stated potential of up to €20 billion in GDP growth (Korczak et al., 2018).

Additionally, in 2018 the Finnish government announced that it has formed a formal collaboration relationship with France regarding AI development, with a common vision to engage in a fair and human-oriented AI strategy (Valtioneuvosto, 2018). According to a report by the Finnish Foreign Ministry of Affairs, France has strong capabilities and resources in AI technology development, being third in the world in the number of AI publications, and both countries are committed to improving EU-cooperation activities (Lindertz, 2018). More recently, the Finnish government announced the creation of a national expert group which was created for AI and digitalisation, with the purpose of examining "the future of intelligent technologies, and in particular -- [AI] research, and to assess the impact of [such] technologies on different sectors of society" (Valtioneuvosto, 2020). The Finnish government has thus engrossed a strategy to nourish and accelerate AI development and utilisation as well as improve European collaboration in the field of AI technologies.

Even though the technological service front is well represented in Finland (see Ailisto et al., 2019), assessing the value attained from AI adoption and development is not as straightforward. Technology does not exist in a vacuum, and therefore should not be viewed or measured independent from other influencing factors, such as the characteristics of the organisation or the environmental context they are operating in (Pumplun et al., 2019). Such a comprehensive assessment of an organisation's AI adoption readiness is the preface for this research.

This paper uses Technology-Organisation-Environment (TOE) framework in order to analyse AI adoption decisions in Finnish organisations. TOE framework looks at the available technology at the organisation's disposal, the external environment that can influence the organisation, such as legislations or market competition, and lastly, both the internal and external characteristics of the organisation itself (DePietro et al., 1990). TOE framework theory has been widely utilised to research innovation adoption and decision-making. Due to the angle from which this paper is approaching the topic, namely, to understand the Finnish AI market from a demand point of view, the purpose for using TOE framework is to provide structure to this research rather than constrain it. Therefore, this paper can be identified as theory elaboration (Ketokivi and Choi, 2014).

The setting for this paper is to uncover what technological, environmental and organisational elements influence organisations in their AI-related decisions. Understanding the importance of each group of elements can be useful for leadership and management to better define their business needs for which AI-tools are created, and also recognise their internal capabilities to support these tools (DePietro, 1990; Zhu et al., 2004; Sun et al., 2018; Pumplun et al., 2019). This motivates the essence of this paper, which is to explore what internal and external variables influence AI decisions within organisations in Finland.

The paper begins with a literature review of the relevant concepts, informed by prior research. Research design section describes the empirical part of this paper for data collection and the methodology used. After, results are stated along with discussion points, followed by the conclusions section with descriptions of implications, limitations and further research suggestions.

The empirical section, which is the main concern of this study, is comprised of semi-structured interviews with large organisations operating within different industries in Finland. A total of 15 experts from 13 organisations participated in this research, improving the relevance of the findings from this research. The interview data was compared against prior literature regarding TOE adaptation, with additional findings that emerged from this study highlighted in the results section.

1.2 Research questions and propositions

The extant research on AI adoption tends to have a strong technology element (e.g. Driessen and Heutinck, 2015; Dunis et al., 2017; Kang and Westskytte, 2018). This tendency leaves room for other influencing themes such as environment and organisational aspects to be assessed. In addition, prior research on AI use cases is commonly industry specific, e.g. the car industry (Demlehner and Laumer, 2020) or financial industry (Kruse et al., 2019), thus lacking an overarching viewpoint. The core research question this paper is looking to answer is:

What elements are relevant for organisations when making AI adoption decisions?

Building from this core questions, the following subtopics arose:

What are the themes which influence the decisions organisations make regarding their AI decisions? How well does TOE framework fit in assessing what topics organisations find important for AI adoption readiness?

As AI-related innovations are one of the defining disruptive forces of the last few years, there is a particular interest for businesses offering or making use of AI services to understand what drives such decisions in the market (e.g. Gartner, 2017; Davenport and Ronanki, 2018).

To improve the validity of this research, a proposition is prepared to act as a guide for the direction of this paper. A research proposition is a way for researchers to improve the scope of their research and guide the analysis of data with a particular outcome in mind, improving the feasibility of the study (Baxter and Jack, 2008). Its purpose is similar to that of a hypothesis, but with a key difference being that propositions are used in situations where research outcomes cannot be verified by experiment (Clay, 2017). According to Baxter and Jack (2008) research propositions can be created based upon “literature, personal/professional experience, theories, and/or generalizations based on empirical data”. This paper proposes that organisations place higher importance on organisational characteristics, and from these, top management support and change management are the most important. This research proposition is based on a mixture of sources, namely the findings of Pumplun et al. (2019) and a professional report on digital transformation (Rajkumari, 2019). The second proposition is that TOE framework adapted to AI adoption context is suitable for assessing an organisation's readiness for AI adoption. This is based upon the vast amount of TOE literature available and its suitability for innovation adoption (see Oliveira and Martins, 2011).

1.3 Research relevance

1.3.1 Business relevance

According to a field study by Microsoft Finland and PwC Finland, artificial intelligence technologies are expected to profoundly change the way businesses and work are run in Finland in the near future, as AI-related technologies have already been projected to significantly increase economic growth on a global scale. In addition, the increased popularity of modern cloud platforms is a key factor in enabling different entities such as organisations, institutes and even individuals to draw benefits from different AI use cases; cloud platforms have made emerging technologies more accessible and scalable to users. (Korczak et al., 2018).

To gain better insight on the AI market globally, the following graphs present the situation in a visual manner. Figure 1 shows expected global revenues of different use cases on a global scale. Voice and speech recognition technologies are expected to bring nearly double the revenues compared to the second highest group, customer service and marketing virtual digital assistants (VDA). Both these use case technologies relate to user data analysis, and the following three are related to operational activities such as monitoring or supply chain management. The more sophisticated the technology (e.g. vehicle object detection, medical image analysis) the smaller the expected revenues. One reason for this can be the type of data that is being processed; for example, medical analysis and patient record data have a much higher risk-profile and therefore require heavier investments in data protection.

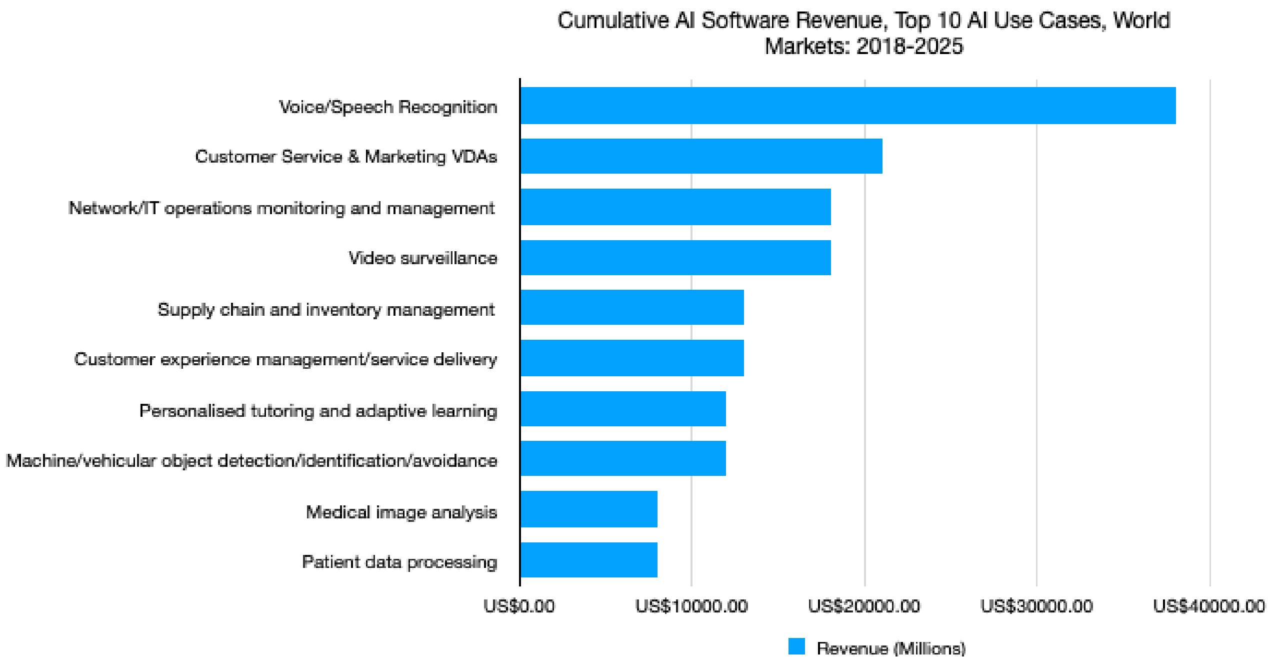

Figure 1 Revenues from AI software years 2018-2025 (sourced from Tractica Omdia, 2019)

Figure 2 is a summary of the planned investments within Nordic organisations in emerging technologies (PwC Sverige, 2017). From this figure, we can see that in 2017 AI technologies were only fourth highest in planned investments in Nordic countries. Incidentally, public cloud, which is in most cases a prerequisite for AI technologies, and Internet of Things (IoT), which is one form of collecting new type of data, were both planned at approximately 20% of the responding organisations. Cyber security was in the plans of only about one in four organisations. On the other hand, data analytics and robotic process automation (RBA) were in the plans of the vast majority of the organisations (respectively ~70% and ~58%) and mobile technology investments were planned by approximately 45% of the organisations in the coming 10 years.

These relatively low investment plans into AI technologies three years ago hint at the slightly slower adoption interest of AI within the Nordics. Since the IT industry has undergone massive leaps in development in the 2000's and 2010's (Kruse et al., 2019), in innovations such as sensor network use, popularization of big data, linkages between cyber and physical worlds and advancements in AI research (Pan, 2016), the investment plans for the coming 10 years do not seem to reflect the current times. One reason for this stagnation could be that large organisations (and not just in the Nordics) have only in very recent years began to undergo transformations towards real digitalization.

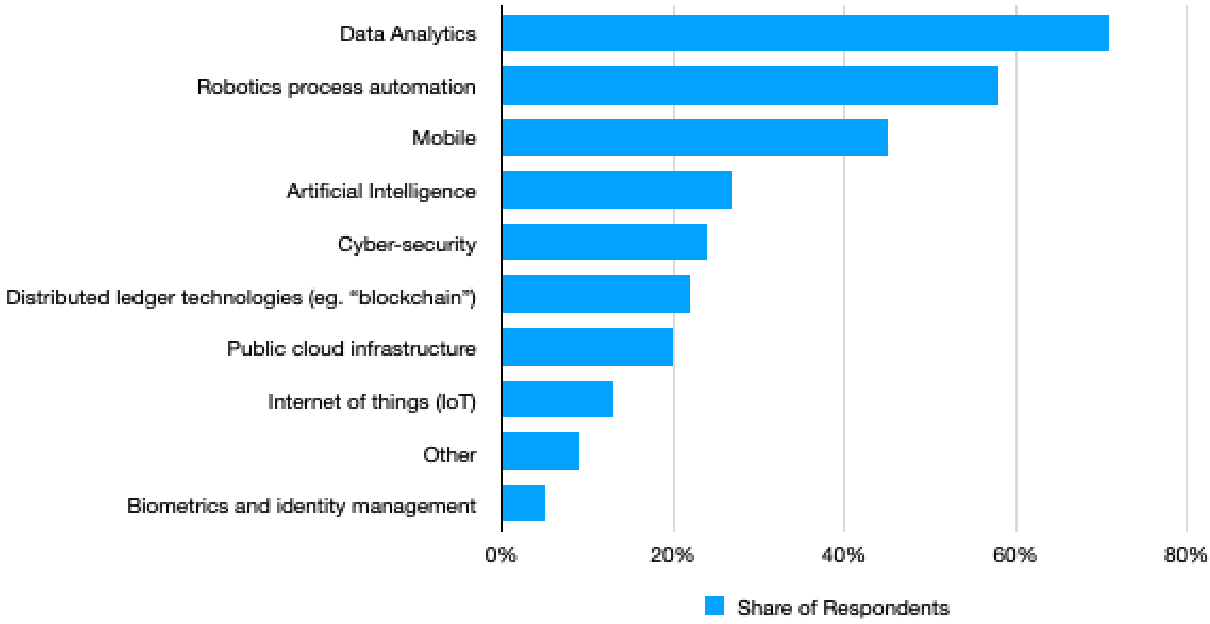

Figure 2 Planned investments in technologies within Nordic countries for the next 10 years (sourced from PwC Sverige, 2017) [1] [2]

1.3.2 Scientific relevance

Due to the highly technical nature of AI research, a large portion of extant IS research is technology-driven, often overlooking the strategic impact of AI investments (see Pumplun et al., 2019).

Research on how the AI domain is developing businesses and how organisations can plan to expand into the field of AI, is plentiful. However, these studies tend to be industry specific or conducted by businesses offering such services, thereby restricting their generalisability. There are a number of anecdotal resources regarding business implementation and uses for AI technology (e.g. Gartner, 2017; Davenport and Ronanki, 2018; Eddy, 2020; Kirkpatrick and Kaul, 2020). However, there is a gap in research conducted purely from an academic point of view. Studies by Pumplun et al. (2019) and Alsheibani et al. (2018) acknowledge the suitability of TOE framework to the context of AI adoption research and recommend revisiting and extending the theory for application. Additionally, both papers were encouraging for future research with empirical data gathering.

According to Ramanathan et al. (2017) TOE framework has a proven record of explaining the interdependencies between technical resources and internal organisational factors (such as strategy, structures, communication etc.) in the context of the

[1] Organisations with >500 employees
[2] Denmark, Finland, Norway, Sweden; 2017; 1,308 respondents

environmental playing field. Using an established framework such as TOE to analyse the AI domain is novel and therefore scientifically relevant to the Information Systems research field.

2 TOE FRAMEWORK

2.1 TOE framework theory and conceptual model

In IS research, there are two prominent models for building theories regarding technology adoption, namely technology-organisation-environment (TOE) framework (DePietro et al., 1990) and DOI or diffusion of innovation theory (Rogers, 1995), that approach technology adoption from a firm level (e.g. Chong et al., 2009; Oliveira and Martins, 2011). There are of course other popular theories examining technology adoption within IS, however these theories view the topic from an individual perspective (Oliveira and Martins, 2011), such as technology acceptance model (TAM) (Davis, 1985), theory of planned behaviour (TPB) (Ajzen, 1985) and unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003). Additionally, these other IS theories tend to be techno-centric, over-looking the interplay between human and non-human actors (Awa et al. 2016).

According to a study by Verma and Bhattacharyya (2016), TOE framework has some benefits over DOI. Firstly, DOI can overlook other influential factors (e.g. organisation's motivation, technological maturity and capabilities etc.) and overemphasise the role of technology (Rui, 2007). Second, TOE framework takes the environmental context into account, which is missing from DOI. Thirdly, there is a multitude of variants for studies utilising TOE framework theory with vast empirical support (Rui, 2007). These reasons are deemed sufficient in choosing TOE framework over DOI for this research paper as well.

The TOE framework is a theory which looks at how technological innovation decisions are impacted by three key factors: 1) technology and its developments, 2) the external environment, in which the decisions are being made, and 3) the internal (and external) characteristics of the organisation in question (DePietro et al., 1990). These three independent factors in turn influence a dependent factor of technology adoption (likelihood, intention and extent of adoption). According to the framework, organisations are influenced by the above three elements when searching for and adopting new technology. The theory explains how these different contexts combined influence a firm's decision-making process regarding technology innovations and its impact on organizational performance (Zhu et al., 2004).

In the context of this paper, the TOE framework theory provides a usable tool to examining the Finnish AI market with its macroeconomic and regulatory context, industry sizes and current competition (external environment), the organisations resources and characteristics (organisation) and both the external and internal technologies, including operational processes (technology). These elements are then viewed in the context of being either beneficial or detrimental towards technological innovation (see figure 3).

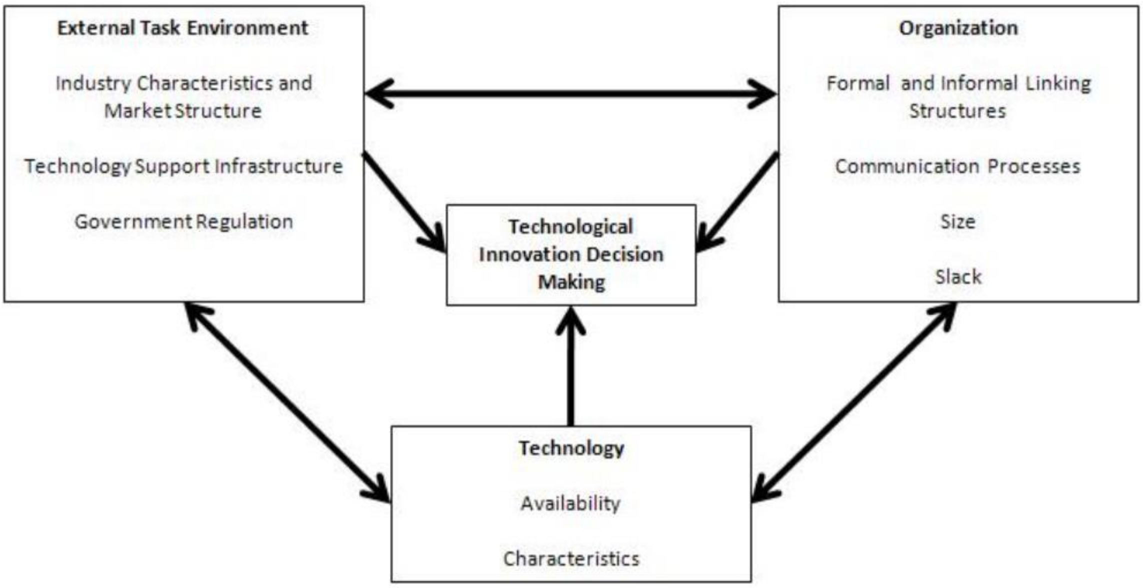

Figure 3 Classic TOE framework (DePietro et al., 1990)

TOE framework as a theory has been utilised with many modern technology development studies (427 citations for the term “TOE framework” in Scopus data base on February 28th, 2020) and continues gaining interest within IS research. Across the globe and in different subject areas ranging from manufacturing to supply chains to medicine, TOE framework has been widely used to explain the internal and external aspects of innovation adoption. The theory has an established theoretical basis with empirical support and has been applied in a variety of IS domains (Bradford et al. 2014). Examples of such domains are cloud computing adoption with 79 publications (e.g. Alshamaila et al. 2013; Oliveira et al. 2014; Lian et al. 2014), e-commerce or e-business with 56 publications (e.g. Zhu et al. 2004; Lin and Lin, 2008; Ghobakhloo et al. 2011), and big data with 26 publications (e.g. Chen et al. 2015; Verma and Bhattacharyya, 2017; Sun et al. 2018).

Zhu et al. (2004) identified six factors which affect an organisation’s value creation abilities in regard to TOE framework. These factors are technology readiness, firm size, global scope, financial resources, competition intensity and regulatory environment. The authors concluded in their paper that technology readiness was the factor with the strongest correlation to value creation in e-business. Other significant contributors to business value creation according to their findings were financial resources, global scope and regulatory environment.

Even though the original research by the authors was studying the effects of innovation adoption on e-business, it can be asserted that the setting fits well also in the context of AI. As the core problem was centred around maintaining a competitive position and business value creation through the use of innovative technology rather than the specific technology, the same factors will be studied in this paper as well.

From the original six factors by Zhu et al., firm size, global scope and technology readiness are mandated by the setup of this research. All of the interviewed companies are large organisations who are at a middle to high level of maturity on IT capabilities. IT capabilities are assessed by what level the organisation's current systems and infrastructure supports and how well they fit with the long-term strategy of the organisation. Lastly, global scope is limited to a national level, as the context of this research is the Finnish market. Thus, only the last three factors, namely financial resources, competition intensity and regulatory environment, are included in this research to study their influence over AI adoption decisions.

2.2 Limitations of TOE framework

TOE framework has been widely used to discover antecedents or influencing factors in innovative technology adoption and is therefore well established as a framework for quantitative studies (e.g. Borgman et al., 2013). There is extant literature on the utilisation of TOE framework for qualitative research as well (Alshamaila et al., 2013), even though these studies are much less numerous. A limitation of the framework is thus that there are limited reference studies for qualitative research. This limitation is however not enough to defer from using the framework in this study.

In addition, prior literature has criticized TOE framework for being too generic (Al Nahian Riyadh et al., 2009) and not being clear in what are the major constructs of the theory (Wang et al., 2010). These limitations warrant for adapting the classic form of TOE to fit with the innovation in question (Ramanathan et al., 2017; Pumplun et al., 2019). Considering this critique, the framework is merely seen as a structuring guideline for this paper, as the intention is to elaborate on the TOE theory by discovering any links between the constructs of the framework and AI innovation adoption interests. Consequently, there is a gap in prior research for utilising TOE framework with AI technologies, making it an appropriate lens to be used for this paper.

2.3 Adaptation of TOE in this paper

In accordance with the points mentioned in the limitations in section 2.5, this paper is utilising TOE framework for general guidance. The interview questions were initially created based on the TOE adaptation by Ramanathan et al., (2017), however during the analysis of the case interviews for this paper, the adaptation by Pumplun et al. (2019) was found to be more suitable. This latter adaptation of TOE is more specific to the context of AI adoption, as it accounts for specific characteristics of AI, namely being efficient and scalable, surpassing human capabilities and comprehension, ability to create its own rules based on collected data and portraying black box behaviour (Pumplun et al., 2019). Black box behaviour refers to the algorithm's decision-making not being transparent due to the self-learning nature of AI and thus being a potential threat (Brundage et al., 2018). Figure 4 depicts the high-level adapted framework for AI, and Figure 5 shows this adaptation in more detail based on the findings from Pumplun et al. (2019).

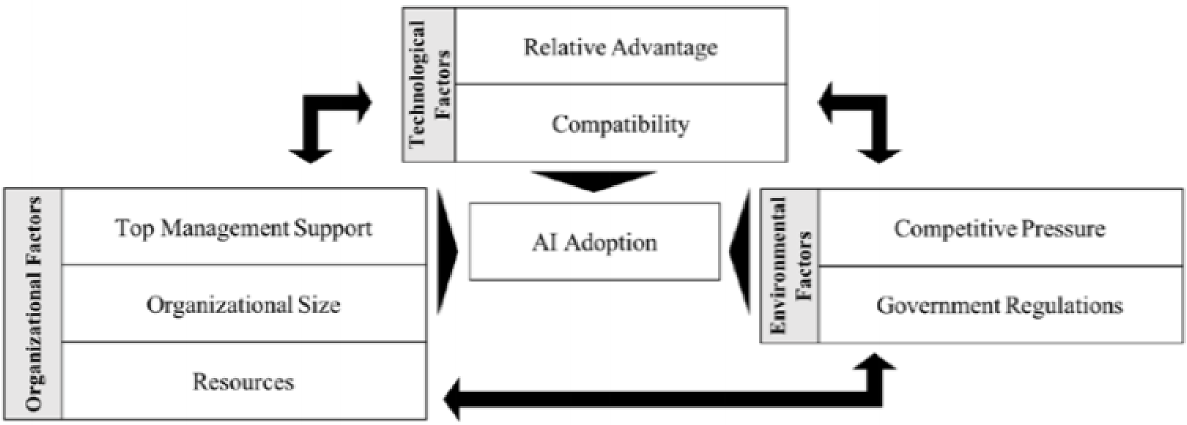

Figure 4 Initial adaptation of TOE framework (Pumplun et al., 2019, based on DePietro, 1990 and Rogers, 1995)

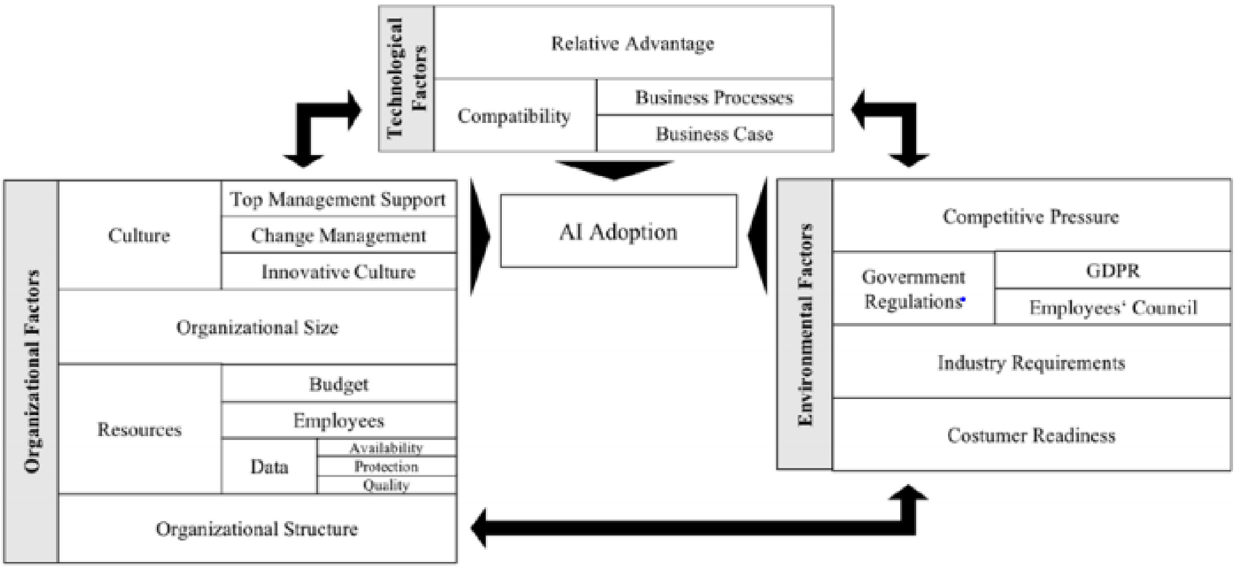

Figure 5 Deepened framework for AI adoption (Pumplun et al., 2019)

2.4 Technology

2.4.1 Characteristics

The technology context of TOE framework entails both the internal and external technologies of the organisation that are relevant, namely the internal practices and equipment of the internal organisation and the available external technology (Oliveira and Martins, 2011). Sun et al. (2018) note that other aspects of technological context are "perceived usefulness, technical and organisational compatibility, complexity and learning curve, pilot test/experimentation and visibility/imagination". According to the authors, perceived usefulness or benefits are not just about the innovation itself but are heavily influenced by the organisational resources and other internal characteristics. Thus, technological context can be viewed as a critical part of a bigger context, but not necessarily enough as a standalone investment.

The following paragraphs will clarify some basic terminology and definitions regarding AI. Slightly more emphasis is placed on this section of the paper due to the association of IS research and technology, however this is not representative of the importance in the TOE theory.

2.4.2 Different layers and definitions of AI

AI is often portrayed as an umbrella term covering all variations of intelligent or augmented technologies, and is also usually used synonymously with 'machine learning'. Evidence for the ambiguity of the used terms can be found in a broad set of fields, as AI, machine learning and advanced analytics are often used interchangeably, despite different meanings (e.g. Eddy, 2020). It is therefore paramount for organisations to have clarity on the different terminology.

It is important to also understand the difference between actual AI and the use of algorithms or computers to solve problems. To make this concept more understandable, one can consider the following example modified from a TED-talk by Shane (2019):

> *When met with a problem of creating a vehicle that needs to move from point A to B with a set of random parts, decisions are required regarding assembly. In a regular situation, a computer is told how to assemble this vehicle part by part, so that everything fits together, and the car can travel the distance A to B. However, there is no artificial intelligence involvement in this first scenario. In the second scenario, a computer, or rather a machine, is given a set of parts, and a goal that it needs to achieve, leaving the machine to come up with the most efficient way to set up the assembly. Thus, in AI, the machine undertakes the required decisions based on sets of rules it has been given. Depending on the level of sophistication and its given algorithms, the machine makes the most optimal choices it can find.*

When speaking about learning, it is important to understand the difference between the so called human-brain learning and *machine learning (ML)*. In machine learning, decisions are based upon incoming data and defined rules, which enables for a machine to learn things like user behaviour, reading the environment and making complex decisions (Pumplun et al., 2019). The machine is unable to make assumptions or leaps like a human brain can. This is where the importance of data, in particular big data, comes in. The amount of data needed to teach a machine is immense, as more and more organisations need to deal with petabyte-scale collections of data (Hadi et al., 2015) and the only way a machine can learn is by *precise* data (compared to a human brain, where it learns with comparable examples, e.g. one cat is the same as another cat).

Beyond this stage is the concept of a self-teaching machine, or *deep learning (DL)*, where the machine utilises trial and error, to find the most optimal solution, like in the second scenario in the above example by Shane (2019). A situation where such a scenario would be used is self-driving vehicles. The data required in this sophisticated form is even greater than before, and at this stage things like the ethical side of data collection and usage become important questions (e.g. Vernon, 2019).

The relationships between AI, ML and DL is visualised in figure 6. AI is often seen as an overarching term and it refers to any technologies that mimic human intelligence. Machine learning is an application of AI where systems create patterns and learn from data with minimal intervention from a human user (Hao, 2018). In short, AI is often referred to as a less specific larger context of its more detailed applications. Depending on the level of complexity of the use case, deep learning can be viewed as a subset of machine learning.

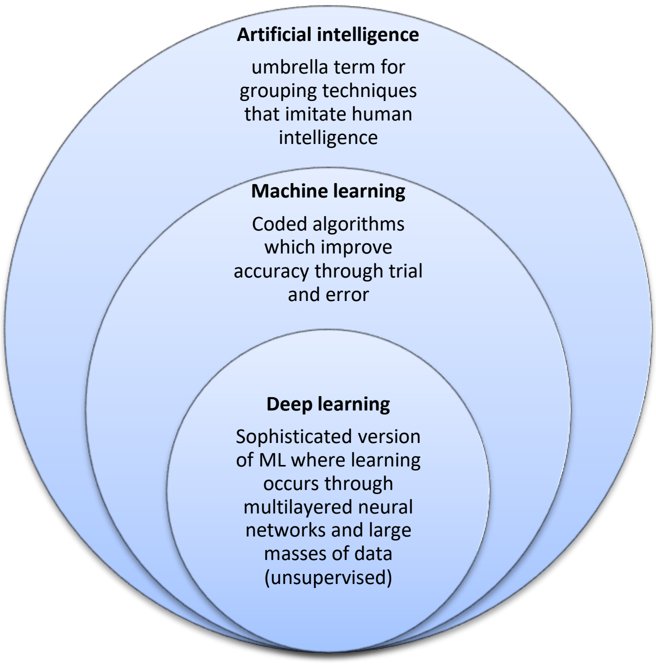

Figure 6 A Brief visualisation of AI, ML and DL layering (adapted from *A.I. Technical: machine vs. deep learning*, 2019)

According to Haenlein and Kaplan (2019), the key variables for classifying an action or tool as artificial intelligence are non-human dependent decision-making, continuous or adaptive learning through pattern-creation and real-time updates facilitated by modern cloud platforms. To further narrow down what activities can be associated as AI, careful consideration needs to be used when making such definitions.

Modern technology advancements have accelerated almost all processes and data transfers regardless of industry or field (Pan, 2016). Assessing processing or transfer speed alone however is not sufficient to define an activity into an AI category (Raisch and Krakowski, 2020). For this reason, pattern formation, non-human decision making through adaptive algorithms and real-time access will be inseparably connected in this research. In the scope of this paper, the focus is on the concepts of advanced analytics and data science, and intelligent forecasting.

2.4.3 Importance of cloud platforms for AI

The development of modern cloud platforms is an integral component in "democratizing AI", as coined by a professional report by Microsoft Finland and PwC Finland (Korczak et al., 2018). As AI is crucially dependent on the quality of and access to massive amounts of data, advancements in cloud platforms have facilitated this by bringing data more readily available to a variety of users, e.g. organisations, researchers, institutions and individuals.

In addition, cloud platforms enable the utilization and access of data at a heavily reduced cost in comparison to conventional platforms, where data needed to be stored in separate servers and access was also more limited (Korczak et al., 2018). Without cloud-based platforms enabling entities of all sizes to have access to both sophisticated data assessment algorithms and easily scalable cloud servers, freeing them from the need to have heavy duty private servers, the utilization of ML and DL solutions would be available to organisations who can afford high costs (Korczak et al., 2018).

2.4.4 Machine learning and deep learning

Machine learning (ML) is present in almost all modern technologies, everywhere from non-human personal assistants on cellular phones to product recommendations on shopping sites to alarm systems monitoring sensors in large scale manufacturing (LeCun et al., 2015). Essentially, a machine can improve its behaviour and decisions by experience, as it learns through trial and error. Machine learning is a subset for artificial intelligence, and in broad terms it can be classified as the study of algorithms and statistical models where decisions are made based on patterns and rules rather than through human intervention. Thus, ML will be the ground point for assessment in this paper, on which activities are classed as artificial intelligence.

Deep learning is built upon machine learning technology, but where neural networks allow for an improved understanding of pattern formation. In its traditional form, ML is fairly limited in its capabilities of assessing raw data and transforming it into recognisable patterns, requiring substantial engineering and domain expertise to do so (LeCun, 2019). Deep learning refers to the added layer of depth that the machine learning network has, and it essentially allows for increasingly complex calculations as it can utilise data, which is more diverse, unstructured and inter-connected. Therefore, deep learning allows for human-like decision making as it learns at an accelerated rate, much like a human brain (Marr, 2018; LeCun, 2019).

The essence of deep learning is to teach the computer how to split data (Shane, 2019). For this, it has to be able to pick up features, separate them from other features, classify them, and perform activities to provide an output. The computer needs to be able to trial different scenarios, learn from each one and form a neural network from its findings, and finally improve its understanding through increased cases of experiences. The difference between DL and ML lies in how the computer learns, as in the latter the computer through experience due to user-defined algorithms. DL has the same learning pattern through sophisticated algorithms. However, it can create much more complex network structures and access them in real time, all without user interference (Mao et al., 2018). Herein lies the reason why DL is far more powerful and varied in what use cases it can be utilised in. This difference is level of sophistication between ML and DL algorithms are simplified in figure 7 for illustration.

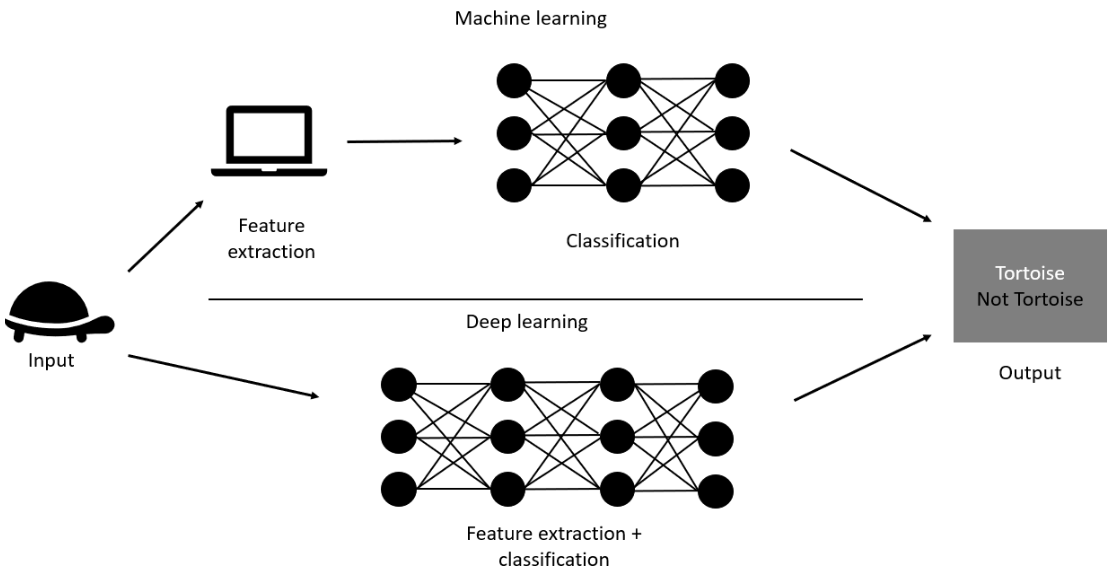

Figure 7 Difference between ML and DL (modelled after Halder et al., 2019)

Most modern AI solutions that conduct complex non-human related activities, such as decisions or predictions, require the more sophisticated algorithms and network structures of DL (Samek et al., 2020). Contemporary literature presents many use cases in a vast variety of fields and industries, e.g. agriculture (Fedotova and Luferov, 2019), financial services (Kruse et al., 2019), climate change (Panchbhaiyye and Ogunfunmi, 2019) and even fashion design (Zhao and Ma, 2019).

Figure 8 depicts the interplay of responsibilities between computer and human for data analysis tasks. The figure can also be a preliminary suggestion of an organisation's maturity level to IT and utilization-skills of business intelligence tools. On level one IT systems are merely for storing and accessing data, followed with creating static reports and elementary level analysis. Organisations on this level are at the very beginning of their digitalization journey and utilise mainly basic IT tools such as excel.

Organisations on level two are beginning to implement predictive analytics in their processes, for example by making use of historical data from multiple sources. The role of the human interaction is still heavy, as deducting insights and building forecasts is still the responsibility of the human user.

Level three is where true AI technologies such as ML begin to take over, creating recommendations based on past data and nearing real-time data analysis. Such activities require vast amounts of computation power through powerful calculation engines and scalable platforms for data management. Humans are still making the actual decisions.

The final level, level four is where organisations reach the highest level of maturity, and sophisticated algorithms continuously learn and adapt to changes, thus being capable of making decisions that lead to an activity. In theory, human interaction is not necessary. A theoretical example of level four are self-driving cars. However, in practice RPA is usually adopted in simple, repetitive, rule-based activities where machine-lead decision-making is low.

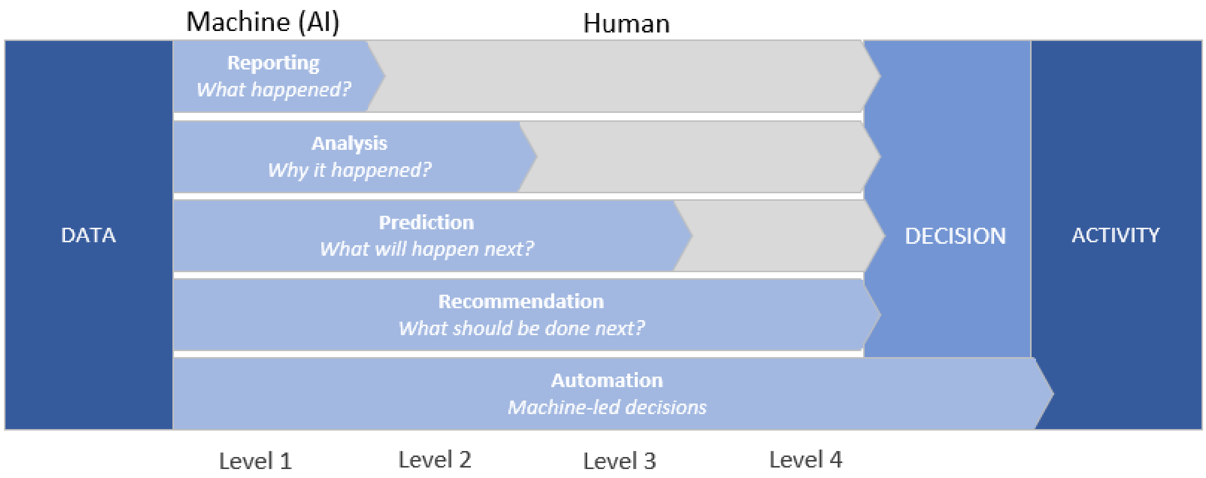

Figure 8 Task responsibility map (adapted from Cubiq Analytics report for Enterprise client, 2019)

2.4.5 Business Use cases for AI

A use case is a common term stemming from software development, and in business context it can be defined as a sequence of actions that results in observable value to an individual actor of the business (Lelli, 2019). According to an AI market forecast report by Kirkpatrick and Kaul (2020), AI software use cases can be divided into three meta categories defined by the enabling technologies: 1) vision, 2) language and 3) analytics. According to the authors, analytics has been the most commonly used tool, due to its affinity to traditional business analytics and ML techniques in creating insights from raw data. However, the report also highlights that the sophistication of deep learning algorithms in human-like recognition of visual and language data allow for a much more advanced and specialized use cases than the traditional AI applications could achieve.

An alternative way to categorize AI is through its business uses instead of the enabling technology. According to Davenport and Ronanki (2018), the three business needs supported by AI are: 1) process automation, 2) cognitive insight and 3) cognitive engagement. According to the authors, robotic process automation (RPA) was the most common type of AI tools currently in use, as it is typically the quickest solution for repetitive tasks (such as administrative, accountancy or audit related), is least expensive and thus brings higher returns on investment more consistently. Due to their simpler nature, RPA solutions are generally not considered intelligent and often lack real sophistication in the algorithms. RPAs are best suited for backend, repetitive tasks across multiple systems.

Then, cognitive insight was noted as the second most common AI type, as it is used in big data analysis (BDA); plying with huge masses of data, detecting patterns and drafting interpretations from them (Davenport and Ronanki, 2018). Cognitive insights are created with machine learning technology, and they differ significantly from traditional analysis tools by assessing a much larger dataset, and by continuously improving the current model over time and making predictions. The authors also placed certain deep learning activities under the cognitive insights-category, the key difference to ML being the human-like pattern recognition without human intervention.

According to the report by Davenport and Ronanki (2018), the least used type for AI was cognitive engagement, where stakeholders such as employees or customers are engaged using natural language processing AI. Common use cases for this category were chatbots, service customizations and personalized recommendations. The authors also pointed out that the most common interaction in this group was with internal users, namely employees, as organisations in this study were not confident in turning their customer interactions to robots due to the immaturity of their current technology. The article concluded that as cognitive technologies are on the rise in organisations, many of them fail due to encountered setbacks and poor planning. Therefore, the authors suggest that organisations take an incremental approach to their AI projects rather than choosing a transformational one.

2.5 Organisation

2.5.1 Characteristics

The organisational context of the TOE framework refers to the descriptive characteristics of the individual organisation (Oliveira and Martins, 2011). In the classic form of TOE, these characteristics are formal and informal linking structures, communication processes, size and slack (DePietro et al., 1990). In the adapted framework for AI adoption, these characteristics are modified to fit the particular context demands of AI, highlighting what elements are expected to be relevant for organisations (Pumplun et al., 2019). These elements are culture, resources, organisational size and organisational structure. Culture is further divided into top management support, change management and innovation culture, and resources are classified into budget, employees and data resources. Further on, data has three subcategories: availability, protection and quality. These characteristics raised by Pumplun et al., (2019) act as the starting point for this research as well.

2.5.2 Organisational culture

In the adapted framework of Pumplun et al. (2019) culture is further divided into top management support, change management and innovation culture. A common theme among TOE literature is the notion that organisational characteristics tend to have more significance in innovation adoption (e.g. Verma and Bhattacharyya, 2016; Sun et al., 2018, Pumplun et al., 2019), reason being that organisational elements are directly in the organisation's control. Environmental and technological elements are implied contexts, and individual organisations have little power to influence them. Top management support reflects the overall acceptance of AI within the organisation, and the lack of sufficient support can be a big detriment to the introduction of AI (Pumplun et al., 2019). According to the authors, c-level leadership needs to understand the technology, in addition to being supportive of adoption efforts. Middle management is seen as problematic, as they tend to be more KPI-focused whilst not having high levels of technological knowledge (Pumplun et al., 2019).

Efforts in change management and an innovative culture usually grow simultaneously and are raised as a key requirement for AI adoption, due to AI's specialised nature (Pumplun et al., 2019). According to Crowston and Bolici (2019) the functionality of an application is dependent on the way internal resources are used, i.e. the input of high-quality data along with the continuous training of employees. Therefore, willingness to accept new technologies, processes and training is paramount in reaching a successful culture (Pumplun et al., 2019).

2.5.3 Organisational resources

In their research regarding big data adoption, Sun et al. (2018) extended the organisational characteristics with elements such as human resources, technology resources, technology readiness, decision-making culture, change efficiency, business strategy orientation, IT/organisation structure, business resources, IS strategy orientation, firm size, and appropriateness. In another research regarding ERP adoption, other descriptive measures such as business scope, top management support, organizational culture, management complexity (centralization), formalisation, vertical differentiation, the quality of human capital and size-related issues were classified as having an impact on adoption decisions (Awa et al., 2016).

Both prior research (Pumplun et al., 2019) and professional reports (Gartner, 2017; Rajkumari, 2019) seem to agree that the human aspects of the organisational context are the defining factor for successful innovation adoption. For example, according to a 2019 global client insights report from CGI, a mere 10% of implemented digital strategies resulted in measurable results at an enterprise level (Rajkumari, 2019). According to Alsheibani et al. (2018) both human and organisational resources are crucially important in supporting any technological resources that an organisation has, as the combination of all three has a positive influence on AI readiness of the organisation.

Based on research, there seems to be a misalignment between investing significant resources in technology-driven efforts and attaining measurable results from those investments. Therefore, we can concur that organisational-level issues are a critical aspect impacting the success or failure of an organisation's adoption and implementation outcomes (DePietro et al., 1990), and potentially need support in from service providers. In fact, the report by Rajkumar (2019) raises inter-organisational collaboration, customer and end-user involvement, talent recognition and attainment, managing partner and supplier eco-systems, and investing in leadership and organisational culture as differentiating factors between successful and non-successful organisations.

2.5.4 Big data and its characteristics

Big data essentially refers to the exponential volume of data, that require specific technological abilities and methods in order to be transformed into value (De Mauro et al., 2016). Having access to the data generated within the bounds of the organisation is a starting point for all organisations looking to move towards mature digitalization, however there is a long way to go for an organisation to be ready for AI adoption from just having access to data (Taylor, 2019). Moving to AI, organisations are faced with much more complex issues regarding data, such as storage problems, analysing capacity constraints and complexity of data (Najafabadi et al., 2015).

Depending on the literature source, the definition for big data differs (Hadi et al., 2015), however the term is associated with a set of characteristic dimensions colloquially referred to as "the V's of big data". The most popular according to De Mauro et al. (2016) are volume (amount of data), velocity (speed of data), variety (different types of data), veracity (accuracy of data) and value (business implications). Sometimes also complexity (variability) and unstructuredness are linked to big data (Hadi et al., 2015; De Mauro et al., 2016). A key point to note regarding big data is that, it has no intrinsic value; the data needs to be collected, cleaned, transformed and analysed with suitable methods and tools in order to draw real value from it (Hadi et al., 2015). The recent and swift appearance of big data has posed difficulties for organisations regarding the maintenance of data, but also, it's protection (Hadi et al., 2015; Taylor, 2019). Organisations are faced with new types of threats regarding data security issues e.g. form hackers and other criminal attacks (Taylor, 2019), that pose additional needs for organisations to deal with.

2.6 Environment

2.6.1 Characteristics

The environmental characteristics of TOE refer to the surrounding realm in which firms operate, such as specific industry characteristics, competitors and other actors on the market and government regulatory context (DePietro et al., 1990). The environment context creates constraints for the organisation regarding their technological innovations, however it also presents opportunities (Oliveira and Martins, 2011). In addition to TOE research, other relevant research also strongly supports the impact of institutional-based variables in innovation adoption (Teo et al., 2003). In the adaptation to AI, environmental elements are competitive pressure, government regulations, industry requirements and customer readiness (Pumplun et al. 2019). Additionally, government regulations are further divided into GDPR (general data protection regulations in EU) and employees' council. The latter of the two is not seen relevant for the scope of this study and is therefore left out.

2.6.2 Institutional perspective

According to a research by Teo et al. (2003) "organisations are embedded in institutional networks", and therefore, institutional pressures can be seen as predictors for adoption intention, they call for greater attention in research.

Environmental context thus presents organisations with competitive pressure, partner readiness, socio-cultural context, government encouragement and support infrastructures such as access to quality service providers (Awa et al., 2016). In addition to these, Sun et al. (2018) continue this list with IS fashion, market turbulence, and institutional based trust as all elements outside the organisation that have an impact on innovation adoption. According to research, there is a strong link between institutional-based variables and adoption intention, and understanding these pressures posed by the government and other institutions is well argued for (Teo et al., 2003).

2.6.3 Data protection laws, regulative constraints and ethics

The popularisation of big data has led to governments also awakening to the possibilities for a new era of digital government services, such as aided policy and decision-making and collaboration between citizens and businesses (Hadi et al., 2015). The large-scale availability and utilization of big data has also brought a more global context into consideration, particularly in the form of EU-legislations regarding data privacy issues (GDPR). How data is now collected, stored and protected is intricately regulated, presenting organisations with a whole new set of challenges (Pumplun et al., 2019)

The report on the State of AI in Finland (Ailisto et al., 2019) has listed ethics, morals, regulation and legislation as of the ten strengths of the Finnish AI market. The report notes that Finland is performing “highly above average” measured in the number of high-quality scientific publications, in addition to placing emphasis on “the increasing awareness from public governance on these challenges”. To conclude, prior research shows that regulatory environment along with support infrastructures and competitive pressure are highly relevant environmental elements in AI adoption decisions.

2.6.4 AI Service Providers on the Finnish market

As a part of this research, a review of service providers was undertaken to shed light on the supplier aspect as an environmental element. This review was done during March and April 2020 and was initially a part of a wider market analysis. An overview research was done by analysing the AI-related offerings of different service providers who are currently offering their services on the market. These organisations were chosen based on their service profile listed on the organisation’s public homepage. Sources for this overview can be found in appendix 1.

The overview contains 14 organisations that operate within the IT and digitalisation consultancy services in Finland. The included organisations were chosen according based on their service offerings, placing emphasis on those who offer data management and AI services. This analysis provides a preliminary view of what the current AI service offering in Finland is like, and what services are offered form a provider point of view. This list does not aim to be exhaustive. The summary of this review is presented in table 1, in no particular order.

In general, the service organisations seem to be mostly technology-driven, with some organisations standing out as more strategic partners, taking on wider digitalisation projects and processes. A popular way to present service portfolios were proof of concepts (POC), which all providers had listed on their website. Possible use cases were presented with previously created solutions to customer organisations, explaining the business problem, with brief details regarding the process and the final solution in a summarised manner.

In many cases, service providers would have a specialty technology they have expertise in (e.g. partner of a platform provider, cloud architecture or AI application). In other cases, no specific technology was announced, but rather a service portfolio for solving problems such as information management, digitalisation services or database migration services, were promoted. Other examples of offered services are system integrations, digitalisation transformations, Development and operations services (DevOps), marketing and sales process automation, predictive maintenance and sensor data analysis, fraud detection, natural language processing, computer vision and object/image recognition, predictive or intelligent analytics and forecasting, optimisation, voice to speech technology, data classification, and customer service activities, cloud migrations.

To conclude, most service providers highlight the importance of strategic alignment and customer-oriented service creation, and many promote their abilities as a holistic partner assisting in all stages of digitalisation efforts, such as migrating from outdated legacy systems, data access, storage and management deficiencies, or solving business needs through novel use cases. However, underlying or organisational issues with a human aspect such as change resistance, low digitalisation maturity levels, gaps or uneven general technological understanding, or discrepancies in consistent management support were mentioned by merely five out of fourteen organisations. It can be inferred, that within these organisations there seems to be a gap in supporting customers with organisational-level issues, which is a critical aspect impacting the success or failure of technology adoption and implementation outcomes (DePietro et al., 1990). Other studies have also found evidence, that organisational and environmental factors have a stronger significance in adoption success compared to technological factors (e.g. Henriksen, 2006).

Table 1 Service provider environment analysis[3]

	Specialisation in AI solutions/data management	Strategy/solution-driven consulting	Organisational-level support (e.g. change management)
Advian	yes	yes	no
Bilot	yes	yes	no
CGI Suomi	yes	yes	yes
Cloud1	yes	yes	no
eCraft Business Insight	yes	yes	no
Enfo	yes	no	no
Fourkind	yes	yes	no
Futurice	yes	yes	yes
Houston Analytics	yes	no	no
KAITO	yes	yes	no
Reaktor	yes	yes	yes
Siili	yes	yes	yes
Silo.ai	yes	no	no
Solita	yes	yes	yes

[3] Market analysis table filled with publicly available information from the organisations' websites; if answers were not clearly stated on said website, notation is 'no' in the above table

3 RESEARCH DESIGN

3.1 Research design for case study research

This research is conducted with empirical section with organisations using AI, and a separate part for triangulation of data, namely an overview of AI service providers on the market. The former is conducted as case study research, using the method of semi-structures interviews for gathering data. The latter looked at which organisations claimed to provide organisational and strategic support in addition to technological consultancy (results are listed in table 1 under chapter 2.6.4).

For the analysis, a thematic approach is used, thus allowing for occurring themes to emerge from the interview data. Braun and Clarke (2006) define thematic analysis as: "A method for identifying, analysing and reporting patterns within data" and according to the authors this method has been widely used in qualitative research. The emerging finding from the interviews is then assessed using deductive logic (Kumar, 2010) through the themes identified from TOE framework, and then analysed following the six-step guideline created by Braun and Clarke (2006).

This thesis will utilise a case study-centric research design, conducting semi-structured interviews firstly with carefully vetted Finnish organisations who are in a mature state of digitalisation. Interviews provide an informative manner for collecting subject data, helping the researcher to gain insights from experts in a more natural way that would be difficult to do otherwise (Eisenhardt, 1989).

Moreover, a semi-structured interview setup allows for a researcher to make use of their prior knowledge on the topic, accompanied by possible presumptions, without limiting the context of the acquired material and thus impacting the outcomes of the interviews (Flick et al., 2004). In addition, theory built upon case study research is appropriate when the topic is novel and there is not yet rigorous knowledge available, or when prior theories do not match the topic well enough (Eisenhardt, 1989). A case study with semi-structured interviews is therefore a suitable method for research in the case of this paper.

To ensure empirical validity, this research is conducted following the eight-step process for qualitative research by Eisenhardt (1989), adapted in table 2. The step- and activity-sections in table 2 are from Eisenhardt, and the results section is adapted to fit the objectives of this paper.

Table 2 Process of building theory from case study research

Step	Activity	Result
1 Getting Started (Defining research questions)	Ensure clear focus prior to conducting interviews (avoiding bias from linking to theory or hypothesis)	What elements are important for organisations when making AI adoption decisions?
2 Selecting Cases	Selection based on specific cases to extend the theory (theoretical sampling)	Large Finnish private and public organisations with high level of IT maturity
3 Crafting instruments and Protocols	Rigor in data collection methods; multiple collection methods	Video-recorded interview data with field notes; Triangulation of data to improve rigor
4 Entering the Field	Flexibility in data collection methods; overlap in data-collection & analysis	Semi-structured interview with questions built based upon adaptation of TOE framework (Ramanathan et al., 2017), but allowing for adjustments
5 Analysing Data	Within-case & cross-case analysis	Following an established process of coding (Braun and Clarke, 2006) for validity in data analysis
6 Shaping Hypothesis	Iterative tabulation of evidence and search evidence; following logic across cases; building validity	Preliminary theory generation, reviewing initial impressions throughout coding process
Enfolding literature	Comparison with conflicting literature	Limitations of TOE framework (Al Nahian Riyadh et al., 2009; Wang et al., 2010)
8 Reaching closure	Theoretical saturation when possible	Interview process was concluded when novel topics were no longer emerging or were industry-specific

The purpose for the interviews was to discover what themes emerge relating to AI adoption decisions in Finnish organisations, and to uncover how well TOE framework corresponds in describing this phenomenon. Thus, the interview questions for this research were created based upon the TOE adaptation of Ramanathan et al. (2017) and on the following factors raised by Zhu et al. (2004), namely financial resources (Organisation), competition intensity and regulatory environment (Environment). This is compliant to the process in table 2, where interview questions should be linked to theory or hypothesis in order to avoid possible bias. Case organisations were selected on the basis of theoretical sampling, i.e. to “develop, refine or fill out the properties of tentative theoretical categories” (Charmaz, 2015).

The point of interest is to find out what elements are relevant to organisations in AI adoption decisions in the Finnish market, and a sub question of this is how well TOE elements corresponds with explaining these elements.

3.2 Data collection method

This research is conducted using qualitative research methodology and can be classified as an exploratory case study. The case study in question is the state of AI in the Finnish business market domain. According to IS literature, case studies are often used when researchers aim for an in depth and generous description on the subject, placing emphasis on the real-world predicaments (Yin, 2012). Despite the danger of researcher’s preconceptions which arise from using case studies, some literature suggests that this is a myth; the juxtaposition offered by case study research requires lateral thinking and connecting different realities, which in turn potentially mitigates any research bias (Eisenhardt, 1989). Considering this, case study research is particularly useful in novel research such as in this particular AI study. Another point in favour of case studies is that the resultant theory is heavily entwined with empirical data, thus improving the validity of the resulting theory (Eisenhardt, 1989).

However, according to the same literature, a categorical weakness of theory built upon case study research is that it generates huge amounts of data, and it can be difficult to assess the most important relationships, and to simplify the findings without any quantitative tools (Eisenhardt, 1989). Thus, a generalising approach based on bottom-up theory building can arise issues from oversimplifying events or misclassification. To mitigate such risks this paper has steered away from attempts to generalise with such a novel research topic and focused on examining the findings with close links to TOE theory, instead of attempting bottom-up theory building.

Ontologically, there are three possible levels for conducting analysis, namely: micro-level (user), meso-level (firm) or macro-level (market/innovation) (Liu et al., 2008). As this research is interested in the firm level context, the lens for this paper is on the meso-level. According to Ketokivi and Choi (2014) there are three approaches to research in relation to case studies: 1) theory generation 2) theory testing and 3) theory elaboration. The third approach merely uses the context of the general theory, and it does not assume the exact same premises in which the general theory was created in. Therefore, the third approach is useful in situations where a general theory is used as a structure for the research, but adaptation is required (e.g. Ramanathan et al., 2017; Pumplun et al., 2019). This research aims to further build on prior research, namely the adaptation of TOE framework for AI adoption, by extending it with relevant and novel findings.

Empirical data is gathered through face-to-face interviews with organisation representatives who have a connection to AI decision-making. According to an emic approach (NurseKillam, 2015), the researcher acknowledges that there is always an interrelationship between informers and researcher. In both deep and semi-structured interview styles the researcher can influence the informers based on their personal interrelations. For this reason, this research is embracing this interrelation rather than ignoring it. In emic approaches, embracing the relationship and involvement of the researcher can aid uncovering further meaning (NurseKillam, 2015), and it is a form of relativism in research.

The empirical scope for this thesis is large organisations from varying industries in Finland. The participating organisations may have operations also outside of Finland, however since the case interviews are examined from the point of view of the local market, this is not a restricting factor.

The organisations that participated are listed in table 3, along with preliminary information. All participants have full anonymity in this study in order to protect any critical business information that was shared during the interviews, and this poses some limitations in the way results are presented.

3.3 Data gathering process

An email invite for participation was sent to 80 Finnish organisations operating in a variety of different fields, to middle management or higher who are either closely linked or directly responsible for IT-related decisions, and therefore also AI (e.g. data science team lead, Centre of excellence i.e. CoE management etc.). The potential participants all have either a specialist role or otherwise extensive knowledge in the use of AI and other emerging trends within their organisation, thus ensuring adequate knowledge of the topic. Out of these 80, 15 organisations initially confirmed participation; however, 2 organisations were unable to participate. Finally, 13 organisations with 15 interviewees were included and interviewed for this study (in two cases there were two interviewees present). The interview questions along with a preface for the interview, which were sent to each participant ahead of time for familiarisation, are included in appendix 2.

All interviews were conducted via a video conference tool, out of which 12 were video recorded; due to confidentiality reasons, one interviewee was not recorded on video. During each interview, extensive notes were taken simultaneously to ensure multiple sources of documentation. In addition, these initial notes were supplemented after each interview with the help of the recordings to mitigate the risk of bias during the interview process (Eisenhardt, 1989).

According to Marshall et al. (2013), to maintain an adequate level of rigor in a qualitative research, a case study research should have 15 to 30 interviews. This guideline is applicable for funded studies e.g. in esteemed journals and aimed at IS researchers to further improve the rigor level of their research. Therefore, the number of interviews is preferable but not a requirement, as research of such scale is not the goal of this master's thesis paper. As this research is exploratory, discovering new aspects into the topic of AI adoption in Finland, it is not aiming to be exhaustive. Therefore, 13 cases are justified and more than enough to provide rigor for this study.

According to step eight in table 2 by Eisenhardt (1989) new interviews should be conducted until no novel topics arise, the objective being to reach saturation in the data. In the case interviews for this study saturation was reached, as any novel topics that arose were industry specific and therefore outside of the scope of this research.

In accordance with the third and fourth steps of Eisenhardt's (1989) list, using more than one mode of recording increases the rigor of the research, and analysing the information both parallel to the data collection (notes) and afterwards (voice-recordings) improves flexibility in the research process. Including such measures in the process of research improves the quality of research and reduces the risk of information loss.

After the completion of three interviews, the list of questions was adjusted to improve the interview process by deleting repetitive or irrelevant questions in subsequent sections. This reduced the total number of questions by two questions (to a total of 23).

Table 3 lists participated organisations with no specific rank; size and approximate turnover information are shown in blocks to ensure anonymity for the participants. Level of digitalisation maturity implies to the expected technology adoption readiness of the organisations. This was to indicate that all participants have adequate readiness for AI adoption, and should not be viewed as an in-depth assessment. Organisation 13 is a government organisation, and therefore it does not have turnover information, but rather an annual budget allocated by the Finnish government.

Table 3 Description of participating companies

Organisation	Size by employees	Industry Description	Approx. Turnover (euros)	Level of digitalisation maturity
Organisation 1	<1 k	Research/scientific development	<0.5 bil	High
Organisation 2	5<10 k	Energy	5<10 bil	High
Organisation 3	5<10 k	Construction/infrastructure	2<5 bil	High
Organisation 4	1<5 k	Finance	<0.5 bil	High
Organisation 5	30<50 k	Consumer goods/retail	10<15 bil	High
Organisation 6	30<50 k	Consumer goods/retail	10<15 bil	High
Organisation 7	20<30 k	Forrest industry	5<10 bil	High
Organisation 8	10>20 k	Logistics	1<2 bil	High
Organisation 9	<1 k	Consumer electronics	2<5 bil	High
Organisation 10	1<5 k	Telecommunications	1<2 bil	High
Organisation 11	1<5 k	Software solutions	<0.5 bil	High
Organisation 12	10>20 k	Finance	2<5 bil	High
Organisation 13	1<5 k	Government organisation	<0.5 bil[4]	High

Table 4 lists the interview-related information with length and date of each interview, and documentation per each interview session. To adhere to anonymity of the results, job titles of participants in alphabetical order are: chief strategy officer, data and business intelligence manager, director in business analytics, director of IT, head of AI CoE, head of business IT, head of data science, information management director, lead data architect, lead data scientist, lead in analytics, research manager, senior officer of digital risk and service manager in analytics (slightly modified for anonymity).

[4] Estimated annual budget for 2020

Table 4 Case study participant interviews

Organisation	Length of interview	Date of interviews	Documentation
Organisation 1	54 min	21.04.2020	Video, notes
Organisation 2	90 min	28.04., 29.04.2020	Video, notes
Organisation 3	55 min	18.05.2020	Video, notes
Organisation 4	60 min	18.05.2020	Video, notes
Organisation 5	56 min	07.05.2020	Notes
Organisation 6	65 min	18.05.2020	Video, notes
Organisation 7	60 min	13.05.2020	Video, notes
Organisation 8	90 min	15.05.2020	Video, notes
Organisation 9	55 min	19.05.2020	Video, notes
Organisation 10	55 min	19.05.2020	Video, notes
Organisation 11	45 min	20.05.2020	Video, notes
Organisation 12	45 min	25.05.2020	Video, notes
Organisation 13	65 min	26.05.2020	Video, notes

3.4 Data analysis method

In order to ensure clarity and transparency in qualitative data analysis, Braun and Clarke (2006) suggest a six-step process for analysing collected data: 1) familiarization with collected data, 2) Assigning preliminary codes to data in order to describe content, 3) searching for patterns or themes in codes across different interviews, 4) reviewing themes, 5) defining and naming themes and 6) producing final report. According to the authors, an important aspect of thematic analysis is looking for "themes or patterns across an (entire) data set, rather than within a data item" (Braun and Clarke, 2006). These steps were followed in the coding part of this thesis, during the process of analysing the primary data from interviews.

Twelve of the case interviews were recorded on video, with extensive notes taken both during and elaborated after the initial interview (step 1). Additionally, one participant wished to stay unrecorded, so in this case the interview was transcribed during the interview. Subsequently, the written data from all interviews were assessed using Quirkos software for qualitative research analysis, first by assigning preliminary codes (step 2) based on the findings from Pumplun et al. (2019), and then after additional patterns and themes were found (step 3) the initial themes were reviewed (step 4). Finally, the newly found themes were merged with the initial themes to form final connections and patterns that were then transferred to the results section for elaboration (steps 5 and 6). In the review of themes and creation of new patterns descriptive coding was used that help in identifying themes that go beyond the initial themes based on literature. Furthermore, additional triangulation of data took place alongside the coding process by utilising multiple sources of evidence (Eisenhardt, 1989; Flick et al., 2004). These other sources include for example professional reports on current practices in AI or digital transformation contexts (e.g. Korczak et al, 2018; Rajkumari, 2019) and the opinions of a consultation expert.

Braun and Clarke (2006) also emphasize the importance of certain prior decisions that have a profound influence on the analysis of gathered data, such as: the definition of a 'theme' in the context of the research, identification of themes in data, level of analysis and epistemology of the analysis. In this research paper, prevalence is given to themes with multiple mentions across interviews; themes are analysed in a deductive manner (i.e. using a theoretical framework as a guide); level of analysis is semantic (surface-level, looking for what has been said rather than latent meaning); and lastly, this research has a relativist approach (belief that truth is contextual).

4 RESULTS

4.1 Case Interview results

For the analysis, the adapted TOE framework by Pumplun et al. (2019) was used. Furthermore, this version of TOE was adapted with relevant findings from the case interviews from this study. In the summary tables, any additional novel or relevant findings that were added based on the findings from this research are emboldened.

4.1.1 Technology

Table 5 Technology characteristics

Characteristic	detail	Number of organisations that mentioned as factor
Cost of adoption	Relative advantage	12
Compatibility	Business case and process **understanding**	13
	Both internal and external expertise	11

** Novel and relevant findings based on the interviews are marked as emboldened*

To improve the initial adapted framework, *cost of adoption* (Sun et al., 2018) are included, as the higher-level characteristic of *relative advantage*.

All thirteen interviewees found in-depth *business case and process understanding* as most important when making technology adoption decisions. Below are examples of quotes that support this notion:

> *"The understanding of the problem and use case design are often deficient, there must be a real understanding in order to attain real benefits. Sometimes traditional analysis or BI is enough […] the problem is not the complexity but the [correct] definition of the problem. In addition, the limited resources determine what can be done! You have to think about what you are doing" – Data and BI manager*

> *"The development process arises close to the business. Understanding the goal is important, ideas are born as a collaboration between business and development; sparring is ongoing, but we do not have a specific process for it, together we consider prioritization. Our teams are autonomous, but naturally we plan together" – Data and BI manager*

> *"We always start from a business perspective, supporting strategy. what is the ultimate business benefit? The real bottleneck is identifying where AI is worth [the effort] or should not be exploited." – Director of IT*

Additionally, twelve organisations stated that AI technology is viewed as merely one of the available options, and in each case, comparison with other technologies or solutions is important. Thus, AI adoption decisions rely heavily on *relative advantage* compared to other available technology. Below are two quotes from respondents:

> *"But, for example, algorithm development, even though it is quite a good skill, it does not make sense for everyone to know those basic things [...]. Here you always have to think about benefit vs. the effort required" – Director of information management*

> *"[The business case] always starts with a business problem, what is the best way to solve it? [...] the problem needs to be solved and then figuring out which solution is best for this. [...]. [The best solution is] not always artificial intelligence, it's just one tool among others. The team notices the problem, we go and then ask the specialists [...] then, as business awareness grows, so does the overall understanding, and [makes it] easier to also adopt AI solutions" – Director of information management*

The above quotes support the notion that AI is seen as a tool rather than having intrinsic value, and that organisations find it important to start from true business case understanding.

One organisation reported to buying all their AI solutions, and they do not aim to have in-house expertise beyond support. Eleven respondents reported using a mix of *both in-house and external expertise*, but the weights between internal and external varied. External services tended to be for specific skills that were not part of their long-term strategy (i.e. not worth investing in in-house skills), for early-stage consulting in new projects, collaboration projects or large organisational changes (such as platform migration). One respondent did not clarify the extent to which they make use of external capabilities. Additionally, five organisations reported placing emphasis on having highly skilled data science teams in-house, who are the main source of AI development. For these organisations, use of external expertise was limited, for example in project initiation or for use case sparring. In addition to accessibility, data preparation is particularly important in time-sensitive and data-intensive cases. According to one respondent, lapses in basic ETL and data cleansing activities can cause major bottlenecks in all data intensive processes.

In almost all cases, technology was named as one of the key starting points for AI, but more in a sense of having the necessary skillset to make use of the available technology. Technology itself was found not to be a limiting factor, as technology is readily available, and the development skills are usually high.

To sum up, all thirteen organisations placed high importance on understanding actual business needs as the starting point for developing tools. The ways this was achieved by the organisations differed (e.g. CoEs, dedicated data science teams etc.) but all emphasised that all AI adoption decisions begin from the needs of the business rather than from the wanting to implement new technology. Additionally, technology was not seen as a problem in its own right, as nearly all organisations viewed their technological abilities above average or felt that alternative solutions were available (e.g. consultancy support, external product development etc.). Most common problems were *data literacy, issues with data infrastructures*, and *business case understanding*.

4.1.2 Organisation

Table 6 Organisation characteristics

Characteristic	detail	Number of organisations that mentioned as factor
Organisation Culture	Top management support	9
	Change management	6
	Enabling culture	8
	Learning mentality	7
	Strategic link	12
Organisational structure	**Centralised expert teams**	10
Employee Resources	**In-house developer skills**	9
	Base-level knowledge of AI	11
Data resources	Data availability and accessibility	11
	Data quality	8

** Novel and relevant findings based on the interviews are marked as emboldened*

Based on the interview responses, there were four detail elements that were most relevant to the respondents. *Link to business strategy* was relevant to 12 organisations, *base-level knowledge* for 11 and *organisational structure* was relevant for 10.

Learning mentality, which in this study entails both incremental learning and continuous testing, was highlighted by seven organisations. Most of these seven also emphasised the importance of being flexible, particularly in the beginning of the development phase.

According to some respondents:

> *"The corporate culture must be enabling, experimental, ideological and supportive, because the first solution is often not very impressive, development takes place little by little. the best result is obtained by gradually developing, this requires understanding from the organization [...] The way of working is iterative." - Data and BI manager*

> *"Culture in the organization is a big problem. When companies are well established, sometimes [innovative] capabilities may be lacking; business value-seeking and experimentation are lacking" - Lead data architect*

Consequently, organisations that had any form of *centralised expert teams* (such as CoEs or specialised AI-teams) helping the business functions with their business problems, reported to having higher levels of general technical understanding throughout the organisation; business owners were found to be more informed about new possibilities on the market and their limitations.

> *"We aim to engage end users already in the development stage, ensuring that they actually use and are open to the system. [...] In piloting, end users are there throughout the process. A common mistake is that you make a great system for digital people, but none of the real users are involved from the beginning, feedback is missing! This leads to problems down the line. There is a lack of 'grassroot' knowledge and information" - Lead data scientist*

Two ways organisations tackled issues stemming from resources were to have *in-house developer skills* and expertise through dedicated data science teams, and also importance of *base-level knowledge* throughout the organisation. Five organisations had recurrent company-wide trainings in place (e.g. workshops, info sessions, forums, panels etc.).

The main objective for most respondents was to use AI as a tool amongst other available ones, thus supporting the organisations strategy to improve e.g. profitability, reduce costs, increase efficiency, improve forecasts and accuracy of actions. AI was not seen any more valuable than other options that can solve the problem.

Organisations who had strong *leadership support* and in-depth understanding of the possibilities of AI for the business within the C-suite, reported to having a more *innovative culture* throughout the organisation. Those organisations who had strong support from the organisation leadership also had less issues regarding AI adoption (e.g. less issues with funding, the general atmosphere was more positive around AI and its possibilities, cross-organisational collaboration was more frequent etc.). The following quotes support this notion:

> *"It's important to accept the initial "child-hood diseases", […] must not be left in the middle of whether [a solution] is in use or not […], and not have 95% completed but then be scared to introduce it because the management or the end user do not understand it […]" - head of business IT*

> *"Current solutions are most often individual use cases that have been developed for a specific problem. There must be a level of basic knowledge and understanding of AI before the solutions can be applied more widely to other business cases as well" – Director of information management*

One interviewee raised extensive testing as one of the key parts of AI adoption process, in order to verify whether the chosen technology matches its expected outcome:

> *" We have had situations where according to calculations written on [a piece of paper] the chosen AI was supposed to bring significant benefits. But when it was actually tried out it just didn't work. These things happen […] That's why it's important to do preliminary testing before taking it to any widescale production." – Research manager*

Lastly, *data resources* arose as being highly relevant throughout the interviews. Most pressing data issues were relating to *accessibility and availability*, meaning that organisations mostly had issues with getting the right kind of data of a sufficient amount, at the right time, or had trouble accessing certain data (e.g. due to compatibility issues or data protection etc.).

> *"In all companies so far, the requirement is data availability, 90% of AI cases crash into data availability or at the expense of getting it! The pilot could create plans quickly, but organisations are still lagging behind in data availability" - head of data science*

Data quality was also mentioned by some organisations, as eight found quality issues relevant. However, some organisations stated that they felt their data was quality-wise at a decent level already, and their main issues tended to be around availability and accessibility.

From the initial graph by Pumplun et al. (2019) budget was left out from the analysis. In large organisations financial resources are more readily available than in smaller organisations. Budget issues tend to be a combination of multiple things, such as relative advantage, allocation decisions and business case knowledge (Pumplun et al., 2019). Therefore, budget is seen as a part of other characteristics and did not warrant its own analysis.

4.1.3 Environment

Table 7 Environment characteristics

Characteristic	detail	Answered organisations
Competitive pressure		8
Industry requirements		7
Customer readiness		9
Government regulations	GDPR	11
Market situation	**regulatory changes**	4
	trends	10

* *Novel and relevant findings based on the interviews are marked as emboldened*

Regulatory environment had a strong impact on organisation's AI adoption decisions, as recent reforms within the EU regarding data protection and privacy laws (*GDPR*) forced a lot of large-scale changes within data collection and management processes (Vernon, 2019). Mostly these reforms were seen as positive, as many of the interviewees noted that such protection laws are improving the liability and transparency of organisations handling e.g. private consumer data. Organisations which operate in industries with highly confidential information and thus are heavily regulated, such as financial, governmental or telecommunication organisations, saw GDPR reforms as particularly important. Many of the interviewed organisations stated that data privacy regulations were of high importance to their business activities, as reforms in data protection laws influence their operations. However, this was seen as no more detrimental than in other EU countries, and Finland was not seen as any more difficult than the rest of EU. Many respondents noted that such privacy enforcements bring positive changes.

On the other hands, *industry requirements* were relevant to seven of the organisations. This can be largely explained by the fact that those organisations that deal with confidential data such as financial or government institutions are more reliant on the regulatory landscape of the market. Also, those organisations who dealt with consumer data were forced to adhere to data protection laws. Consequently, *customer readiness* or responding to customer needs and changes in demand was relevant to nine organisations when they make AI adoption decisions.

Competitive pressure was found relevant by eight organisations, which suggests that about half of the organisations find it important to know what competitors are doing and keep up with them or wished to stay ahead of competition. Many interviewees reported that they monitor and benchmark the market intently.

> *"Pioneering is not of intrinsic value, the goal is to still be able to maintain profitability [...] through special collaboration days we become familiar with what other competitors do in Finland, it is known that we are beyond them when it comes to 'won euros', successful applications, etc." - Chief strategy officer*

Lastly, an addition to the above TOE model, *market situation* arose as an important determinant for AI adoption. Ten organisations found *market trends* as relevant for adoption decisions, such as urbanization, aging population or other mega trends, or the state of the global (or domestic) economy. For example, the sudden emergence of a global downturn in spring 2020 had impacted the short-term activities of many of the organisations.

4.2 Discussion

4.2.1 General points of overall results

Based on the interview results from the 13 participating organisations, this research found clear links between the three elements of TOE framework and AI adoption decisions. Organisational and environmental characteristics seemed to have a stronger impact on AI adoption and implementation than technology characteristics.

One discovery from this research however was that on its own, the classical TOE framework is useful only as a starting point for research, and as prior research supports, it should be adapted according to the innovative technology in question. Examples of such adaptations for TOE are e-business (Zhu et al., 2004), cloud computing (Alshamaila et al., 2013; Borgman et al., 2013), business analytics and big data (Ramanathan et al., 2017; Sun et al., 2018) and AI (Alsheibani et al., 2018; Pumplun et al., 2019). After the data analysis phase, the themes which emerged from the interviews reflect largely on the adaptation of TOE for AI by Pumplun et al. (2019).

4.2.2 Technology

Nearly all the respondents stated that technology itself was not an issue, nor were the technical capabilities of the organisation (many rated their technological skill base as advanced, due to investments in in-house data scientists and other skilled employees).

Compatibility characteristics, namely business case and process understanding were positioned as most relevant for organisations. This finding was in line with Pumplun et al. (2019) as their findings concluded that business processes need to be adapted, and agility in ways of working are a prerequisite to get full use of AI. For example, the authors find that one key element is ensuring success in AI solutions development in the early stages. In addition, the importance of early successes was mentioned in many of the interviews, as this can greatly impact many other elements of AI adoption readiness, such as ensuring future funding, decreasing change resistance and improving the organisation culture. This also adheres to compatibility requirement (Pumplun et al., 2019).

Many organisations assessed themselves above average in IT maturity, and still saw AI as a tool amongst others. This would also explain the numerous mentions of the relative advantage or AI compared to other solutions. Above all else, business case understanding arose as the starting point for all participants, meaning that outside of random experimentation, all created use cases begin with a need from the business, or a problem that needs to be solved. Thus, in-depth understanding of the true requirements of the business is necessary for successful use case creation. If the business problem is not properly understood, it is difficult to create solutions that are answering to the real need. This can create inefficiencies, reduced returns on investment (ROI) and resistance in the organisation. According to Rzepka and Berger (2018), AI is more suitable in certain use cases than others, which supports the findings from this study. Considering these points, relative advantage was placed as a subtype of cost of adoption to better describe this characteristic.

In sum, technology itself was not seen as a detriment to AI adoption, as many of the organisations interviewed had significant efforts in place for business case and process understanding. In addition, information about recent innovations and improvement are readily available and shared openly for example through partnerships with other market participants, discussion forums or workshop events, which increases understanding and supports relative advantage compared to alternative technologies.

4.2.3 Organisation

From this research, it was clear that the first-level issue organisations face when dealing with AI development relate to data. This notion was confirmed by the findings from the interviews, as all organisations reported having some kind of issues relating to their data. From the case interviews, the biggest bottlenecks organisations faced were accessibility to data (how easily available is the data, is it in multiple locations etc.), availability of the right data (is there enough of the exact data that is needed?) and the quality of the data (e.g. badly managed meta data, missing or incomplete data, incompatible legacy system data etc.). This finding regarding the unique issues data poses on organisations is supported by prior literature as well (Hadi et al., 2015; De Mauro et al., 2016).

For AI technologies to be of use, there needs to be a substantial amount of data, as the more sophisticated the technology the more data is required (e.g. DL solutions). Other issues that were mentioned were workflow issues (e.g. combining data from different sources) and data literacy issues within the organisation. Prior literature confirms data resources as being relevant in AI adoption, however the significance in prior literature (e.g. Crowston and Bolici, 2019; Pumplun et al., 2019) was not quite as high as it was in this research.

Resources in human capital were increased through investments in attaining in-house expertise and through improving the basic-level knowledge of employees. Those organisations who invested in the educating the general employee base reported that by increasing the general understanding of AI and what possibilities it presents allowed for better application to solving business problems. Therefore, increasing basic-level knowledge has much wider implications, as it indirectly impacts also innovative culture (organisation) and business case application (technology). The importance of in-house resources has also been raised in prior research (e.g. Kruse et al., 2019). Alternatively, some research also suggests growing in-house expertise by bringing in new blood, i.e. new work force from outside of the organisation (Ramanthan et al., 2017), in contrast to picking internal talent with business knowledge and training them into data science roles (Pumplun et al., 2019).

Organisation structure was highlighted by the majority of organisations as relevant in AI adoption. However, prior literature poses organisation structures being directly linked to organisation culture (Pumplun et al., 2019) as strict structures and bureaucracy are a direct hindrance to agile organisation cultures that support learning. Most of the organisations claimed to have a centralised expert team who is dedicated to proactively push AI solutions and other technologies to the business. However, according to literature if such overarching and highly specialised groups are tied to tight budgets and performance targets, it will have a detrimental effect on organisation culture and innovation (Pumplun et al., 2019).

From the interviews, management support, link to business strategy, enabling organisation culture and resources emerged as having high importance consistently throughout different interviews. These characteristics were also noted in multiple studies (e.g. Awa et al., 2016; Sun et al. 2018; Pumplun et al., 2019). Many of these characteristics are directly linked to each other, for example silo issues can be mitigated through improving internal communication processes and an enabling culture can be both a prerequisite and an outcome of management support, learning mentality and adequate change management. The concept of causal relationships between different characteristics was also noted by research (Pumplun et al., 2019).

To conclude, the most common issues that emerged from the interviews were data-related, and sufficient data-management efforts which are tailored into the organisations' individual business strategies were a major requirement for many.

4.2.4 Environment

The relevance of government regulations on AI adoption was in line with prior research (Teo et al., 2003), as the prediction was that due to newly introduced GDPR in 2018 there would be noticeable impact on all organisations utilising personal data. As such, prior literature suggested that such strict laws regulating the processing of personal data would hinder organisations and be of negative impact (Pumplun et al., 2019). However, the general notion regarding GDPR from this research was positive, as organisations found it to be a necessary and welcomed change. Of course, the resulting need for changes in internal processes due to new data protection laws was also noted in prior research (Teo et al., 2003).

Customer readiness, competitive pressure and industry requirements had all a relatively large impact on the organisations, however all three tended to be intertwined. Namely, specific industries were more demanding than others with regards to competitive pressure and placing efforts in being customer ready. For example, responding to customer needs was more important in retail and financial industries, and competitive pressure was more relevant in industries that were tech oriented. Thus, industry requirements can either support, hinder or encourage AI adoption (Kruse et al., 2019).

Those organisations that had a stronger link to research tended to have a more positive opinion about Finland as an environment; on the other hand, there were a few respondents who felt that there are still some things that could be improved. This suggests that the Finnish government efforts into AI research is more visible to those involved in research, as opposed to those organisations who are less active in research. Zhu et al. (2004) findings support the impact of regulatory environment.

The impact of the overall market situation was largely dependent on the industry of the organisation. Namely, those industries that are directly impacted by chances in consumer behavior (e.g. financial institutions) reported paying more attention to the changes on the market and incurring pressure to adapt quicker. In relation, customer readiness, which is influenced by customer behavior in the market, was an important element for those respondents.

5 CONCLUSION

5.1 Summary of research

The preface for this paper was to uncover what elements organisations found relevant when making AI adoption decisions. The research was set up as a case study research, where 13 large Finnish organisations participated in semi-structured interviews. The results from the interviews were assessed against a popular theoretical framework in IS research, namely TOE framework, which assesses the technological, organisational and environmental elements that influence organisations regarding their innovation adoption decisions. In this study, an adaptation of the classic TOE framework was used and further extended to incorporate novel findings.

Based on this research, Finnish organisations raise business case and process understanding, organisational culture, strategic linking and data-related issues as the most important elements that have an impact on the adoption of artificial intelligence. Data related-issues account for both data resources and the data protection needs. The findings from this paper are placed in a framework in figure 10, that includes the relevant and novel findings that arose from the interviews.

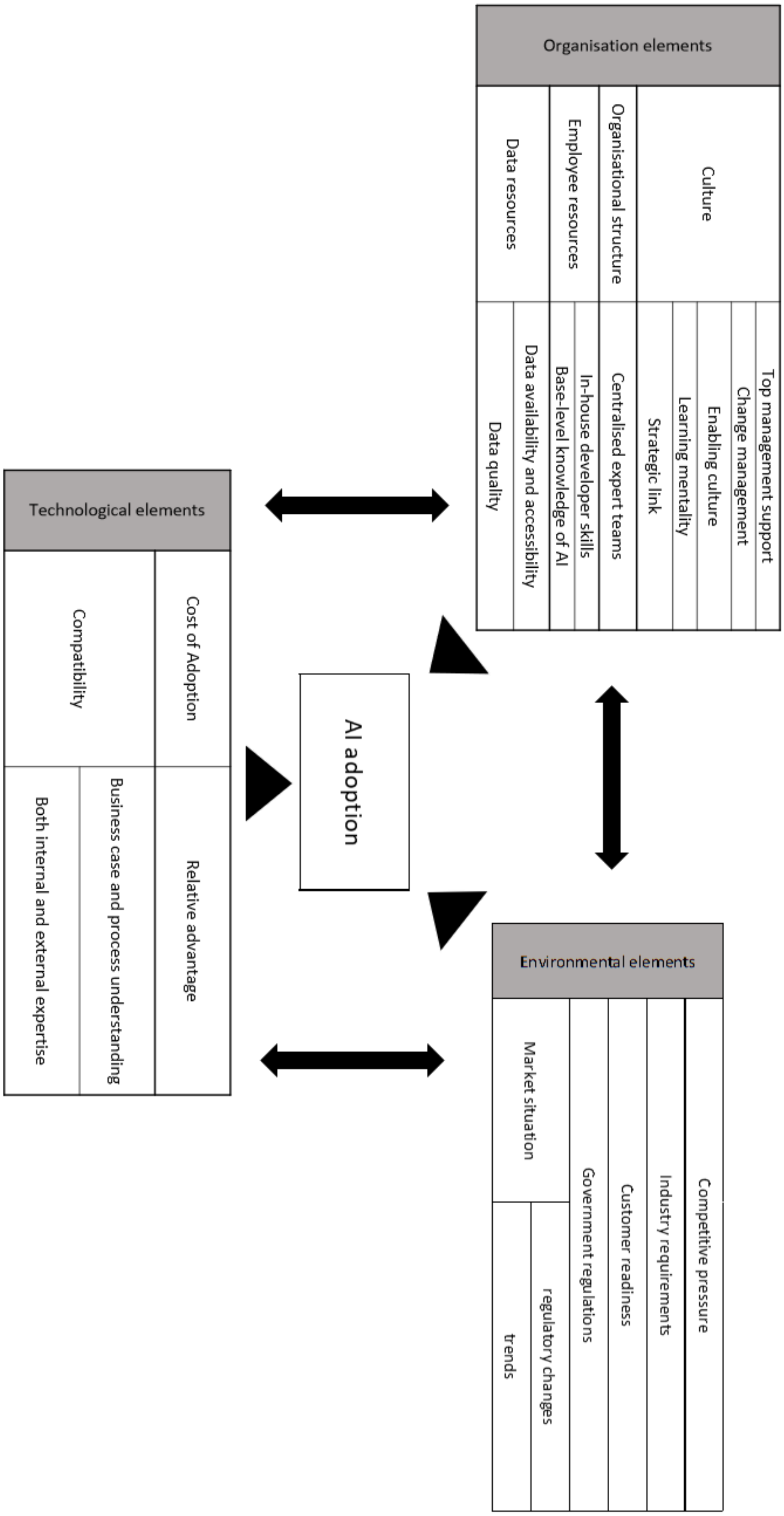

Figure 9 Further developed TOE framework for AI adoption

In the research proposal section of this paper, it was proposed that organisations find organisational characteristics as most important elements in AI adoption decisions. One finding that partly supports this proposition is that there is not an even weight between the three elements of TOE. For example, technological issues, such as having most up to date knowledge of current innovations or understanding the relative advantage between different solutions, are merely first-level issues when it comes to AI adoption. Past this first level the other two elements, organisational and environmental, outweigh technological issues. However, this is not to state that technological elements are not relevant.

Consequently, nearly all respondents claimed that technology alone almost never is found as a true problem, but rather the in-depth understanding of the needs of the business. Having insightful understanding of the business problem and building a proper business case prior to investing in AI was a key starting point for all organisations. Based on the results, organisations need to first look at their available data, assess their business model and customers, then ask the right questions to form a hypothesis, which then needs to be validated prior to investing in a novel AI-based solution.

An interesting finding was the importance of relative advantage in AI adoption. Of course, in order to stay profitable organisations need to carefully weigh investment costs against expected value, and to accurately assess this is not always so straightforward ahead of time. However, this could also hint at the reason why large established organisations (who are not from the tech industry) are statistically behind in AI implementation. With new technology, it can be hard to forecast possible uses 5 to 10 years ahead, and organisations tend to therefore focus more on solving today's business problems.

Furthermore, based on prior literature and preliminary phases of the data collection, top management support and change management would be the most important. This was partly confirmed by this study, as organisational elements were collectively the most important for the interviewed organisations. However, in the final data analysis part it was found that top management support and change management were not the most important, but rather having a strong link with the business strategy and resources relating to data and employees stood out as more concerning for Finnish organisations. Nevertheless, top management support and change management were still found to be relevant, albeit perhaps will become more pressing at other stages of an AI adoption processes. Alternatively, some of the organisations might have been able to place adequate investments in change management and had high top management involvement, and therefore the

respondents did not see these as issues anymore. Such differences in approaches and level of maturity in the organisations can skew the analysis of this research.
As supported by prior literature, the findings of this study adhere to the heightened relevance of organisational elements in AI adoption. Furthermore, organisations that were aware of the importance of these aspects and allocated appropriate resources to address them, reported more successful adoption activities.

Based on the findings of this research, it cannot be definitely stated which of the three TOE elements hold the highest importance to organisations. However, it can be stated that all three elements should be considered by leadership for cases of AI adoption. Importance weighting on specific characteristics should be assessed on a case by case basis according to the industry and internal capabilities of the organisation in question. This will then in turn assist with effective allocation of resources.

5.2 Validity, reliability and limitations

The goal of this paper was to find interesting patterns and themes that can be useful for practical application, and that could also have a link to prior research. But, as pointed out by Braun and Clarke (2006), it is important to note the "active role the researcher always plays in identifying patterns/themes" when conducting qualitative research. Therefore, it must also be considered that there is inevitable influence of the personal theoretical positions, values and even prior experience of the researcher in qualitative research. Reliability for this thesis should therefore be viewed as transparency in the research and analysis process, and clarity in practice of method (Braun and Clarke, 2006).

In order to ensure adequate research quality, triangulation of data was an important part of data gathering. To complete the triangulation, and thereby improving the rigor and validity of findings, primary data collection was complemented with an overview of current participants offering AI solutions in Finland.

To improve the validity of the findings from this paper, a well-established framework (TOE) was used as a guide during the analysis process, which was also adapted to fit the context of this study (Pumplun et al., 2019). Moreover, careful consideration was placed on achieving academic validity through following vetted and peer-reviewed steps for qualitative research (Eisenhardt, 1989) and the data analysis process (Braun and Clarke, 2006).

The results cannot be directly applied for all occasions, but rather are presented as one possible point of view. But, since the concepts studied in this paper are universal, the findings of this paper can be adapted to other domains as well.

There are several possible limitations that can be identified in this study. First, there are inherent limitations to qualitative research, and thematic analysis is no exception. It allows for flexibility in the research set up and is useful in analysing large data sets in broader concepts (Braun and Clarke, 2006). However, due to this flexibility in design, thematic analysis is prone to researcher bias, as the analysis is highly subjective and relies on the judgement of the researcher. As suggested by Braun and Clarke (2006), this limitation was mitigated as much as possible through careful reflection on choices made. In addition, research design and coding parts were following confirmed step-by-step research guides.

Another possible bias arises from the participated interviewees. From each case interview, only one team or function was represented, and usually the interviewees were from either expert teams or management. This is classed as elite bias, when only one point of view is included in the interviews, or the data is homogenous (Miles and Huberman, 1994).

Another limitation is that the analysis style for coding in this paper was semantic, i.e. results are based on the number of organisations that mentioned a characteristic during interviews. If the analysis was latent, the underlying meaning behind statements would be assessed; this could lead to different weighting of characteristics. However, to be able to make absolute statements on which elements or characteristics organisations find most relevant would require further research.

Lastly, a categorical weakness of case study research is the difficulties in assessing relationships and simplifying findings (Eisenhardt, 1989). This weakness was addressed by using an established framework as the basis of the study (TOE framework) and adapting it according to emerging findings. Also, an analysis software (Quirkos) was used to improve the reliability of the process of analysis.

5.3 Business implications, academic implications and future research

This research paper found definite links between AI adoption decisions and TOE framework, in particular to explain the importance of organisational characteristics and environmental context. Research question was answered, and the resulting findings were mostly in accordance with expectations of literature. Furthermore, additional points were found outside of the version of the TOE framework by Pumplun et al. (2019) that expanded current knowledge on AI adoption.

In business context, the outcomes of this paper can provide valuable insight for top level managers in making better informed decisions regarding AI adoption processes. Additionally, the findings from the case interviews and assessment of service providers can aid in expanding knowledge of what pain points large organisations have regarding AI adoption.

As a foundation for further studies regarding AI adoption, this paper provides a starting point in theory testing for future empirical studies. This thesis has successfully extended AI adoption research and will hopefully direct more in-depth research regarding influencing factors. One aspect for future research could be to measure return on investment (ROI) from implementing AI resources, for example in acquired savings or increases in revenue.

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APPENDICES

Appendix 1. Overview of service providers offering AI consultancy (with sources)

	Specialisation in AI solutions/data management	Strategy/solution-driven consulting	Organisational-level support (e.g. change management)	Source
Solita	yes	yes	yes	https://www.solita.fi/solita/#tietoa-solitasta
Enfo	yes	no	no	https://www.enfogroup.com/services
eCraft Business Insight	yes	yes	no	https://www.ecraft.com/fin/bi
Houston Analytics	yes	no	no	https://www.houston-analytics.com/project-methodology
KAITO	yes	yes	no	https://www.kaito.fi/services
Fourkind	yes	yes	no	https://www.fourkind.com/services
Cloud1	yes	yes	no	https://www.cloud1.fi/en/services
Advian	yes	yes	no	https://www.advian.fi/en/services
Bilot	yes	yes	no	https://bilot.group/fi/mita-teemme/?gclid=EAIaIQobChMIir7t-vzq6QIVQcKyCh0k1AazEAAYASACEgKpkPD_BwE
Silo.ai	yes	no	no	https://silo.ai/services/
Futurice	yes	yes	yes	https://futurice.com/services
Reaktor	yes	yes	yes	https://www.reaktor.com/about/
Siili	yes	yes	yes	https://www.siili.com/services
CGI Suomi	yes	yes	yes	https://www.cgi.fi/fi/white-paper/human-connections

Appendix 2. Prelude for interview and Interview questions

Tekoäly Suomalaisessa liiketoimintakentässä

Teemahaastattelu

Mia Paul

Turun Yliopisto

Tilburg University

Aix-Marseille Graduate School of Management

Pro Gradu työ, toteutus yhteistyössä Cubiq Analytics – organisaation kanssa

Saatekirje (in English below)

Tämän kyselyn tarkoituksena on kartoittaa Suomalaisen liiketoimintamarkkinan nykytilaa tekoälyn hyödyntämisen näkökulmasta, fokusoiden erityisesti tekoälyä hyödyntäviin käyttökohteisiin (engl. use case) liiketoiminnan eri toiminnoissa. Mielenkiinnon kohteena on selvittää, millaisia ongelmia ja tarpeita suomalaiset yritykset kohtaavat liiketoiminnassaan, joihin voitaisiin vastata tekoälyä hyödyntävillä ratkaisuilla. Tämä kysely toteutetaan Pro Gradu- työn yhteydessä, ja kaikki osallistuvat yritykset jäävät lopullisesta työstä anonyymeiksi, noudattaen GDPR-lain säännöksiä. Tutkimuksen datakeräys toteutetaan teemahaastatteluna, jolloin haastateltava keskustelee vapaasti tässä lomakkeessa eritellyistä aiheista haastattelijan kanssa.
Tämä kysymyslomake on lähetetty osallistuville yrityksille etukäteen tutustuttavaksi, jotta haastattelu sujuisi mahdollisimman sulavasti. Haastatteluosuuteen kuluu keskimäärin 30-45 minuuttia, joten aikaa on hyvä varata vähintään 45 min. Osana tutkimusprosessia haastattelut pyritään nauhoittamaan, mutta tämä ei ole kuitenkaan pakollista. Ilmoitathan etukäteen, mikäli et halua haastattelun nauhoitusta.

Mahdolliset etukäteiskysymykset voidaan esittää suoraan tutkimuksen toteuttajalle. Kaikista haastatteluista tehdään lisäksi yhteenvetona loppuraportti, joka jaetaan tutkimukseen osallistuneille heidän halutessaan.

Kiitos tärkeästä osallistumisestasi tutkimukseen!

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Ohjeistus:

Tavoitteena on keskustella vapaasti mainituista teemoista. Alla eritellyt kysymykset ovat suuntaa-antavia helpottamaan keskustelun kulkua. Ei haittaa, vaikka kaikkiin kysymyksiin ei tule vastausta tai toisiin teemoihin käytettäisiin enemmän aikaa.

Keskusteltavat teemat:

Teknologia

- Määrittele omin sanoin tekoäly (AI). Mitä eri asioita termi pitää sisällään? Mitä synonyymejä käytätte organisaatiossanne?
- Mitä mahdollisia käyttötarkoituksia (use cases) tiedät tekoälylle?
- Mitä asioita tekoäly vaatii yleisesti toimiakseen? Entä teidän yrityksessänne? (esim. tekniset vaatimukset, datan laatu, käyttäjien osaamisaste, yrityskulttuuri jne.)
- Kuvaile yrityksesi yleistä teknologista kompetenssitasoa. Onko osaaminen rajoittunut tietyille osastoille/osaajille? Onko se tasalaatuista vai vaihtelevaa organisaatiossa?
- Kuvaile lyhyesti, millainen on tavanomainen prosessi, jossa johonkin ongelmaan on otettu käyttöön/suunniteltu tekoälyratkaisu. (Mistä prosessi lähtee, kenen aloitteesta, miten se etenee?)
- Miten tunnistatte/paikannatte ne liiketoiminnan alueet, joihin etsitte ratkaisua tekoälystä?

Organisaatio

- Miten organisaatiossanne suhtaudutaan tekoälyyn? Miten kuvailisit yleistä ilmapiiriä sanojen [haastateltavan mainitsemat termit] ympärillä?
- Mitä käyttötapauksia (use cases) yrityksessänne on tällä käytössä? Entä, mitä on suunnitteilla? Miksi juuri nämä?
- Kuinka edellä mainitut käyttötarkoitukset on toteutettu? (in-house/ostettu tuote)
- Miten tekoälyratkaisut toteutetaan/on toteutettu organisaatiossanne? Kuinka laajasti ne ovat käytössä eri osastojen/toimintojen kesken? Mitä liiketoiminnan hyötyjä näillä toimenpiteillä tavoitellaan?
- Kenen aloitteesta tekoälyprojektit alkavat? Entä kuka johtaa projektia, kuka tekee kriittiset päätökset projektiin liittyen?

- Kuka on tekoälyratkaisujen loppukäyttäjä (yrityksen sisäinen/ulkoinen/molemmat)?
- Millaisia sisäisiä ongelmia on ilmennyt tekoälyratkaisuihin liittyen (esim. käyttöönotto ja käyttäjien IT-osaamisen taso, ”bugit”, viiveet tuotannossa/toimituksessa jne.)? Miten näitä on ratkottu?
- Mikä on organisaation johdon rooli tekoälyratkaisuissa?
- Millainen on tavanomainen vastuutiimi tekoälyratkaisuprojekteissa? Millaisia muutoksia tekoälyprojektit vaativat onnistuakseen (esim. organisaatiorakenteeseen)?
- Miten uudet tekoälyratkaisut istuvat yrityksen pitkän aikavälin strategiaan?

Toimintaympäristö

- Mitä eri lähteitä hyödynnetään tekoälyyn liittyen? Mistä/keneltä saatte informaatiota mahdollisuuksista?
- Koetko nykyisen toimintaympäristön tekoälyä tukevaksi vai hankaloittavaksi? (esim. valtion määräykset/avustukset, teknologisen infrastruktuurin laatu)?
- Miten helpoksi/hyödylliseksi koet yhteistyöprojektit (esim. asiakkaiden/toimittajien ym.) tekoälyn hyödyntämiseen? Ovatko käyttökohteet rajoittuneet pienelle ryhmälle, vai yltääkö hyödyt esimerkiksi toimitusketjuihin tai asiakkaisiin?
- Omin sanoin, millä tasolla koet organisaationne olevan IT:n hyödyntämisessä verrattuna kilpailijoihin? Entä markkinoiden muihin toimijoihin? (ks. DOI-kaavio haastattelussa)
- Mitä erityisiä tavoitteita tekoälyratkaisuilla on haluttu saavuttaa?
- Mitkä tekijät vaikuttavat mielestäsi eniten liiketoimintanne muutoksiin?
- Miten liiketoiminnassanne reagoidaan muutoksiin markkinoilla?

Prelude

The purpose of this survey is to map the current state of the Finnish business market from the perspective of the utilization of artificial intelligence, focusing in particular on the use case of artificial intelligence in various business functions. The object of interest is to find out what kind of problems and needs Finnish companies face in their business, which could be answered with solutions utilizing artificial intelligence. This survey will be conducted in the context of a master's thesis, and all participating companies will remain anonymous in the final work, in accordance with the provisions of the GDPR Act. The data collection of the study is carried out as a semi-structured interview, in which case the interviewee freely discusses the topics specified in this form with the interviewer.

This questionnaire has been sent to the participating companies for reference in advance in order to make the interview as smooth as possible. The interview part takes on average 30-45 minutes, so it is a good idea to set aside at least 45 minutes. As part of the research process, interviews are sought to be recorded, but this is not mandatory. Please let me know in advance if you do not wish to me recorded.

Any questions can be asked directly to the researcher. All interviews are further summarized in a final report, which is distributed to study participants if they wish.

Thank you again for your participation!

Kind regards
Mia Paul

Guidance: The aim is to discuss the mentioned topics freely. The questions detailed below are indicative to facilitate the discussion. It doesn’t matter if not all questions are answered or more time is spent on certain topics than others.

Topics to discuss:

Technology

- Define artificial intelligence (AI) in your own words. What different aspects does the term include? What synonyms do you use in your organization?
- What possible use cases do you know for artificial intelligence?

- What does AI generally require to function, in your opinion? What about within your organisation? (e.g. technical requirements, data quality, level of user skills, corporate culture, etc.)
- Describe the general level of technological competence of [organisation]. Is the competence limited to certain departments / experts? Is it homogeneous or variable within the organization?
- Briefly describe the usual process in which an AI solution has been implemented / planned for a problem. (Where does the process start, on whose initiative, how does it proceed?)
- How do you identify / locate the business areas where you are looking to solve a problem with an AI solution?

Organisation

- How is artificial intelligence perceived in your organisation? How would you describe the general atmosphere regarding AI?
- What use cases does your company currently have? What are planned? Why these?
- How have the above uses been implemented? (in-house / purchased product)
- How are / are implemented in your organization? To what extent are they used between different departments / functions? What are the business benefits of these measures?
- On whose initiative do artificial intelligence projects begin? And who leads the project, who makes the critical decisions related to the project?

- Who is the end user of artificial intelligence solutions (internal / external / both)?
- What internal problems have arisen with AI solutions (eg deployment and level of user IT skills, "bugs", delays in production / delivery, etc.)? How have these been resolved?
- What is the role of organizational management in artificial intelligence solutions?
- What is the usual responsibility team for artificial intelligence projects? What changes do artificial intelligence projects require to succeed (eg organizational structure)?
- How do new AI solutions fit into a company's long-term strategy?

Operating environment

- What different sources does your organisation use to find out about artificial intelligence? Where / from whom do you get information about opportunities?
- Do you find the current operating environment to support AI or complicate it? (eg government regulations / grants, quality of technological infrastructure)?
- How easy / useful do you find collaborative projects (eg customers / suppliers, etc.) to utilize artificial intelligence? Are the uses limited to a small group, or do the benefits reach, for example, supply chains or customers?
- In your own words, what level do you feel your organization has in terms of IT utilization compared to competitors? What about other market players? (see DOI chart in the interview)
- What specific goals have the artificial intelligence solutions wanted to achieve?
- What factors do you think are most influencing changes in your business?
- How does your business react to changes in the market?