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Technology Acceptance for AI implementations

A case study in the Defense Industry about 3D Generative Models

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by

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Master of Science Thesis TRITA-ITM-EX 2023:172
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Teknologisk Acceptans för AI implementationer

En fallstudie i försvarsindustrin om 3D Generativa Modeller

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Abstract

Advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has emerged into 3D object creation processes through the rise of 3D Generative Adversarial Networks (3D GAN). These networks contain 3D generative models capable of analyzing and constructing 3D objects. 3D generative models have therefore become an increasingly important area to consider for the automation of design processes in the manufacturing and defense industry. This case study explores areas of automation enabled by 3D generative models for an incumbent in the Swedish defense industry. This study additionally evaluates discovered types of implementations of 3D generative models from a sociotechnical perspective by conducting qualitative interviews with employees. This study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) for understanding the adoption and intention to use 3D generative models. A description of 3D objects, CAD, 3D generative models, and point cloud data is given in this study. A literature review is additionally given in the three fields of AI, technology acceptance, and the defense industry to funnel the literature to the context of this study. 21 types of implementations are discovered and categorized into four distinct groups. In conclusion a lot of potential is found for the adoption of 3D generative models for especially AI simulation processes, but challenges with data collection and security are discovered as the most significant obstacle to overcome.

Key-words

Technology Acceptance, Artificial Intelligence, Machine Learning, 3D Generative Models, Innovation

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Sammanfattning

Framsteg inom artificiell intelligens (AI), maskininlärning (ML) och djupinlärning (DL) har resulterat i att 3D-objektskapandeprocesser har utvecklats genom framväxten av 3D Generative Adversarial Networks (3D GAN). Dessa nätverk innehåller 3D-generativa modeller som är kapabla till att analysera och konstruera 3D-objekt. 3D-generativa modeller har därmed blivit ett allt viktigare område att beakta för automatisering av designprocesser inom tillverknings- och försvarsindustrin. Denna fallstudie undersöker automatiseringsområden som möjliggörs av 3D-generativa modeller för en etablerad aktör inom den svenska försvarsindustrin. Studien utvärderar dessutom identifierade typer av implementeringar av 3D-generativa modeller ur ett socio-tekniskt perspektiv genom att genomföra kvalitativa intervjuer med anställda. Denna studie tillämpar Unified Theory of Acceptance and Use of Technology (UTAUT) för att förstå acceptans och avsikt att använda 3D-generativa modeller. En beskrivning av 3D-objekt, CAD, 3D-generativa modeller och punktmolnsdata ges i denna studie. Dessutom ges en litteraturöversikt inom tre områden: AI, teknologianvändning och försvarsindustrin för att rikta in litteraturen mot denna studiens sammanhang. 21 typer av tillämpningar identifieras och kategoriseras i fyra distinkta grupper. Som slutsats finns det stor potential för antagande av 3D-generativa modeller, särskilt inom AI-simuleringsprocesser, men utmaningar med datainsamling och säkerhet identifieras som de mest betydande hindren att överkomma.

Nyckelord

Teknologisk Acceptans, Artificiell Inteligens, Maskininlärning, 3D Generativa Modeller, Innovation

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Acronyms

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
NN	Neural Network
DNN	Deep Neural Network
3D GAN	3D Generative Adversarial Networks
XAI	Explainable Artificial Intelligence
CAD	Computer-Aided Design
NURBS	Nonuniform Rational B-splines
VR	Virtual Reality
AR	Augmented Reality
IS	Information Systems
UN	United Nations
SDG	Sustainable Development Goals
UTAUT	Unified Theory of Acceptance and Use of Technology
TRA	Theory of Reasoned Action
TAM	Technology Acceptance Model
MM	Motivational Model
TPB	Theory of Planned Behaviour
C-TAM-TPB	Combined TAM and TPB framework
MPCU	Model of PC Utilization
IDT	Innovation Diffusion Theory
SCT	Social Congitive Theory
VAM	Value-based Adoption Model
AI RMF	Artificial Intelligence Risk Management Framework
NIST	National Institute of Standards and Technology

OECD Organisation for Economic Co-operation and Development

Contents

Chapter 1

Introduction

This chapter provides an introduction to the study and motivates the need to conduct this type of study. The first section in this chapter is the background which introduces the setting and some key literature. This is followed by the problem formulation where the problem that this study addresses is summarized. The purpose of this study is then presented followed by the aim and research questions. Delimitations are then stated followed by a brief discussion regarding which actors that benefit from this study. Lastly, an overview of the structure of the report is presented.

1.1 Background

Technological advancements in Artificial Intelligence (AI), Machine Learning (ML) and computer visualization has affected many fields and industries with new opportunities and challenges. The manufacturing industry and the defense industry is no exception to this (Hunde and Woldeyohannes 2022; Sajjad 2016; Cirincione et al. 2019). While there are countless of applications and contexts where ML can be incorporated, the adoption of specifically generative machine learning processes for the creation of 3D object has gained an increasingly important role for product design and innovation (Hunde and Woldeyohannes 2022). This increased importance is due to extensive utilization of 3D designs and 3D objects in workflows such as the design of products and prototypes (Pearl et al. 2022), objects for simulations (Hunde and Woldeyohannes 2022), and image generation processes (Guo, Wang, et al. 2021). Previously, the introduction of Computer-Aided Design (CAD) as a technology for designing 3D objects, was able to reshape processes in various industries such as the dental industry (Sajjad 2016), product design and fabrication processes (Savini and Savini 2015), and the automotive industry

(Field 2004), by introducing new tools and workflows that provided increased efficiency (Sajjad 2016). Additionally, CAD workflows have been increasingly utilized and adopted with the rising popularity of Virtual Reality (VR) and Augmented Reality (AR) into the manufacturing industry, through the pursuit of industry 4.0 (Gunal 2019).

Recently, an additional novel technology has been introduced to further leverage the potential of CAD software. Generative machine learning using 3D objects in product design workflows has increasingly been applied and pursued through advances and emerging capabilities of ML-models (Hunde and Woldeyohannes 2022). This far the creation of 3D objects for the design of products has been performed by designers using CAD software or other 3D creation platforms (Hunde and Woldeyohannes 2022). However, the emergence of ML has introduced new tools and workflows that bring both benefits and challenges to designers (Palviainen et al. 2020; Pearl et al. 2022). Both technical and social challenges have been identified from the pursuit of automated product design workflows that employ ML-models. These sociotechnical challenges are linked to the novelty of the technology and the involvement of people in current processes (Hunde and Woldeyohannes 2022; Palviainen et al. 2020; Pearl et al. 2022). While 3D objects can be generatively produced by a designer without the use of ML, the use of ML is necessary for analytical automation, such as for identification of the popular 3D data type called 3D point clouds. 3D point clouds are commonly collected by scanning real-world objects (Guo, Cai, et al. 2020). Therefore, the use of 3D generative models combined with machine learning is perceived as the most promising solution for generating numerous 3D objects based on point cloud data (Pearl et al. 2022; Guo, Cai, et al. 2020). Other common data types for 3D creation processes exists, such as polygonal meshes and Nonuniform Rational B-splines (NURBS), although the point cloud data type has shown particular advantages that are covered further in chapter 2. This study refers to generative machine learning using 3D objects or working with 3D synthesis as simply a *3D generative model*. A more detailed description of 3D generative models is covered in chapter 2.

Mapping of the many challenges that exist when implementing ML into various workflows has revealed a need for more empirical research in predictive analysis that applies ML (Shmueli and Koppius 2011). Holistic frameworks focusing on implementation of AI have also been introduced to support research in AI and ML with sociotechnical objectives (NIST 2023; OECD 2022). Implementations of this technology has thus increasingly shed light on challenges and risks originating not only from a utility-focused technical perspective, but also from the perspective of users of the technology due to factors such as behaviour and acceptance (Palviainen et al. 2020). While AI systems have been thoroughly mapped out and defined from a technical standpoint using various frameworks by both the National Institute of Standards and Technology (NIST 2023) and the Organisation for Economic Co-operation and Development (OECD 2022), the sociotechnical aspects are less researched as well as application of concepts and frameworks that are already in use for other types of technologies (Sovacool and Hess 2017). Various reviews note that there is a need for more research about sociotechnical aspects, especially in the context of ML and CAD (Palviainen et al. 2020; Collins et al. 2021). Sociotechnical frameworks are expected to be significant to technologies in the field of Information Systems (IS), including AI and ML, and as such can be expected to reveal valuable insight if applied to the application of ML in specific contexts (Venkatesh, Thong, and Xu 2016; Sovacool and Hess 2017; Collins et al. 2021). While technology acceptance and social expectation frameworks have been applied on many technologies in various fields already (Venkatesh, Thong, and Xu 2016), there is no published research that applies these frameworks to the use of specifically 3D generative models in the defense industry despite evidence for the need of such research (Palviainen et al. 2020; Harris 2008).

The importance of ML in the field of IS cannot be understated. One particularly useful application of ML and Neural Network (NN) in the context of IS is the capture of user requirements that can be re-applied outside of the ML-dataset that the neural network used for training (Purao, Storey, and Han 2003). This has the benefit of providing reusability of resources (Purao, Storey, and Han 2003). Furthermore, the use of machine learning for capturing user requirements has shown value in especially software development by being able to both shorten the development life cycle, and by also being able to reduce the use of resources (Purao, Storey, and Han 2003). Machine learning is also expected to be able to provide benefits of reusability outside of the domain of software development, and is in addition suggested for future research in more domains (Purao, Storey, and Han 2003). AI and 3D generative models also reveal a potential to support innovation and to automate many designer workflows through optimization, recommendation, generation, and prediction according to trends in the manufacturing industry (Hunde and Woldeyohannes 2022; Gröger, Schwarz, and Mitschang 2014; Sun et al. 2018), and the defense industry (Cirincione et al. 2019).

1.2 Problem Formulation

AI and ML are showing significant benefits for innovation and automation in 3D design workflows relevant to the defense industry. However, challenges have been identified when attempting to implement and adopt this type of technology. While many of these challenges have been identified as technical challenges, the discovery of social and sociotechnical challenges has emerged. Yet, while the awareness of these sociotechnical challenges has been growing, the topic of sociotechnical challenges surrounding AI remains largely unexplored. Studies of AI in specifically the defense industry has also revealed sociotechnical challenges on its own which needs to be explored further if wanting to pursue advantages provided by AI technology. By exploring these sociotechnical challenges, any pursuit of AI technologies and especially implementations of 3D generative models can be performed with more guidance. This extra guidance and awareness may be essential for a successful implementation and adoption of this type of technology.

1.3 Purpose

The purpose of this study is to contribute with sociotechnical insight into opportunities and challenges associated with the adoption of implementations of 3D generative models. This purpose intends to provide guidance for an organization that pursues 3D generative models into their design workflows and to also contribute with insight for adoption and acceptance research in the context of AI and the defense industry.

1.4 Aim

To fulfill the purpose, this study works in two ways that makes up a research questions each. The first way being to explore types of implementations that exist of 3D generative models, that are also relevant to the defense industry. This is done since the novelty of 3D generative models, the vast number of use-cases that this technology provides, and the secrecy and scarcity of articles in the context of the defense industry has the consequence of making it nearly impossible to define or obtain a complete list of available and relevant implementations of 3D generative models. Hence, inclusion of the exploration of at least the most obvious and relevant implementations is expected to build an encompassing understanding of and consideration for 3D generative models. The second way being to build an understanding for the drivers and barriers for adoption of 3D generative models. The perspective of those who might use this technology in the defense industry is therefore pursued.

1.5 Research Questions

This study aims to fulfill the purpose by answering the following two research questions:

- RQ1: *What types of 3D generative models are relevant to the defense industry?*
- RQ2: *What are the drivers and barriers for adopting 3D generative models in the defense industry?*

1.6 Delimitations

This study examines types of automation provided by 3D generative models relevant to the defense industry in Sweden. The focus is to conduct this study on only one incumbent in the defense industry in Sweden. However, public documents from European and North American defense industries regarding user-focused development standards and innovation relevant to the topic of AI is still considered for this study. For this study, only one technology acceptance framework that fits the context and purpose of the study is used, in this case the UTAUT which is introduced in section 3.1. This study only conducts qualitative interviews. To respect security and secrecy and to avoid publication of potentially sensitive information, a level of generalization of specific findings is performed that is deemed appropriate. Hence, this study discusses implementations as types of implementations rather than describing specific implementations in detail. All interviews are recorded either through audio or in text, where there is a target of audio-recording about half of the interviews. Analysis considering gender is also excluded from this study due to challenges with acquiring enough respondents with characteristics needed for such an analysis.

1.7 Benefits

As 3D generative models introduce new areas of automation, there exists both benefits in efficiency as well as ethical risks with this type of implementation. The use of automation can provide various benefits such as reducing the amount of resources, effort, complexity, and time it takes to achieve something, which can increase accessibility and ease of entry for users of this technology (Purao, Storey, and Han 2003). However, there can also be ethical consequences if replacing a workforce with automation (NIST 2023). These ethical risks and consequences are important to consider when studying implementation of new technologies (NIST 2023; Venkatesh, Morris, et al. 2003). This study applies a theory which focuses on specifically the users of 3D generative model-technology within an organization, where the users are the workforce within the organization. This means that ethical risks and challenges are an essential part of this study. This study can therefore be expected to balance benefits between an organization pursuing implementation of these technical automation, and the workforce which might face ethical risks and challenges associated with these implementations. While this study benefits mainly defense industry research, the generalization of findings as well as the similarities to the manufacturing industry makes this study beneficial for other industries as well. Furthermore, this study benefits technology acceptance research by applying technology acceptance in a defense industry setting where it has not been applied before.

1.8 Overview of Structure of the Report

As this report combines multiple complex and deep topics, the following chapter is designed to focus on informing the reader of the technical context and background of this study. Hence, chapter 2 is the empirical background that is dedicated to enable the reader to understand and distinguish the phenomenon that is being studied. Additionally the empirical background is designed to introduce the reader to processes and technologies involved in this study. The chapter after that, chapter 3 theory and relevant literature, presents the main framework that is applied in this study followed by this study's literature review. This is then followed by the method in chapter 4 that presents the case, the case company, the research design, and the process of collecting and analysing data. Chapter 5 is about the results and analysis. Chapter 6 is then presented with a discussion of the results as well as a reflection on the implications and limitations of the study. Finally, chapter 7 draws a final conclusions from this study and present some aspects for future studies.

Chapter 2

Empirical Background

3D Generative Models is presented in this section by first introducing the process of creating 3D objects in section 2.1, followed by an explanation of 3D generative models' context within the field of AI in section 2.2. This is then followed by a presentation of how the combination of the two topics ties into 3D generative models and some brief state-of-the-art insight into 3D generative models in section 2.3. The focus-topic of this study regarding 3D generative models is then presented in section 2.4. Finally, a framework for actors involved in the lifecycle of AI systems is presented in section 2.5.

2.1 Creation Process of 3D Objects

Creation of 3D objects using generative tools, also referred to as 3D modeling, is a topic that falls within the field of information systems and computer science and that belongs to the domain of both computer-graphics and product design depending on how it is used and what it is used for. It involves the combination of 3D modeling, the creation of visualizable objects within a 3-dimensional space, and software development for the design of an automatic executable and interactive system that can produce 3D objects (IBM 2023). This process is typically performed by an artist, designer, or programmer who creates 3D objects using softwares with various tools for manipulating geometry, or by programming using programming-like semantics (Pearl et al. 2022). Figure 2.1.1 shows an example of these programming-like semantics within a software called Blender (2023).

Manipulation of geometry is most commonly done by either working with polygonal meshes, or by working with NURBS. Polygonal meshes and polygon manipulation tools are usually

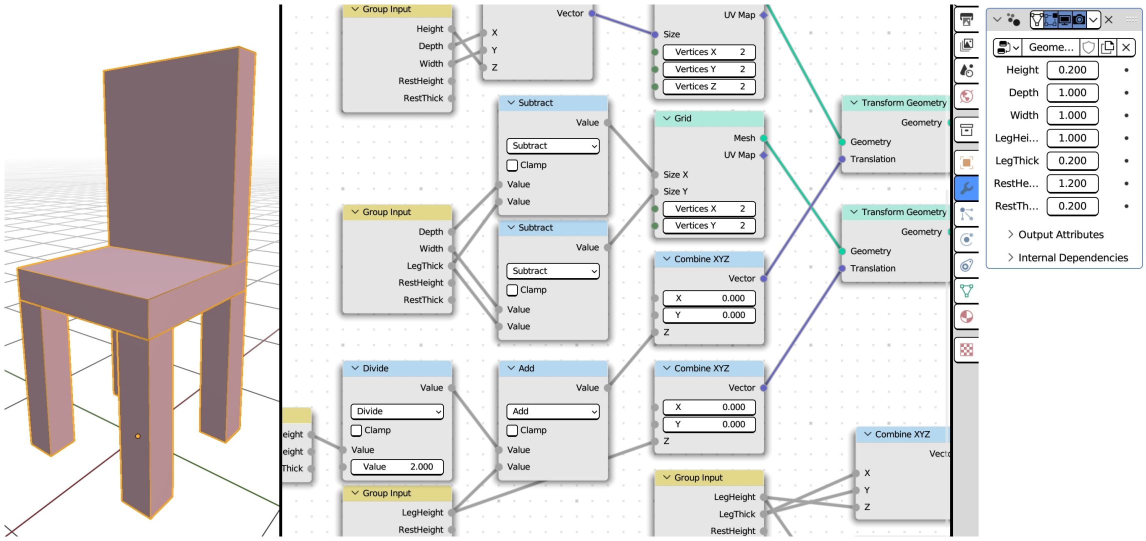

Figure 2.1.1: A visualization of Geometry Nodes within the software called Blender (2023) for the design of a simple chair.

less precise, and as such more common for artistic purposes, such as for the production of games or animations, while NURBS is mostly used for CAD to ensure a higher precision which is required for the manufacture of products and product design (Hunde and Woldeyohannes 2022; Field 2004). Alternatively, 3D modeling can be done by programmers through the use of programming-like semantics which have been introduced to various polygon-oriented softwares used in computer-graphics referred to as nodes. Nodes have increasingly become popular in 3D creation platforms such as Blender (Blender Foundation 2023), SideFX's Houdini (SideFX 2023), Adobe's Designer (Adobe 2021), and Epic Games' Unreal Engine 4 (Unreal Engine 2023). These nodes enable artists to increasingly transition to a programmer-like role which has introduced benefits to production speed, resources needed, and shorter production cycles, and as such is capable of competing with conventional processes depending on the requirements and specifications of the task (Pearl et al. 2022; Guo, Cai, et al. 2020; Palviainen et al. 2020).

2.2 Artificial Intelligence for the Creation of 3D Objects

Working with programming-like semantics has an especially potent advantage that has risen with the expansion of algorithms known as Artificial Intelligence (AI) and Machine Learning (ML)-models that are capable of working in 3D-space. The term used for the algorithm which can create 3D objects using AI and ML is, as mentioned in the introduction, referred to as 3D generative models. A 3D generative model is part of what's known as a 3D Generative Adversarial Networks (3D GAN) (Wu, Zhang, et al. 2016), which needs some further explanation of its connection to AI as can be observed in Figure 2.2.1.

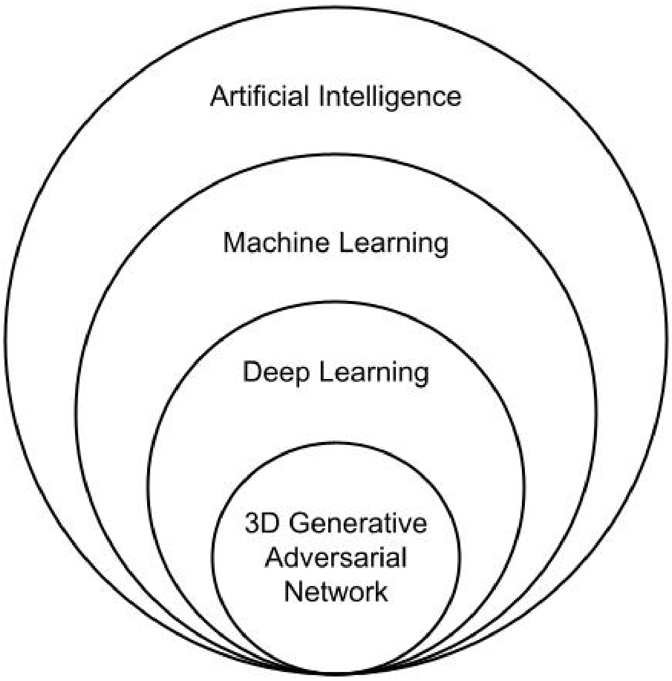

Figure 2.2.1: The topics where 3D GAN can be found within.

AI is a term which refers to the construction of machines that can sense, reason and react in a way perceived as similar to a human (Mondal 2020). ML is a topic within the field of AI which involves machines designed to in addition to performing a task, also being capable to learn a tasks (Murphy 2012 cited by Mondal 2020). A more extensive review of research and the state-of-the-art within the topic of AI and ML is covered in section 3.2. The level of understanding that an AI is capable of is sometimes referred to as strong AI or weak AI, where typical implementations of ML tend to be regarded as weak AI (Sevakula et al. 2020). ML is typically implemented using a data structure called NN which consists of perceptrons that are interconnected in a structured manner (Sevakula et al. 2020). Within the field of ML there is an even more novel and relevant topic to this study called Deep Learning (DL) which is performed by a Deep Neural Network (DNN) that require a far vaster set of data to train on (Goodfellow 2016 cited by Mondal 2020; Sevakula et al. 2020). Finally within the topic of DNN the topic of 3D GAN resides, as it is designed for the purpose of learning how to generate 3D objects, which can also involve learning how to perform tasks used within the process of creating 3D objects (Sevakula et al. 2020).

3D GAN are designed and trained using two parts, a generative model and a discriminatory

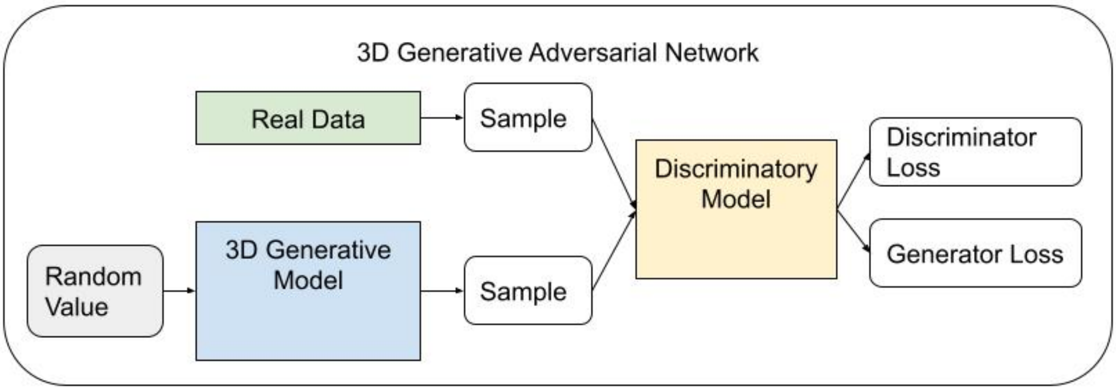

Figure 2.2.2: The structure of a 3D GAN and the context of a 3D generative model within the 3D GAN.

model as can be seen in Figure 2.2.2 (Wu, Zhang, et al. 2016; Alma 2022). The generative part of the 3D GAN is referred to as the 3D generative model, and is the essential component of the model that enables generation of 3D objects (Wu, Zhang, et al. 2016; Chan et al. 2022; Alma 2022). A brief overview of the interaction between the 3D generative model and the discriminator can be observed in Figure 2.2.2 which shows the structure of a 3D GAN. 3D GANs are currently one of the most promising designs for the making and training of 3D generative models (Smith and Meger 2017).

2.3 State-of-the-Art 3D Generative Models

There are multiple ways in which 3D GAN is capable of pursuing creation and generation of 3D objects, each with its own trade-offs (Sevakula et al. 2020). Inspired by CAD procedures, the use of shapes using boolean-logic operators for producing either polygonal mesh geometry or NURBS geometry was fairly common during early research of 3D GAN due to the rapid growth and accessibility of libraries consisting of CAD models enabling supervised learning using this method (Wu, Zhang, et al. 2016). This however often produced artifacts in the form of holes in the geometry (Wu, Zhang, et al. 2016; Mondal 2020; Sevakula et al. 2020). Another approach which solved the issue of holes in the 3D objects was to work using voxels, which works in a 3 dimensional volumetric grid where each square unit within this volume is either a part of the shape or not (Alma 2022). The disadvantage with voxel-based generations was however the loss of precision that occurred from being limited to the volumetric grid and also the jagged shape and poorly optimized topology that the produced geometry would obtain (Pearl et al. 2022; Wu, Zhang, et al. 2016). A third and more novel solution has been proposed and researched more recently which involves the use of the previously mentioned introduction of nodes, programming-like semantics used in 3D creation platforms. Nodes can be interpreted and analyzed by DL- and 3D GAN-models at a significant efficiency due to the design process's use of abstraction layers that can be encoded and decoded by these algorithms (Pearl et al. 2022; Zhang et al. 2023).

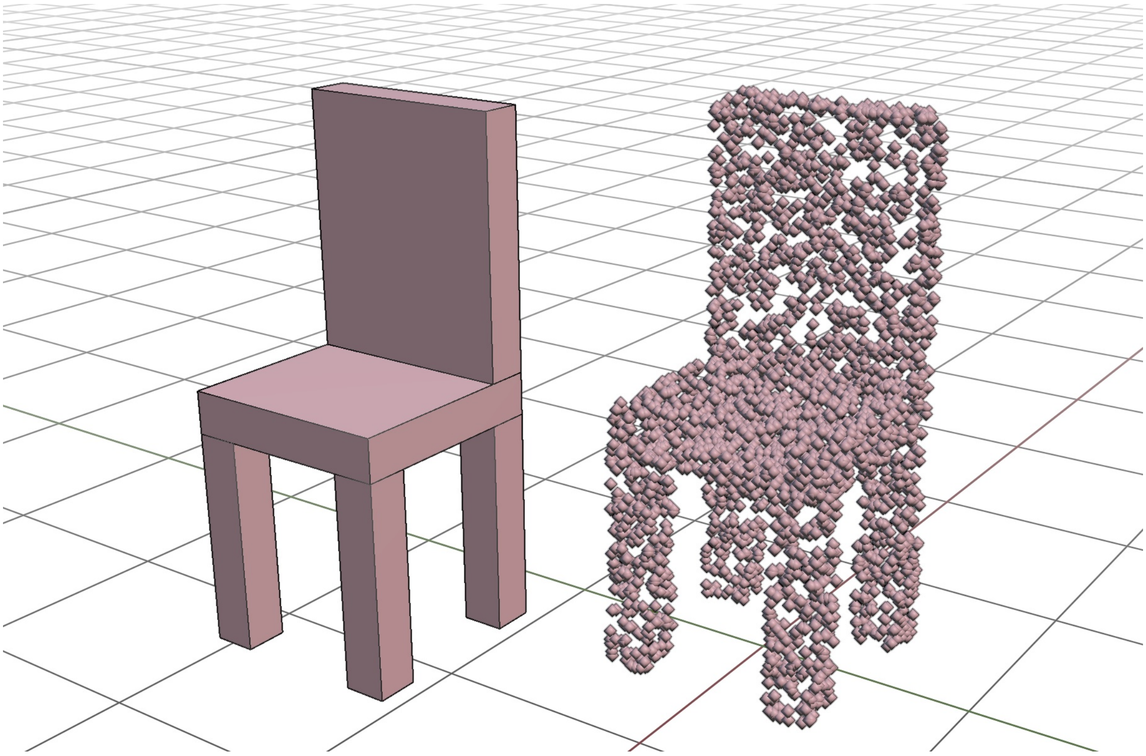

Figure 2.3.1: A visualization of a simple chair model (left) next to a point cloud of the same model (right) within the software called Blender.

Any level of these abstraction can be trained on by a ML-model with varying resultant quality depending on the complexity and scale of the abstraction levels as well as the quality and quantity of the training data (Pearl et al. 2022). As can be observed from the GeoCode implementation by Pearl et al (2022), this has the downside of not necessarily automating the whole process of generating 3D objects as a programmer may have to design the interface and to some extent the general capabilities that the 3D generative model are able to perform. The specific implementation by Pearl et al (2022) takes advantage of the recent growth of libraries that consist of point cloud data structures that have been made by scanning real-world objects (Guo, Cai, et al. 2020; Guo, Wang, et al. 2021). An example between a polygonal mesh and a point cloud can be observed in Figure 2.3.1 where the left representation of the chair is the format of a polygonal mesh, while the right representation of the chair is in the format of a point cloud data type.

2.4 3D Generative Models using Point Clouds

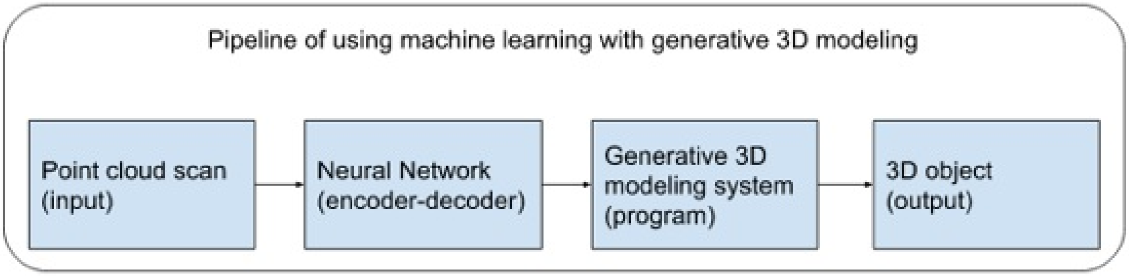

Figure 2.4.1: Simplified pipeline for converting point cloud data scans into 3D objects using a 3D generative model.

The introduction and utilization of machine learning algorithms into the creation of 3D objects has increasingly become a popular research topic due to 3D scanning technologies such as LiDARs and RGB-D cameras that can be applied to robotics, autonomous driving and augmented reality for scanning, sensing and identifying surrounding environments (Guo, Wang, et al. 2021; Liu et al. 2021). The preferred type of data representation used by these scanners and applications is the point cloud data type (Guo, Wang, et al. 2021). A point cloud representation consists of data points in a 3-dimensional space that resembles the spatial geometry of the scanned shape (Guo, Wang, et al. 2021). 3D point clouds enable the use of convolutional machine learning models to perform predictive analysis on 3D objects and can be trained to output parametric values that are directly transferable to a 3D generative model. Hence, it becomes possible to utilize 3D generative models for producing 3D objects based on scanned data, which can leverage the workload of the designer so that work can be transitioned into the production of the 3D generative model. However, this demands a large and relevant library of scanned objects, something that is uncommon to be in possession of (Palviainen et al. 2020). Nevertheless, point cloud libraries are increasingly getting addressed through publicly shared libraries depending on the intended application (Guo, Wang, et al. 2021). A simplified pipeline for converting point cloud data scans into 3D objects using machine learning and 3D generative models can be observed in Figure 2.4.1. Figure 2.4.1 visualizes the pipeline used when producing 3D objects using scanned data in the form of a point cloud that is analyzed by a neural network using ML that controls the parameters of a generative 3D model.

2.5 Lifecycle and Key Dimensions of an AI system

The lifecycle and key dimensions of an AI system is a concept and frameowrk from the Artificial Intelligence Risk Management Framework (AI RMF) by the National Institute of Standards and Technology (NIST) based on the OECD framework for the Classification of AI systems by the Organisation for Economic Co-operation and Development (OECD) (NIST 2023; OECD 2022). The lifecycle and key dimensions of an AI system is a generalization of the operational context of an AI system and can be used as a basis for identification and mapping of other AI systems as well as for identification and mapping of AI actors (NIST 2023). AI actors can be defined as people who are involved in the lifecycle of an AI system in different ways. The framework also provides a derived functionality of being usable for classifying AI systems when applied according to its original form as designed by OECD (2022) as it can be used to identify properties of traits and design patterns that all AI systems share in common to some level.

Figure 2.5.1: Visualization of the lifecycle and key dimensions of an AI system made by NIST (2023) based on the OECD framework for the Classification of AI systems (2022).

The lifecycle and key dimensions of an AI system framework is separated into five sections called key socio-technical dimensions as can be seen in Figure 2.5.1. These dimensions are further split into lifecycle stages that each contain descriptions of the types of risks that need to be considered, and also lists AI actors that are involved in each stage. The listing of AI actors makes the lifecycle and key dimensions of AI systems from the AI RMF framework especially useful as these actors can be directly used as a map of the many types of people that could and should be considered during the conduct of this study. The listed AI actors can support interviews by guiding which types of people that should be sought for to provide an encompassing representation of interviews in the context of AI systems. This framework can be used to ensure consideration is taken during interviews by connecting different roles and stakeholders with their influence and thoughts regarding the components that an AI system consists of.

The roles of representative actors for each of the lifecycle stages as provided by NIST (2023) can be observed in Figure 2.5.1, a full list of representative actors that are of relevance to each lifecycle stage can be found in Table 2.5.1. These actors are people involved in the planning and theoretical design of an AI system, the people that collect and process the training data for an AI system, the people that build and train the model using the collected data, the people that verify and validate the model, the people that implement and start the intended use of the AI system, the people who operate and monitor the AI system, and finally the people who will use and be impacted by the AI system. These people can be identified and considered for this study as they have an impact on the AI system. Additionally, the types of roles that are relevant to each lifecycle stage can be identified as well, as there are typically specific specialized roles that would work with each stage.

The people involved in the planning and design of an AI system can be managers who pursue AI and business analysts as these people would be looking into the opportunities and planning of the system (NIST 2023). Additionally, AI specialists and data scientists might be part of this planing and design stage as they would be necessary for a technical perspectives and preparations for the AI system project (NIST 2023). The people who collect and process data may usually consisting of the people who are closest to the work task where data can be or intends to be collected, and also data analysts as they do the processing and evaluation of the data (NIST 2023). The people who build and use the model work as either data analysts or software developers as both of these roles are necessary and relevant to the practical design of an AI system (NIST 2023). The people who verify and validate the AI system can be data analysts, software developers, and test-related roles (NIST 2023). The people who are involved in the deployment and implementation to the real use-case of the AI system are usually software developers and systems engineers (NIST 2023). The people who operate and monitor the model are usually the clients and users of the AI system who might have specific operators that are AI

Lifecycle Stage	Representative Actors
Plan and Design	System operators, end users, domain experts, AI designers, impact assessors, TEVV experts, product managers, compliance experts, auditors, governance experts, organizational management, c-suite executives, impacted individuals, impacted communities, evaluators (NIST 2023)
Collect and Process Data	Data scientists, data engineers, data providers, domain experts, socio-cultural analysts, human factors experts, TEVV experts (NIST 2023)
Build and Use Model	Modelers, model engineers, developers, domain experts, socio-cultural analysts familiar with the application context, TEVV experts. (NIST 2023)
Verify and Validate	Modelers, model engineers, developers, domain experts, socio-cultural analysts familiar with the application context, TEVV experts (NIST 2023)
Deploy and Use Model	System integrators, developers, systems engineers, software engineers, domain experts, procurement experts, third-party suppliers, C-suite executives, human factors experts, socio-cultural analysts, governance experts, TEVV experts (NIST 2023)
Operate and Monitor	System operators, end users, practitioners, domain experts, AI designers, impact assessors, TEVV experts, system funders, product managers, compliance experts, auditors, governance experts, organizational management, impacted individuals, impacted communities, evaluators (NIST 2023)
Use or Impacted by	End users, operators, practitioners, impacted individuals, impacted communities, general public, policy makers, standards organizations, trade associations, advocacy groups, environmental groups, civil society organizations, researchers (NIST 2023)

Table 2.5.1: The actors that are relevant to each lifecycle stage in the Lifecycle and Key Dimension of an AI system from the AI RMF framework by NIST (2023).

specialists and management (NIST 2023). The people who can be impacted by the AI system are necessary to consider as well, which typically consist of end users (NIST 2023).

Chapter 3

Theory and Relevant Literature

This chapter contains the main theory used in this study, which is a technology acceptance framework that is covered in section 3.1. Relevant literature to this study is then covered as a literature review in Section 3.2.

3.1 Unified Theory of Acceptance and Use of Technology

Unified Theory of Acceptance and Use of Technology (UTAUT) is a framework intended for explaining adoption of new technology among employees, which are referred to as users (Blut et al. 2021; Al-Saedi et al. 2019). UTAUT consists of various key factors and moderators that help explain intent to adopt new technology and behaviour to adopt technology (Blut et al. 2021). These key factors and moderators were discovered and collected using eight synthesized theories: the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), the Combined TAM and TPB framework (C-TAM-TPB), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), and the Social Congitive Theory (SCT) (Wu, Tao, and Yang 2007; Williams, Rana, and Dwivedi 2015). All of these theories have been considered dominant but are outperformed by UTAUT in the ability to explain variance in intention to use new technology (Williams, Rana, and Dwivedi 2015).

3.1.1 Strengths

UTAUT is able to explain 77 percent of the variance in behavioural intention and 52 percent of the variance in technology use (Venkatesh, Thong, and Xu 2016), making it more robust than other technology acceptance models for investigating intention and adoption of technology (Taiwo and Downe 2013 cited by Sovacool and Hess 2017). Technology adoption and diffusion research is considered among the most mature research areas in the field of IS and IT, which is why these frameworks are considered robust (Dwivedi et al. 2019; 2015). UTAUT is especially useful for explaining the adoption of technology in workplaces such as computing systems in offices (Sovacool and Hess 2017). UTAUT has also shown strong potential even in the topic of AI, where it looses only to context specific models, making UTAUT a strong contender for applications in the context of AI (Sohn and Kwon 2020). UTAUT has also been tested thoroughly in especially the healthcare industry (Kim et al. 2015; Blut et al. 2021; Taiwo and Downe 2013).

The UTAUT framework is suitable for application in novel contexts as it provides a broad and holistic view of user intention and behavioural aspects regarding the use of technology (Sohn and Kwon 2020). UTAUT is also suitable for the topic of innovation due to its integration of innovation diffusion theory among other theories (Blut et al. 2021). This study intends to look at specifically the technology of the 3D generative model, which is a subset of AI technology. Another advantage with UTAUT is its usefulness for probing representative samples of subjects and analyzing causal relationships (Sovacool and Hess 2017), which fits the research questions of this study as it intends to consider a wide range of different implementations of 3D generative models while also exploring and understanding the circumstances and settings that these types of implementations face.

The UTAUT framework's second version called UTAUT2 introduced improvements in generalizability, making the framework applicable also in non-organizational contexts as the notion of users was expanded to also include customers (Venkatesh, Thong, and Xu 2016). However, this study focuses on the first version of UTAUT as the generalizability of UTAUT2 does not benefit the context of this study more than what the first version of UTAUT already does. The context of the first version of UTAUT also fits the specific research setting of this study by focusing on especially office workers (Venkatesh, Morris, et al. 2003).

UTAUT is most commonly utilized quantitatively by calculating the relationships between UTAUT variables mathematically (Williams, Rana, and Dwivedi 2015), but is increasingly being applied qualitatively as well (Kiwanuka 2015). Qualitative use of UTAUT has been applied in various fields such as in elderly care (Renaud and Van Biljon 2008; Bixter et al. 2019), health care (Ami-Narh and Williams 2012; Jayaseelan, Kadeswaran, and Brindha 2020), and in education (Williams, Saunderson, and Dhoest 2021; Birch and Irvine 2009). The use of UTAUT in a qualitative method is common for exploratory studies that work with a small sample-size, which is also the intent of this study.

3.1.2 Drawbacks

While UTAUT is a promising tool, it comes with limitations such as only focusing on office workers and also on consumers for its second version, UTAUT2 (Sovacool and Hess 2017). Drawbacks with using UTAUT is also the lack of scales and relative weights between its elements (Sovacool and Hess 2017), which makes it both important and recommended for applications of UTAUT to contextualize the framework to the research setting (Venkatesh, Morris, et al. 2003), something which has been done considerably as discovered in reviews conducted a decade later (Venkatesh, Thong, and Xu 2016;). Other drawbacks include the design of UTAUT as it was using only linear relationship and non-monotonic algorithms as well as consisting of non-objective modeling which may not necessarily reflect the full complexity of user intention and adoption (Alwabel and Zeng 2021). The design of UTAUT has also shown to be especially important for quantitative studies, where adaption of the model to fit the context increases the robustness of the analysis (Andrews, Ward, and Yoon 2021). UTAUT is also not personalized by default, built based on previous existing theories, and as such risks missing the discovery of new variables depending on the context it is used on (Alwabel and Zeng 2021). An adaption of UTAUT to its applied context can therefore be regarded as a necessity.

3.1.3 Adaption

Since the regular UTAUT framework may not be enough to explain adoption and intention of use in the context of AI, a modification considering some of its vulnerabilities is added. Additionally, since the ability to include and analyze the gender moderator has been limited in this study, this study excludes the gender component of the UTAUT framework. The inclusion of gender as a factor was at first pursued for this study but then discovered to be challenging to satisfy during the conduct of the interviews. Gender as a factor could hence still be influential and provide valuable insight, which is why it can be suggested for future studies.

UTAUT does not consider some external factors that are deemed necessary for application of UTAUT in a context of AI (Venkatesh 2022). To address these factors, Venkatesh (2022) and also Lichtenthaler (2020) proposed the inclusion of external factors called characteristics which are used to catch dynamics that have been deemed relevant in an AI context. However, while these factors are considered, they are not independently analysed in the same detail and with the same weight as the key factors, and are therefore grouped into one external key factor called ”External Characteristics”. This is done to keep much of the focus on the original UTAUT framework so that the well researched and thoroughly tested core of the UTAUT design is maintained. The external characteristics will hence function as a separate dimension to inspect which links directly to the key factors of the UTAUT framework.

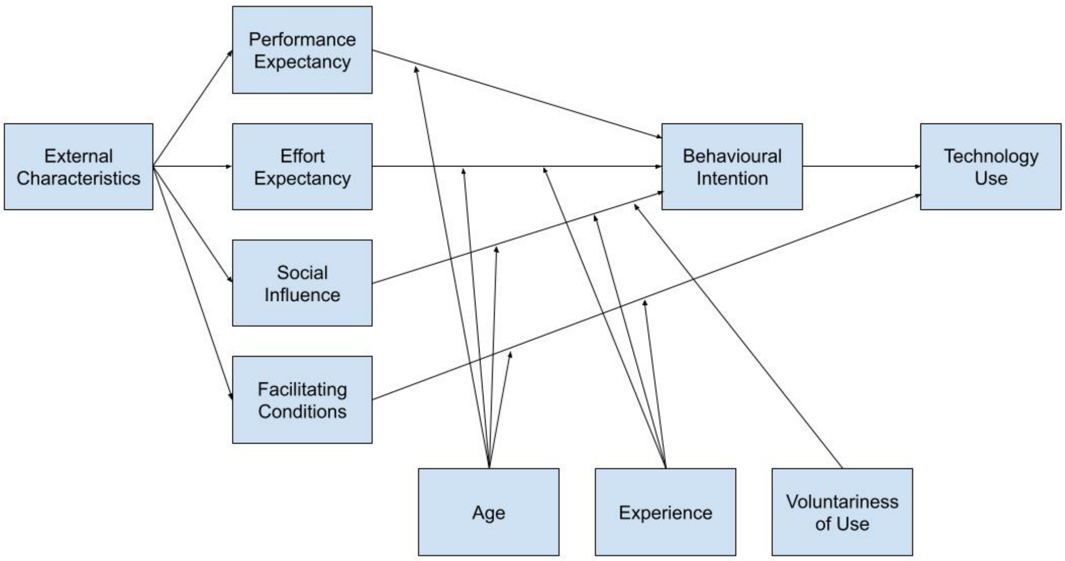

Figure 3.1.1: Visualization of the modified version of UTAUT that is used for the conduct of this study.

The link between the external characteristics and the key factors is explained by the discovery that acceptance of AI technology is affected by the characteristics of the AI technology and also various properties in the context and setting it is investigated in (Venkatesh 2022; Lichtenthaler 2020). The novelty of this factor additionally comes with a lack of consensus regarding how external characteristics should link to the UTAUT framework. Since this study works from the key dimensions of the UTAUT framework, the external characteristics have been connected to the key factors so that external characteristics can be investigated for each key factor independently. Additionally, the external characteristics is intended to be answered and analysed on its own so that insight that could potentially be linked to other areas of the UTAUT framework.

The addition of external characteristics as a separately discussed component enables findings and analysis that could be used for exploring if external characteristics could link to other components of the UTAUT framework as well. Another potential insight that a separate external characteristics discussion could provide is the exploration of insight that could suggest a need for new components for possible future modifications of the UTAUT framework. Hence, the novelty and unexplored nature of the external characteristics component makes an exploration of this component useful for exploring its relevance in this study's context as well as for future studies that intend to include it.

The rest of the UTAUT framework is kept unchanged since it follows the design of UTAUT that is proposed for use in the context of this study. Hence this study intends to apply the UTAUT framework fitting for AI with the exclusion of the gender factor. The final design of the UTAUT framework that is applied in this study can hence be observed in Figure 3.1.1. The components of this version of the UTAUT framework is described in detail in the following subsections.

3.1.4 Key Factors

As can be observed in 3.1.1, the four vertical elements on the left are the constructs called key factors of the UTAUT framework (Wu, Tao, and Yang 2007; Venkatesh, Morris, et al. 2003), while the three horizontal constructs at the bottom are called the moderators (Wu, Tao, and Yang 2007; Venkatesh, Morris, et al. 2003. The key factors can largely be used to explain the behavioural intention of the use of technology which functions as the first prediction output of the UTAUT framework, and use behaviour of technology that function as the final prediction output of the UTAUT framework (Venkatesh, Morris, et al. 2003). The strength of the key factor links is affected by the moderators in the UTAUT framework, where different properties among users influences the salience of users in regards to each key factor (Venkatesh, Morris, et al. 2003). The four key factors are Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Wu, Tao, and Yang 2007; Venkatesh, Thong, and Xu 2016). The UTAUT moderators affect and influence the results from the key factors, such as their prediction power of behavioural intention of the use of technology followed by the prediction of the use of technology by users in organizational settings (Venkatesh, Thong, and Xu 2016).

Performance Expectancy

The first key factor from the UTAUT framework is performance expectancy which is defined as the degree to which a user believes that the use of a system benefits the user in certain activities (Blut et al. 2021). Performance expectancy has an acknowledged connection to the notion of ”usefulness” and is found in TAM, TAM2, C-TAM-TPB, MM, MPCU, IDT, and SCT (Venkatesh, Morris, et al. 2003). The significance of performance expectancy exists in both voluntary and mandatory settings, and is significant pre-, during and post- adoption (Venkatesh, Morris, et al. 2003). Performance expectancy is moderated by age. Younger people were discovered to value extrinsic rewards which increased their salience to performance expectancy (Hall and Mansfield 1975 cited by Venkatesh, Morris, et al. 2003; Porter 1963 cited by Venkatesh, Morris, et al. 2003).

Effort Expectancy

The second key factor from the UTAUT framework is effort expectancy which is defined as the degree of ease associated with the use of the system (Blut et al. 2021). Effort expectancy originates from the perceived ease of use found in TAM and TAM2, by the complexity construct in the MPCU, and by the ease of use construct by IDT (Venkatesh, Morris, et al. 2003). The significance of effort expectancy is also found in both voluntary and mandatory settings, but has the highest significance in before and in the early phase of adoption that declines over time (Venkatesh, Morris, et al. 2003). Effort expectancy is moderated by age and experience. Experience was assumed as the most significant moderator for effort expectancy as it would directly reduce the effort needed to adopt a new system (Venkatesh, Morris, et al. 2003). Younger age was discovered to be more salient toward effort expectancy as increased age also increased difficulties in processing and allocating attention to new adopt systems (Venkatesh, Morris, et al. 2003).

Social Influence

The third key factor from the UTAUT framework is social influence which is defined as: the degree to which a user believe that others think it is important for the user to use the system (Blut et al. 2021). Social influence is based on the corresponding construct named Subjective Norm in TAM2, TPB/DTPB, and C-TAM, as Social Norm in TRA, as Social Factors in MPCU and as image in MPCU (Venkatesh, Morris, et al. 2003). The significance of social influence is found in almost exclusively mandatory settings where it directly affects intention, while it only affects by influencing perception through internalization and identification in voluntary settings (Venkatesh, Morris, et al. 2003). Social influence is also found to be the strongest in early phases of adoption as it erodes and becomes non-significant over time (Venkatesh, Morris, et al. 2003). Social influence is moderated by compliance as pressure to adopt on an individual can alter intention. Other moderators of social influence are internalization and identification, where an increased response to status gains can alter an individuals belief structure and as such stimulate adoption. Age was found to increase salience (Rhodes 1983 cited by Venkatesh, Morris, et al. 2003). Age salience in regards to social influence was reduced with increased experience, meaning experience contributed with inverse proportionality to social influence (Morris and Venkatesh 2000 cited by Venkatesh, Morris, et al. 2003).

Facilitating Conditions

The fourth and final key factor from the UTAUT framework is facilitating conditions which is defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system (Blut et al. 2021). Facilitating conditions encompasses both tools that can support the adoption and use of the system, and tools or mechanics that remove barriers to adoption and use (Venkatesh, Morris, et al. 2003). It can be found as the construct of perceived behavioral control in TPB/DTPB and C-TAM-TPB, as facilitating conditions in MPCU and as compatibility in IDT (Venkatesh, Morris, et al. 2003). The significance of facilitating conditions is found in both voluntary and mandatory settings immediately after adoption, but decays rapidly to become non-significant. While facilitating conditions is able to predict intention of use, the two factors of performance expectancy and effort expectancy together encompasses the mechanisms of intention that facilitating conditions can generate (Venkatesh, Morris, et al. 2003). Nevertheless, facilitating conditions is uniquely useful for predicting the use of technology (Venkatesh, Morris, et al. 2003). Age was discovered to influence facilitating conditions with increased salience for older people as they were observed to be more in need of help and also more inclined toward asking for help (Morris and Venatesh 2000 cited by Venkatesh, Morris, et al. 2003). Experience was also found to greatly increase facilitating conditions as support tools became more understood and accessible to experienced users (Morris and Venatesh 2000 cited by Venkatesh, Morris, et al. 2003).

External Characteristics

External characteristics consists of four components that have been identified so far for the UTAUT framework (Venkatesh 2022). The effects, weights, and dynamics of these components have however not been measured or assessed thoroughly yet due to the novelty of this discovery (Andrews, Ward, and Yoon 2021; Venkatesh 2022). The four components are therefore presented here briefly as possible characteristics could be identified and linked with any of these components. The first component is Individual Characteristics, which considers the personality of the users since it could be possible that individuals who are daring and knowledge-pursuing may be more eager to adopt AI (Venkatesh 2022). The second component is the Technology Characteristics, which considers the perception of the technology such as if it is an important technology to pursue due to the likelihood of it being disruptive to the industry, and if it has apparent advantages (Venkatesh 2022). The third component is the Environmental characteristics, which is a factor that considers the organizations influence on the employee, such as company values that could influence the openness and eagerness to new technology by the employee (Venkatesh 2022). The last component is interventions, which is about the certainty or uncertainty surrounding the AI systems, such as management being aware of the purpose of the system, and the use of a business plan with clearly defined specifications for the system, so that the system can be guaranteed to provide the benefits that were desired and intended (Venkatesh 2022).

3.2 Literature Review

This section reviews relevant literature to this study. As this study focuses on the combined context of defense industry, AI and technology acceptance, literature from these three topics are presented in the mentioned order and gradually transitioned from one topic to the next.

3.2.1 The Defense Industry

The field of Information Systems (IS) is a vast and growing field of science which encompasses many technologies and managerial frameworks, including Industry 4.0, AI technology, and acceptance models (Collins et al. 2021; Aslan, Çetin, and Özbilgin 2019; Dwivedi et al. 2019). Industry 4.0 is an essential field for the manufacturing industry as it involves automation and optimization that can be considered disruptive as was found in the Industry 4.0 state-of-the-art review by Woschank et al (2020). The term Industry 4.0 refers to the massive leap in industrialization that is introduced through the introduction and advancements of many recent technologies (Gunal 2019; Kerin and Pham 2019). Technologies such as the internet, robotics, automation, additive manufacturing, simulation, cloud, and data analytics were expected to be current and future topics of focus for research relevant to IS and Industry 4.0 as was concluded in the state-of-the-art and future prospects study regarding Industry 4.0 by Gunal (2019). Gunal additionally concluded that AI for simulation, sometimes referred to as Simulation 4.0, was one of the especially emergent technologies in the topic of Industry 4.0 (Gunal 2019). The emerging technologies review by Kerin and Pham (2019) also highlights the importance to pursue industry 4.0. In their study they conclude that some of the future prospects relevant to industry 4.0 include sociotechnical areas such as organizational change and also the adoption of AI technology to manufacturing processes (Kerin and Pham 2019).

Closely tied with industry 4.0 and the manufacturing industry is the defense industry which involves the production of products such as defense weapon systems, vehicles, and equipment (Lele and Lele 2019; David et al. 2020). The defense industry involves the innovation, development, and manufacture of these kinds of systems, and as such focuses on the making of defense-related products that are made using the same processes as other types of industries (Lele and Lele 2019). Due to there existing many similarities between the defense industry and the manufacturing industry, such as robotics, aerospace, vehicles, innovation and production, many of the processes are transferable between the two industries (Lele and Lele 2019; David et al. 2020). The same technologies found in industry 4.0 in other industries were discovered to be just as emergent in the defense industry as well, as was discovered by the review of AI technology for the defense industry by David et al (2020). David et al (2020) concluded that many Industry 4.0 technologies were indeed transitive to the defense industry, but also challenging to implement from a technical, security, and ethical perspective. The security and safety concerns of deploying weapons that used or were produced using AI processes, such as AI simulation softwares, was discovered as some of the most important areas that would need more research focus (David et al. 2020).

Challenges involving sensitivity, confidentiality, and lethality of defense industry technologies carries economical implications for innovation. These challenges cause a demand for especially large investments for the defense industry to innovate in order to maintain global relevance (Kurç and Neuman 2017). Hence, from a financial perspective, international collaboration and the opening up of the defense industry to include institutions, other industries, and start-ups has been a solution which vastly accelerated and enabled national defense industries in developed countries to maintain an innovative edge despite reduced national spending as found by Kurç and Neuman (2017). Kurç and Neuman (2017) conducted a study investigating Turkey's defense industry and the pursuit of a self-sufficient defense industry. The study discovered trade-offs in the pursuit of a self-sufficient defense industry versus an innovative and cutting-edge defense industry which is covered further in the following section (Kurç and Neuman 2017).

Innovative Edge

Multinational collaboration has been a common solution for especially developed countries, as it carried the advantage of accelerating innovation, research, and development (Kurç and Neuman 2017). The benefits of opening up the national defense industry seemingly outweighted the drawbacks. This was especially true during times of peace as the benefits of having a self-sufficient defense industry was not as important as having a technological edge of defense weapons at a time when the demand to produce large quantities was low (Kurç and Neuman 2017). Instead, a technological advantage introduced opportunities for the national economy and trading power as these systems could be sold to collaborating nations and partners (Kurç and Neuman 2017; Lele and Lele 2019). A technological advantage also introduced global political power as these systems were discovered to be attractive to other nations who could become potential customers and partners (Kurç and Neuman 2017; Lele and Lele 2019). Multinational collaboration came with a vulnerability however, as the complexity of supply chains increased, and through the reduction of self-sufficiency of a nations defense industry (Kurç and Neuman 2017). This trade-off was discovered when investigating the independence and self-sufficiency of the Swedish defense industry by Ikegam (2013). The Swedish model was found to utilize multinational collaboration, which helped the Swedish defense industry to survive and to even flourish despite historically reduced national investments in its national defense industry (Ikegami 2013). On the other hand, this multinational collaboration introduced a challenge if a conflict would happen due to a multinational dependence on partners for the production to be maintained (Ikegami 2013; Kurç and Neuman 2017). In contrast, developing countries pursued self-sufficiency of its defense industry, yet this came at the cost of vast defense industry spending that may still not have been enough to maintain and ensure a competitive technological and innovative edge globally (Kurç and Neuman 2017). Some of the main explanations for why these multinational collaborations deployed by developed countries were so potent could be traced to technology and knowledge transfer and encouraged specialization by nations to focus on specific areas (Kurç and Neuman 2017). This specialized focus was effective for achieving a competitive technological and innovative edge by the collaborating nations (Kurç and Neuman 2017).

Collaboration and Open Innovation

Collaboration in the defense industry allowed for effective use of resources that could be spent on developing a competitive technological and innovative edge in each specialized field, and to additionally create international compatibility of products that further promoted competition of products as investigated by Kerr et al (2008). The use of technology insertion was one such benefit that was driving the competition speed of open and collaborative defense industry development and processes (Kerr, Phaal, and Probert 2008). Technology insertion is a design philosophy of extending the life-span and life-cycle of defense industry products by preparing them for possible future upgrades and innovations (Kerr, Phaal, and Probert 2008). Technology insertion was found to introduce long-term savings and costs, while also increasing the ability to customize products so that the product could maintain a competitive edge over a longer time-span (Kerr, Phaal, and Probert 2008). Regarding the manufacturing process itself, the introduced pursuit of industry 4.0 came with efficiency and an increased ability to develop complex defense weapon systems as found by Latif and Starly (2020). To achieve this, the use of Digital Twins, AI, simulations, and visualization has become increasingly important to pursue (Latif and Starly 2020). Additionally, more research is found to be needed that investigates the use of ML in both the defense weapon systems and manufacturing processes within the defense industry (Latif and Starly 2020). Furthermore, the study by Cirincione et al (2019) investigates key areas and outlines a strategy for the US Defense Industry which concludes that AI for visualization and simulation application are some of the most essential technological focus areas for future research. Cirincione et al (2019) additionally outlines a distribution strategy between institutions for the purpose of concentrating the pursuit of these technologies. The pursuit of AI in the defense industry can therefore be concluded to be among the most focused areas of research in defense industry literature.

3.2.2 Pursuit of AI

Considering the significance of industry 4.0 to the defense industry, it is no surprise that AI technology is an increasingly researched technology that is being pursued within the defense industry for use in products and processes (David et al. 2020). The competitive edge that AI is expected to provide to the defense industry can already be found in aerospace, automotive, and defense industry technologies, such as manufacture, simulation and visualization (Cirincione et al. 2019; Field 2004). Open innovation has additionally enabled the integration of cutting edge IS technology into the defense industry as shown by a state-of-the-art analysis on AR technologies for the defense industry by Aslan et al (2019). The use of AI is found to be an especially important area of research in the field of IS that also lacks in research focus in sociotechnical areas as well as research on AI as a tool in work-related environments (Collins et al. 2021). The novelty of AI is also evident from the lack of industrial applications as discovered in the review by Woschank, Rauch, and Zsifkovit (2020). In their review of AI in the field of industry 4.0, it is discovered that the novelty and complexity of the technology is visible in how research mostly consists of concepts, laboratory experiments, and very early testing phases (Woschank, Rauch, and Zsifkovits 2020). Additionally, mature industrial applications were found to be missing (Woschank, Rauch, and Zsifkovits 2020).

The increased use of visualization tools such as AR and VR has pushed scanning technologies, computer hardware, and visualization-focused AI which has further driven the adoption of AI into defense industry processes due to the shared use of LiDAR and AI-technology (Aslan, Çetin, and Özbilgin 2019). The review by Hunde and Woldeyohannes (2022) investigates the significance of AI in the manufacturing industry in general. The review concludes that emerging simulation technologies is what drives CAD processes to new capabilities (Hunde and Woldeyohannes 2022). To further prove the importance of AI simulation tools in the defense industry, the study by Ongsulee (2017) looks at the current research focus and future prospects of AI, ML, and DL. Ongsulee concludes that there are many future prospects where these technologies can be applied, such as autonomous cars, data analysis, and military simulations (Ongsulee 2017).

AI tools for users, such as AI simulation tools and softwares, are therefore one of the most important areas where AI can be applied in the defense industry that is also in a growing demand for research from especially a sociotechnical perspective (Aslan, Çetin, and Özbilgin 2019; Collins et al. 2021; Kurç and Neuman 2017).

Simulation AI

One of the most promising areas where AI can be applied in the defense industry has been identified as the area of simulation (Gunal 2019; Cirincione et al. 2019; David et al. 2020). The study on multi-agent modeling and simulation by Fan et al (2021) reviews the various methods and use cases where AI can benefit simulation software that is relevant to the defense industry. AI as applied to simulation software is discovered to be promising in a multitude of ways for various types of softwares and use cases (Fan et al. 2021). The most basic use case of simulation is to use simulation in material science, such as for analysing deformation, explosives, and pressures, while other more complex types of simulations involve the use of agents, such as robots, machines, and people (Fan et al. 2021). The more complex simulation environments such as economic simulation, organizational simulation, warfare simulation, evolutionary simulation, and decision-making are discovered as areas that are expected to be relevant for simulation software that deploy advanced AI algorithms in the future (Fan et al.

2021).

Since both simulation software and computer visualizations function using 3D point cloud data there are promising use cases of AI in the recognition and processing of such data. The review by Doellner (2020) investigates some of the most promising applications of ML in the manufacturing industry and industry 4.0, and discovers the importance of geospatial AI for processing 3D data. In this review, the use of 3D point cloud data, as covered in section 2.4, is concluded to be the most promising type of use case of ML in regards to geospatial processes in the manufacturing industry (Doellner 2020). This is explained through similarities with tasks solved by natural language models (Doellner 2020). The study by Y. Guo et al (2021) further reinforces this discovery with an investigation of the state-of-the-art performance of various ML and DL algorithms when applied to 3D point cloud data that is used for recognition of scanned objects. The use of ML with point cloud data is stated in this review to be a promising applications of DL for analysis of 3D scans and point cloud data (Guo, Wang, et al. 2021). The study by (2020) also supports this claim by concluding that ML for encoding and decoding of 3D point cloud data as being a useful technology for object reconstruction, which is useful for simulation as well. Furthermore, the article by Palviainen et al (2020) investigates the use of AI for analysing 3D point cloud data from an organizational perspective, and discovers sociotechnical challenges such as challenges with the adoption of these AI tools.

Adoption of AI

There are many studies that raise the need for sociotechnical research in the field of AI. The multiple-case qualitative study by Palviainen et al (2020) looks at a mostly functional-level perspective of ten Finnish firms involved in processes using 3D point clouds and reconstruction using automated 3D modeling. Palvainen et al (2020) performed semi-structured interviews with only a few types of stakeholders from each company, consisting of people involved in both business development and technical development. The study also discovered challenges and concerns by these stakeholders that can contribute with insight into challenges from an individual and organization-level perspective such as the lack of training data requiring increased effort from personnel, combined with concerns about the risk of increased effort being required by co-workers (Palviainen et al. 2020). Other stakeholder concerns relevant to the individuals at the business were if the potential of this technological implementation could be appropriately identified as well as concerns about the opinions and possible resistance from the workforce when performing the change of the pipeline that this implementation would provide (Palviainen et al. 2020). This study hence further suggests that AI simulation software research should benefit from sociotechnical studies that look from the perspective of the user of such technology.

This need for sociotechnical research that focuses on the user perspective was additionally made evident by the following studies. The study by Field (2004) concludes that the use of CAD in the automotives industry needs research and more focus on supportive tools and promoting willingness to change among CAD users. CAD users who are open to change were found to be advantageous when considering emerging technologies that were likely to affect the use of CAD tools (Field 2004). This need of user perspective was especially evident from the study by Janiesch, Zschech, and Heinrich (2021) discovered challenges regarding human factors. This study introduces novel concepts and current challenges regarding the implementation and use of ML and DL (Janiesch, Zschech, and Heinrich 2021). Current challenges are found to constitute to the IS-community as it involves technical knowledge, the consideration of human factors, and the ecosystem of the application (Janiesch, Zschech, and Heinrich 2021). The need for explainability through Explainable Artificial Intelligence (XAI) was additionally raised by the study, as this was discovered to increase the security of the model and also the trust by humans and organizations who attempted to adopt such models (Janiesch, Zschech, and Heinrich 2021). The need for user perspective was also shown by the review on IS systems by Collins et al (2021) which reviewed the current state of ML reserach, and outlined a future research agenda. Collins et al (2021) also revealed the need to study the people and users who would work next to or with new tools. Users who were prepared to adopt new technologies were expected to ease the adoption and use of new technologies for the business (Collins et al. 2021). A lack of studies that focus on AI as a tool in work-environments was discovered and outlined as an important area for future research (Collins et al. 2021). A term used to describe the use and adoption of new technologies, such as AI tools, is technology acceptance.

3.2.3 Technology Acceptance

Technology acceptance is among the most well researched and mature areas in IS research (Dwivedi et al. 2019). Its importance can be linked to the rapid pace of new technological innovations that can be found in today's society, where the rate in which workflows and processes get out-dated can be found at an unprecedented level (Venkatesh, Morris, et al. 2003). The analysis of how people are ready to adopt, and willing to accept and use new technology has therefore been a large and important area of research (Venkatesh, Morris, et al. 2003; Dwivedi et al. 2019). This sociotechnical dimension has additionally been found to be especially important for a changing environment, something which has been growing in research focus, especially with the advent of new technologies relevant to industry 4.0 (Janiesch, Zschech, and Heinrich 2021; Collins et al. 2021). A multitude of frameworks have been developed over time to explain technology acceptance (Sovacool and Hess 2017). As this study focuses on the novel technology of AI, ML, and DL in the context of simulation software, the focus lies on the dynamics involved during the acceptance and adoption of such technology from a users perspective.

Acceptance of Technology and AI

The article by Lichtenthaler (2020) reviews literature on technology acceptance for applications relevant to AI technology, and discovers the importance to consider attitudes. Additionally, it is discovered through this review that AI technology is especially susceptible to attitude, as individuals can have positive and negative attitudes toward AI technology depending on their characteristics (Lichtenthaler 2020). The review concludes that over time, people should become increasingly accepting of new technology such as AI technology (Lichtenthaler 2020).

The meta-analysis by Blut et al (2021) presented UTAUT as being one of the best available frameworks for the purpose of predicting user acceptance. Therefore, UTAUT was deemed preferable as a framework to apply for the technology explored in this study. There is a lot of literature that can be used to further support the decision to use UTAUT for this study. There have been many findings which reveal the importance and value of conducting sociotechnical analysis on the introduction of new technology to a workforce or for new processes involved in any industry. The review by Sovacool and Hess (2017) reviewed many of these technology acceptance frameworks and concluded that UTAUT was a popular and powerful framework for the purpose of predicting intention to use and use behaviour (2017). The review concludes that the UTAUT is perceived by researchers as among the top 14 most important theories for explaining sociotechnical change in the field of IS (Sovacool and Hess 2017). Another type of acceptance that is worth noting is that for customers who could buy products involving AI technology. The comparative study by Sohn and Kwon (2020) explores which models that best explain purchase intention. The models compared in this study are the TAM, TPB, UTAUT, and Value-based Adoption Model (VAM) (Sohn and Kwon 2020). In this study, it is concluded that VAM was the best, followed by UTAUT for user acceptance of products involving AI technology (Sohn and Kwon 2020).

The review by Williams, Rana, and Dwivedi (2015) presents the patterns and trends of UTAUT research. It concludes that while UTAUT research in the field of IS has been growing, there are many signs of it still developing, and a potential to achieve further maturity (Williams, Rana, and Dwivedi 2015). The UTAUT framework is concluded to be suitable for exploration in new fields (Williams, Rana, and Dwivedi 2015). This same phenomenon is discovered by Blut et al (2021) as well. When comparing the use of technology acceptance between cultures, the review by Im, Hong, and Kang (2011) investigates functions of UTAUT between U.S and Korean users. The study concludes that technology acceptance variables can indeed differ depending on culture and individual characteristics (Im, Hong, and Kang 2011).

User-focus in the Defense Industry

A look-up of Technology Acceptance in the defense industry yields no results on Web of Science using the search query *'("Technology Acceptance"OR "UTAUT") AND ("Defence Industry" OR "Defense Industry")'*. Google Scholar also provides few results on this topic. Yet, a the thesis by Garrison (2021) was found that applies TAM to the acceptance of VR technology in the defense industry. The thesis concluded that technology acceptance could indeed be found in this research setting and topic (Garrison 2021). While the mentioned search query yielded few results, acceptance studies in the defense industry could still be found by looking for standardization-codes for U.S and U.K directives.

Articles for a U.S standard called Department of Defense Design Criteria Standard Human Engineering, was found under the code MIL-STD-1472 (Swain 2013). The review by Furman, Theofanos, and Wald (2014) was one article found by searching using this code. This article was made by the organization NIST which introduces and concludes the importance of applying a Human-Centered Design Process, coded ISO 9241-210 (Furman, Theofanos, and Wald 2014). Human-Centered Design Process is presented as a design philosophy that should be pursued and applied further for future applications and development of defense systems and products (Furman, Theofanos, and Wald 2014). The article by Nesteruk (2009) reviewed the dated standard of MIL-STD-1472F called Human Factors and concluded the importance of updating this standard as well as the importance of increasing usability for especially novel users of defense industry technologies (Nesteruk 2009). More articles are found regarding user-focused design (Zielinski, Ii, and Frank 2022; Smith, Steinhauer, et al. 2019). However, these studies don not include primary data from users and instead look at technical solutions that considers or addresses risks to the user. This may be explained by how open the standard is to interpretation as mentioned by Zielinski, Ii, and Frank (2022).

The U.K counterpart to the MIL-STD-1472 is the Human Factors Integration for Defence Systems, coded DEF-STD 00251. The article by Harris (2008) provides an overview of this standard and highlights the importance for sociotechnical research and human-centered design processes for military products. The article additionally highlights the challenges with implementing these standards and the areas where the standards are most applied and researched (Harris 2008). Still, these studies do not include primary data from users and instead look at technical solutions that considers or addresses risks to the user, which further suggests that technology acceptance is an area that needs more research focus in the defense industry.

UTAUT for AI

The article by Andrews, Ward, and Yoon (2021) investigates the use of UTAUT to describe adoption and acceptance of AI technology. The article presents how important this is for industry 4.0 while also presenting many challenges that are unique to AI technology and that need to be considered for applications of UTAUT in this topic (Andrews, Ward, and Yoon 2021). The article concludes that more research is needed that attempts to apply and adapt UTAUT to a context involving AI technology (Andrews, Ward, and Yoon 2021). The author of UTAUT, Venkatesh (2022) also performed an analysis on the framework's applicability to AI technology. In his review he also noted that there were unique characteristics with AI technology that had to be considered when applying UTAUT (2022). The UTAUT framework presented in Section 3.1 was therefore adapted to consider these discoveries. The UTAUT framework with this adaption was also deemed one of the most robust candidates for this study, combined with the nonexistence of its application in the context of the defense industry. Hence there is a strong motivation for the use of UTAUT in this study.

Chapter 4

Method

This chapter begins with a presentation of the research setting of this study in section 4.1 with a description of the organization and case. The research design is then presented in section 4.2 where the structure of the study is defined. The use of data and data collection is described in section 4.3

4.1 Research Setting

This section begins by introducing the case company of this study in section 4.1.1. A description of the case is then given in section 4.1.2.

4.1.1 Case Company

The case company for this study is Saab Dynamics which is a Swedish company in the defense industry, under the parent organization Saab AB which is in both the aerospace and defense industry (Saab AB 2023). Saab Dynamics has many sister organizations such as Saab Aeronautics and Saab Kockums (Saab AB 2023). Saab Dynamics has multiple departments and is involved in many areas of research, innovation, and production that involves software development, system development, and product development (Saab AB 2023). Saab dynamics develop a wide range of different systems, both lethal and non-lethal, such as robots, rockets, sensors, softwares, and aquatic vehicles (Saab AB 2023). By being in both the manufacturing industry and defense industry, Saab is motivated to stay up to date with cutting-edge technologies and innovations for the purpose of contributing to people's security (Saab AB 2023). Furthermore, Saab has existed for nearly 100 years and is also a large company consisting of almost 20,000 employees worldwide as of 2022 (Saab AB 2023), making it both a large and enduring organization. This study focuses on one department within Saab Dynamics which focuses on 3D simulation and the use of 3D objects for the development of some of Saab Dynamics' products.

4.1.2 Case Description

Saab is an organization that has an interest for cutting-edge technologies such as AI, ML, and 3D generative models. This is why the organization has an interest in studies that can help them explore this technology and its relevance to their business. Additionally, Saab Dynamics are deeply invested in product development and innovation and continuously strive to enhance and accelerate their own innovative processes, which is why a study on technology adoption is suitable for them. Furthermore, the blend of routines and habits with adaption and modernization makes Saab Dynamics a suitable company for testing and analysis of change management concepts, as a company of this size and age has had to face many challenges due to changing environments. This study should therefore contribute with insight into the application and adoption of 3D generative models by a large and established incumbent in the Swedish defense industry. Additionally, insight consisting of employee's perspectives of 3D generative models is hence pursued with this case, which incorporates theories from change management and technology acceptance. This study is therefore beneficial for both Saab Dynamics as well as organizations in the manufacturing industry to some extent, as adoption of 3D generative models and application of technology acceptance frameworks is not exclusive to the defense industry.

Saab Dynamics was open to the sociotechnical direction of this study as sociotechnical studies were less frequent for this specific department and especially for this specific technology. Saab Dynamic's expectations were hence open and flexible to the ideas of the researcher as this study would provide perspectives and insights that could be previously unfamiliar to the department, yet increasingly revealed to be of interest throughout the conduct of the study. The only challenge to manage for this study that was linked to the case company was the added consideration of secrecy depending on the sensitivity of information. However, the researcher of this study was made aware that information that could be considered too sensitive would be kept away from the researcher by default. This combined with the researcher's intention of maintaining generalizability of findings by not discussing specific implementations and instead discuss types of implementations was hence deemed enough as a solution. The conduct of this study was performed with autonomy where the researcher was able to design the study freely and to take it in any direction which the researcher perceived as most fitting for both the organization and for empirical research. Meetings with the university supervisor were mainly performed to pursue contribution to empirical research and for improving the design and structure of the thesis, while meetings with the organization supervisor were mainly performed to discuss relevant literature and empirical findings that could be used for the pursuit of value for the organization in terms of practical implications and for future studies. The case period started at the end of January and lasted until the beginning of June.

4.2 Research Design

This study is designed as an explorative single case study as it was commissioned by the organization Saab Dynamics, as introduced in section 4.1.1. This study was commissioned with the intent of focusing the analysis on their own organization and setting, which is why an explorative single case study is suitable for this case. This type of study is especially suitable for this case as the aim is to provide the organization with in-depth insights into a real-life context phenomenon (Yin 2009). Furthermore, this study deploys a qualitative case study with an abductive approach due to having not well known and not well understood challenges that exist in this novel technology (Dubois and Gadde 2014). An abductive approach strives to discover what's new rather than confirming something that is already known, which is the aim of this study (Dubois and Gadde 2014). An abductive approach is typical when working with qualitative data as literature is explored in parallel with the analysis process to increase the understanding of the findings (Blomkvist and Hallin 2015). A qualitative case study is suitable to this study as it allows this study to deeply explore drivers and barriers that may arise from the implementation of a specific technology (Yin 2009).

Two research questions were formulated for this study, RQ1 for exploring types of implementations of 3D generative models that can be considered relevant, and the second research question being RQ2, to discover drivers and barriers with the adoption of these 3D generative models. This study works at an individual and organization-level perspective by focusing on people and users, also called AI actors as defined in section 2.5, for the adoption of 3D generative models (Blomkvist and Hallin 2015). This study therefore contributes with research in a less researched topic as there are currently no available articles on the application of UTAUT for AI technology in the defense industry, and neither of the application of UTAUT for specifically the technology of 3D generative models. This lack exists despite the importance for organizations in the manufacture and defense industry that pursue implementations of this kind of technology. Empirical data collection through less standardizable methods is suggested for this type of explorative study (Saunders, Lewis, and Thornhill 2009). It is important to consider multiple perspectives for a qualitative study, hence why a heterogeneous research choice was made using the Lifecycle and Key Dimensions of an AI system in section 2.5 (Saunders, Lewis, and Thornhill 2009). Additionally, subjectivity is embraced by qualitative epistemology which is important for emphasizing various different opinions (Saunders, Lewis, and Thornhill 2009). Therefore, an interpretivistic approach is suitable for this study where the gathered knowledge is understood to be subjective for every individual and influenced by external and surrounding factors (Saunders, Lewis, and Thornhill 2009). Semi-structured interviews were used to collect qualitative data which is useful for analysing the perspectives of people (Saunders, Lewis, and Thornhill 2009). With a qualitative approach, a large emphasis and weight is put on each sample, meaning the selection of samples would be of high importance for the quality of the results (Saunders, Lewis, and Thornhill 2009). Additionally, semi-structured interviews can be supported with methodological triangulation for ensuring accurate results are being collected (Gibbert, Ruigrok, and Wicki 2008). Triangulation is performed in this study by using observations, public documents, and demonstrations alongside the interviews.

4.3 Data Collection

This section contains information about the data collection process employed by this study. Section 4.3.1 explains the selection process for interview respondents in this study. This is followed by section 4.3.2 which explains how data was collected for this study from mainly interviews, but also from other methods. Section 4.3.3 discusses the collection of secondary data that is useful for supporting findings from the primary data.

4.3.1 Respondent Selection

For this study, 13 qualitative interviews were conducted. The primary sampling strategy for this study was to use snowball sampling technique since this would help with reaching a diverse range of respondents which is useful for probing discoveries (Saunders, Lewis, and Thornhill 2009). To additionally guide and support the diversity of samples, a framework used in the AI RMF by NIST (2023) was used called the Lifecycle and Key Dimensions of an AI system which was brought up in detail in section 2.5. The Lifecycle and Key Dimensions of an AI system identified various kinds of actors that were important to consider throughout the lifecycle of an AI system such as a 3D generative model. Therefore, this framework was useful for the purpose of finding a diverse range of respondents that could be expected to influence and be part of this lifecycle. As such, the sampling technique was additionally supported to a lesser degree by a purposive sampling technique with specifically the research choice of finding samples with heterogeneous representation (Saunders, Lewis, and Thornhill 2009). The use of snowball sampling together with purposive sampling had the advantages of not demanding a large sample size while simultaneously being able to probe for cases that were less known (Saunders, Lewis, and Thornhill 2009). The respondents can be observed in Table 4.3.2.

The technical topic of this study involves the intersection of defense industry, AI, and 3D processes such as CAD and simulation. Hence, all respondents were selected with the requirement of being relevant to at least one, but preferably two of these three topics. Since all respondents were working at Saab Dynamics, they all fulfilled the topic of being part of the defense industry. Therefore, emphasis was put on finding respondents who had different types and combinations of involvement with the AI and 3D processes topics.

A final influence for the purposive part of the sampling strategy was the discovery of all early respondents being males, which could be a problem with the study if wanting to considering the original UTAUT frameworks gender moderator. UTAUT mentions how gender can be an influencing moderator when inspecting technology acceptance (Venkatesh, Morris, et al. 2003). Since there were challenges with obtaining a representative sample size of females for this study, the gender moderator was decided to be excluded from the study as was discussed in section 3.1.

4.3.2 Primary Data

This section presents how data was collected from each type of collection method that was used in this study. The interviews were the main source of data used in this study but observations and implementations in the form of demonstrations were two other sources of data that could contribute to the findings at a lesser degree.

Interviews

Interviews were conducted with a total of 13 respondents. The interviews were conducted from the beginning of March 2023 to the middle of May 2023. The structure of the interviews followed the guidelines of UTAUT (Venkatesh, Morris, et al. 2003) but were combined into three questions with a funnelling effect going from an open and unstructured question and down to specific semi-structured questions that would cover the points that had not been answered already. A full overview of the structure of the interview with its many stages can be found in Table 4.3.1. All questions were designed in Swedish and the interviews were held in Swedish due to all the respondents and also the interviewer having Swedish as a primary language. Translations to English of the questions designed for guiding the interviews can be found in Table 4.3.1. While Table 4.3.1 contains the question guide for the interview, the conduct did not follow the structure of the guide closely and was instead fluid, which is recommended for semi-structured interviews (Saunders, Lewis, and Thornhill 2009). Respondents were often times able to automatically transition or address all questions in the same stage without the need to ask every question in the guide. Usually the transitions happened in-between questions from the same stage, shortly after the first question in a stage had been answered. This could be explained by how the followup questions seemed natural to go on to for respondents even though the question was not asked. The fluidity was introduced to make sure to guide the interview toward the targeted insight without having to be very direct about it.

Question Stage	**Translated Question (English)**	**Targeted Insights**
Open Questions	• **What do you think of AI/3D Generative Models?** • Do you feel for example worry or potential with AI/3D Generative Models?	Alignment, social influence, anxiety, and expectancy
Identify Cases	• **Where can you imagine seeing AI/3D Generative Models?** • Where do you think AI/3D Generative Models should be used in your surrounding? • Have you tried using some AI/3D Generative Models? • How can AI/3D Generative Models help you in your daily life and at work?	Identify cases, expectancy, self-efficacy, intention of use
Assess Cases	• **What technical and social challenges/opportunities do you see with <Implementation of AI/3D Generative Models>?**	Identify challenges and opportunities

Table 4.3.1: Information about main questions (in bold) and follow-up questions for each question stage that were used to guide the interviews of this study.

Every interview started with an introduction of the interviewer followed by an introduction of the study explaining what the purpose of the study was as well as an explanation of how the data would be collected and used in the study. Consent regarding the collection and use of the data was verified with every respondent. For some respondents, the question was asked if they would like to contribute to the study by letting the interviewer audio-record the interview for the purpose of increasing the ability to quote the respondent for some findings. About half of the respondents were asked this way and nearly everyone who was asked gave their permission to be audio-recorded. The audio-recordings were deleted as soon as the corresponding transcription was completed. The first question was to ask the respondent to present themselves briefly with who they are and what they work with so that their relevance to the Lifecycle and key Dimensions of an AI system could be identified as well as to verify some data about the respondent which was relevant to the UTAUT framework's moderators such as the age group.

Three main stages in the interview process were defined and used for all interviews. The first stage was the open question stage, where the intention was to ask openly what the respondent thought of AI and then trying to listen to the respondent as much as possible without influencing the respondents line of thought. The second stage was about identifying cases where implementations of AI and 3D generative models could be made. This was done with a funneling effect in usually two rounds where the first round asked about AI in general, and the second round being about 3D generative models. If the respondent did not know much about 3D generative models from beforehand when reaching this question, a brief introduction to the technology was provided with some communicated example and in one case by showing one of the demonstrations of it, which depended on what seemed appropriate under each circumstance and when considering the prior experience and knowledge of the respondent. The third stage was a stage for assessing implementations, which had the intention of finding technical and social challenges and opportunities for discussed types of implementations as well as for implementations discovered from previous interviews. Finally, after all these questions had been asked, the respondent was free to keep reflecting on and discussing more implementations and perspectives regarding 3D generative models that could be relevant and useful for the study. While no interview managed to follow the structure of the guide fully, answers to all the questions in the guide were collected with enough similarity in the structure to ease the analysis process of all responses.

Each respondent was placed inside of appropriate lifecycle stages provided by the Lifecycle and Key Dimensions of an AI system framework that was discussed in section 2.5. A table with the identified relevance of each respondent to each stage can be observed in Table 4.3.3. The identification and allocation of each respondent to each lifecycle stage was performed using Table 2.5.1 from section 2.5.

Respondent	Age group	Works with	Length	Recording method
A	30s	Simulation and AI	115 min	detailed notes, compiled
B	30s	Systems and AI	100 min	detailed notes, compiled
C	20s	CAD	65 min	detailed notes, compiled
D	50s	CAD and Simulation	45 min	detailed notes, compiled
E	20s	CAD and Simulation	45 min	detailed notes, compiled
F	20s	Simulation	60 min	detailed notes, compiled
G	40s	Management	60 min	detailed notes, compiled
H	40s	Management and AI	60 min	audio-recorded, transcribed
I	20s	AI	60 min	audio-recorded, transcribed
J	30s	CAD	30 min	audio-recorded, transcribed
K	30s	Simulation	30 min	audio-recorded, transcribed
L	20s	Simulation	30 min	audio-recorded, transcribed
M	30s	Simulation	20 min	audio-recorded, transcribed

Table 4.3.2: Information about the people who were interviewed for this study.

Five out of thirteen interviews were recorded and transcribed, while the seven other interviews were recorded using detailed note taking. For audio-recorded interviews, a transcript was created shortly after the interview, while the interviews conducted using note taking were compiled right after the interview so that the information would be as complete as possible as recommended by Saunders et al (2009). This was tried out with the purpose of making the respondent more comfortable to speak openly and provide reliable in-depth answers. This worked very well as the topic of AI resulted in the respondent frequently pausing to think through their answers, which meant that pressure on the interviewer to write down answers could be neglected as there was enough time for the interviewer to write down full answers in detail while reflecting on what the respondent meant to say.

A risk with real-time non-verbatim scripts is the risk of errors since it can put more pressure on the interviewer during the conduct of the interview, and also lacks the possibility of playback that would have made it possible to correct errors. There can also be a lack of verbatim detail when not recording and then transcribing the interview, details which could in some cases play a role in changing the meaning of answers (Rutakumwa et al. 2020). Additionally, real-time non-verbatim transcription has the risk of making the interviews less engaging for the respondent, which can have a negative impact on the quality of less structured interviews, especially if the interviewer is less experienced with conducting interviews or has less knowledge about the topic (Rutakumwa et al. 2020). These concerns were addressed to some extent with the presentation

Lifecycle Stage	Respondent
Plan and Design	A, B, G, H
Collect and Process Data	C, D, E, F, J, K, L, M
Build and Use Model	A, B, H, I
Verify and Validate	A, B, G, H
Deploy and Use Model	A, B, G, H, I
Operate and Monitor	A, C, D, E, F, H, I, J, K, L, M
Use or Impacted by	A, C, D, E, F, I, J, K, L, M

Table 4.3.3: The actors that are relevant to each lifecycle stage in the Lifecycle and Key Dimension of an AI system from the AI RMF framework by NIST (2023).

format of the interviews combined with the topic and questions producing a slow pace.

For audio-recorded interviews, a somewhat verbatim transcript was made for the purpose of generating highly precise and reliable citations to support findings made by this study. The respondent was informed about the study and asked for consent before starting the recording, so that trust could be built, which could otherwise be a threat to the quality of a recorded interview (Rutakumwa et al. 2020; Saunders, Lewis, and Thornhill 2009). After performing the careful verbatim transcription process, the voice recording file was destroyed.

The interview was designed using PowerPoint, where the first question of each stage in Table 4.3.1 of the interview were used as the titles for the presentation slides. The presentation can be found in the Appendix in Figure B.0.1.The presentation was not played, instead it remained in edit-view so that the slides could be updated and interacted with. Answers by the respondent were written down as text for each slide, meaning the respondent was able to observe their answer as it was written. This made it possible for the respondent to engage with what was being written by for example rephrasing their answer. This also made it easier for the respondent to follow their own line of thought and to remember what they had covered already, which could cause a reduction of the amount of repetition in answers. The risk of error was minimized as respondents were able to check their answers, and as the interviewer was able to ask again or verify that they heard and understood correctly, which further strengthened the reliability of the notes.

Advantages of conducting non-audio-recorded interviews is the minimizing of the risk of respondents not feeling comfortable or inclined to opening up, resulting in answers with reduced reliability (Rutakumwa et al. 2020; Saunders, Lewis, and Thornhill 2009). This is why it is beneficial for interviewers to continue the interview even after the audio-recorder has been turned off. However, even the use of an audio-recorder during part of the interview could be a threat to the respondent's comfort, especially for sensitive topics (Rutakumwa et al. 2020). A mix between audio-recorded interviews and interviews that did not use audio-recording was therefore advantageous, especially in a sensitive environment or topic (Saunders, Lewis, and Thornhill 2009). Due to the possible risk of security concerns that could exist if for example sensitive data would happen to be disclosed and collected, this strategy of using non-audio-recorded and instead real-time non-verbatim note-taking of the interviews, with full disclosure and increased control of what is being written during the interview, may have built valuable trust with the respondent. As the inclusion of exact phrasing of answers could be guaranteed, the quality and accuracy of the answers was strengthened. Additionally, since the notes sometimes contained exact matching phrases that were marked as quotes from the interview, the ability of quoting the interview was retained for specifically those notes, which is important to have for strengthening the reliability of the results of this study.

Observations

While working on this master thesis at Saab Dynamics, it has been possible to interact with various employees and experience the organization's culture and values, as well as learning to understand how this culture and values may be reflected on the people who work at the organization. This insight is useful for building a deep and general understanding of the organization which can contribute with possible insights and explanations from an organizational and individual-level perspective (Blomkvist and Hallin 2015). Since the case study organization is involved in the defense industry, there can be security issues with using observation as a method for obtaining data. Hence, this study carefully considers the use and value of any observation to an extent that respects the secrecy and security of the organization, agreements and policies, and Swedish Engineer's (Sveriges Ingenjörer 2023) code of honour. This is done by not revealing any observations that could be a concern or have a negative effect on the organization, and by making sure to not use or present any insight originating from observations of potentially classified information, or quantity of information that combined can cause security concern.

An example of a use case where observation can contribute with valuable insight while not being of any security concerns is the observed value of coffee breaks for potential knowledge sharing as relevant discussion topics could be covered during such without the involvement of the researcher. One discussion topic that was discovered and that is connected to the Secondary Data findings in section 4.3.3 was the awareness of new and widely accessible AI models such as ChatGPT and Midjourney. Another example of a contributing observation was to observe the general reaction or response toward this thesis' topic when mentioning it to employees. Both of these observations could indicate if the respondent sample failed to represent the department as a whole since it could be compared to the reactions and general answers found during the interviews.

The contribution of the observation for this study was hence limited to the verification of how representative the responses by respondents were, and to the link between the values of the organization and employees. Since the researcher of this study was located in a mostly fixed environment, the risk for bias due to for example nearby employees being especially aware of the research topic and already interested in the technology was inevitable and will be discussed further in the Discussion in chapter 6.

Implementations

As Saab Dynamics had an interest in exploring implementations of prototypes, the design of prototypes was investigated in parallel with the conduct of this study. The prototypes consisted of some basic 3D GAN demonstrations based on a few publicly available demonstrations such as GeoCode (Pearl et al. 2022), and EG3D (Chan et al. 2022). Technical insight and challenges became apparent when attempting to develop these prototypes, which provided some extra contribution to the understanding of the technology and with insights to this study's technical challenges section.

From a sociotechnical perspective, these demonstrations were mostly useful after the conduct of the interviews for the purpose of finding out what thoughts respondents had upon seeing these demonstrations. The demonstrations additionally provided the benefit of making respondents more excited about the study as became apparent by how they offered their support with establishing contact with other relevant interview respondents. The implementations were not used for any other purpose than for demonstration after the interviews and for technical insight which is why less emphasis was put on this type of data.

4.3.3 Secondary Data

The organization's website, public speeches, and annual report was used in this study to gain insight from an organization-level perspective (Blomkvist and Hallin 2015). Public documents relevant to user focused design and standards that the organization is aware of, such as MIL-STD-1472 and DEF-STD 00251, were also discovered, as discussed in section 3.2.3. To be aware of public documents that can be sources of inspiration for the organization can help explain values and ideas of the organization and employees. A public interview with the CEO of Saab, Micael Johansson conducted by Sveriges Radio (2023) from the organization was used in this study to identify external characteristics of the organization that could influence the results of the study and the view on the studied technology. Saab's annual report was found through Saab's website which contained a lot of insight into the values of the company as well as a description of the ambitions and goals of the specific department that this study focused on, namely one of the department within Saab Dynamics with a focus on 3D objects and 3D simulations, as was presented in section 4.1.1.

Since this study's organization is based in Sweden and has ties with the Swedish Government (Saab AB 2023), there could be statements by politicians, media and news coverage, and global political events which can be relevant and of value to the analysis in regards to especially external characteristics. An example of relevant news coverage for the analysis is the widespread social-media coverage and influence of recent AI models for art, such as Midjourney and Stable Diffusion, as well as natural language models, such as ChatGPT and Bard. These news could be considered and used during the interviews and observations throughout this study to investigate if it could influence the acceptance through especially the external characteristics construct of the UTAUT framework. It was discovered that these AI models were frequently covered in both public and private newspapers as well as Swedish TV. Political factors worth considering are defense industry investments and an ongoing conflict in Europe due to the war in Ukraine, which can influence the organization, the business, and employees.

Additionally, directives regarding AI such as the EU AI Act, AI RMF by NIST, and the OECD Framework for the Classification of an AI system were discovered through this method. The later two were considered and used for the purposive sampling technique as was discussed in section 4.3.1.

4.4 Data Analysis

This study intends to combine empirical findings with the analysis of findings in an intertwined method which has the advantage of producing better alignment (Blomkvist and Hallin 2015). Findings and analysis are therefore presented together, starting with the discovered types of implementations and then proceeding to the findings of applying UTAUT for analysing adoption of 3D generative models. The findings for the types of implementations are sorted into groups which have been identified based on the empirical data, which falls within the method used for thematic analysis according to Blomqvist and Sjödin (Blomkvist and Hallin 2015). Findings from the application of UTAUT are presented in a flowing text that analyses the findings in the context of the key function. This flowing text is similar to the use of a narrative analysis method as different types of insights that fall within each key function is presented in sequence, starting with results based on the framework and ending with analysis that may fall outside of the defined design of the framework (Blomkvist and Hallin 2015). This method is suitable when having a lot of different data from different data sources as insights from multiple data sources can be presented and analysed together (Blomkvist and Hallin 2015).

The analysis was performed in two parts, one for each research question. The analysis was performed in a semi-sequential order as it could be performed in two distinct yet connected directions. The firs direction concerned RQ1 and focused on the discovery of types of implementations of 3D generative models. Findings from each individual implementation could then be used in the interviews as types of implementations that could be discussed using UTAUT for analysing adoption. The second direction corresponds to answering RQ2, and focused the application of UTAUT for analysing adoption of 3D generative models in the defense industry. This was done by focusing on the key factors of the UTAUT framework and then investigating how the various types of moderators and external characteristics showed support for the intention or behaviour to adopt 3D generative models.

To answer RQ1, *"What types of 3D generative models are relevant to the defense industry?"*, the first part of the analysis was about exploring individual implementations. This was followed by the identification of what type of implementation that this would belong to. To categorize implementations into types, the input and output of the 3D generative model was used, as this would decide for what process and where in the process that the 3D generative model would be used. This was an abductive approach where types of implementations were discovered and sorted with the help of empirical background knowledge, and then generalized into types of implementations that had similar input and output, but where their functionality and design could contain differences. As the discovered types of implementations grew in quantity, they were categorized into groups that revolved around similar steps in the processes. In this case a clear difference could be drawn between the focus on 3D objects, and the focus on 3D simulations, with some types of implementations spanning both or beyond these topics, called innovative processes, while others only touched on these topics, such as analysis of data quality. These four groups were identified over time and used to sort the findings.

To answer RQ2, *"What are the drivers and barriers for adopting 3D generative models in the defense industry?"* an abductive approach was utilized (Blomkvist and Hallin 2015). The structure for these results was sorted and analysed following the structure of the adapted UTAUT framework as presented in section 3.1. Hence, the results and analysis was performed abductively since it combined theory with empirical findings (Blomkvist and Hallin 2015). The findings and answers for each key function and characteristics of the theory were obtained from the interviews and interpreted using the theory as support. An additional section was added called technical challenges as these were found when analysing the responses by respondents. Respondents were quoted to support findings, and since respondents answered in Swedish, the responses were translated manually to also attempt to retain the feeling and non-verbal features that were recorded in the original language. The used quotes are included in their original language next to the corresponding translations in the Appendix section A.1.

4.4.1 Quality of Research

There are four criteria that can be used to determine the quality and rigor of a case study, these are Internal validity, External Validity, Construct Validity, and Reliability (Gibbert, Ruigrok, and Wicki 2008).

The first one, external validity, addresses the generalizability of the study, which can be done by for example conducting a multiple case study (Yin 1984 cited by Dubois and Gadde 2014). This study is performed as a single case study due to it being the most suited for providing insights for the studied organisation, and therefore does not provide the generalizability that a multiple case study is capable of (Dubois and Gadde 2014). Single case studies additionally lack in replication due to the data not always being provided or accessible, which is the case for this study, and which further reduces external validity (Goffin et al. 2019). However, external validity can still be found in this study through its synthesis of many types of implementations that is conducted inductively which can be connected and are related to findings from previous literature. Therefore, this study provides a degree of generalizability as the implementations themselves and their challenges are generalized into types that are applicable, verifiable, and still relevant outside of the context of the studied organization.

Internal validity concerns the use of multiple perspectives for triangulation of the used theory for a study (Gibbert, Ruigrok, and Wicki 2008). This study performs a degree of triangulation of theory by not entirely relying on only the main theory used in this study, the UTAUT, but by also by introducing the Lifecycle of Key Diensions of an AI system, and by also exploring and considering weaknesses and trade-offs of the theory when applied to the context of the study and studied organization. However, the Lifecycle of Key Diensions of an AI system is not synthesized with UTAUT in this study, and no explicit modification of UTAUT is performed for the conduct of this study, which limits the degree of internal validity achieved with this study. Triangulation of theory was hence performed by reading up on the applied theory in relevant fields to the research topic followed by considering updates to the framework based on the findings from these studies. The used framework presented in section 3.1.3 is therefore the result of this study's performed triangulation of the applied theoretical framework.

Rigor is achieved through construct validity, which is mainly done by performing triangulation of data collection (Gibbert, Ruigrok, and Wicki 2008). This study achieves construct validity by collecting primary data through multiple different methods such as interviews, observations, and attempted implementations, and by additionally analyzing using insights from secondary data to further support the internal validity of this study. The main method for collecting data throughout this study was using the conducted semi-structured interviews which produced insights that could be analysed and sorted to answer the research questions. Triangulation of data was hence performed by comparing these qualitative interview findings with findings from the organization's annual report, with a public interview with the CEO of the organization, with the observation of the representation of answers by respondents when compared to general interactions with other employees, and though the meager attempt at implementing a model which verified some of the technical challenges that were discovered from the interviews.

Reliability of this study concerns the possibility of researchers to carry out similar studies to attempt to reproduce this study, which is done through transparency and replicability of the study (Saunders, Lewis, and Thornhill 2009; Gibbert, Ruigrok, and Wicki 2008). Transparency has been achieved in this study by providing detailed description of the method and conduct of this study, such that it should enable other researchers to conduct a similar study that is capable of achieving a similar result. Additionally, replicability could be ensured by keeping a database of the collected data from the case study (Gibbert, Ruigrok, and Wicki 2008). This study has handled all data inside of a device owned by the organization. Any remaining data is therefore kept by and passed on to the organization. Hence, replicability is only possible by obtaining the data from the organization, with consent from the organization. This is done to respect the organization's security policy.

4.4.2 Ethics

This study carefully follows the principles presented by the Swedish Research Council (Vetenskapsrådet 2017). For every interview that was conducted, the respondent was made aware of the purpose and use of the data that was to be collected from them, so that the information requirement was followed and fulfilled according to the principles (Vetenskapsrådet 2017). They were also always asked for consent before starting the interview, and also for consent again when asking to audio-record the interview. Therefore, the consent requirement was followed and fulfilled according to the principles (Vetenskapsrådet 2017). The confidentiality requirements was ensured by informing participants that their data would be used anonymously and ensured that they would not be identifiable though the data. Finally, the good use requirement was followed by informing the participants that the data would only be used for this study. It is important to consider that while the data is anonymized and not able to be used to identify individual participants, someone well aware of the study, who works at the organization, and knows the people in the departments might be able to narrow down and potentially identify an individual. Considering this, effort is made to support the anonymity of individuals in the data so that no individual has to stand out in the data in a way that risks identification while also considering the value that the data carries for the quality of the research.

Chapter 5

Results and Analysis

This chapter covers the results and analysis by presenting the findings for each research question in consecutive order. The data that was collected from the conduct of this study is presented and analysed in the following sections.

5.1 Types of Relevant 3D Generative Models

As RQ1 intended to explore the types of implementations that exist of 3D generative models that are relevant to the defense industry, this section is dedicated to the many types of applications of 3D generative models that were discovered from the conduct of this study.

A 3D generative model is capable of providing automation or benefits in multiple ways as is discussed for each finding in the following sections. All discovered implementations are therefore covered in the subsections bellow. 21 implementations of 3D generative models were discovered from the conduct of this study. As this step involves quantitative data extracted from qualitative sources, a results table was deemed suitable for providing an overview. The full table with findings can be observed in the Appendix Table A.2.1.

5.1.1 Simulation Software

In total, five types of implementations were discovered to be relevant to the use of simulation software or the simulation process. These implementations were therefore grouped into a simulation software category. The five types of implementations, implementation 1, 2, 3, 4, and 5, are presented and analyzed in this section.

Implementation 1 attempts to forecast the output produced by the simulation software. This is

ID	Type of Automation	Implementation	Respondent
1	Replace Simulation Software Point Cloud	Reads simulation data to predict an outcome (Forecast)	A, B, C
2	Accelerate Simulation Software	Reads point cloud simulation data to give an indicative outcome prediction	A, B
3	Reinforce Simulation Process	Optimizes the properties of a point cloud simulation data by mutating it and testing results, applying reinforcement learning method	A
4	Accelerate Simulation Algorithm	Reads point cloud simulation data to incrementally simulate steps within the software faster or with less cost of resources or computation power	A, B, L, M
5	Accelerate Simulation Software	Reads point cloud simulation data to give recommendation on adjustments	A, F

Table 5.1.1: This table contains a list of implementations relevant to the use of a simulation software and simulation process. These results were discovered from the conduct of this study.

done by replacing the need of a simulation software by instead having a 3D generative model encode the 3D point cloud, that is normally used by the simulation software, to instead predict the simulation outcome. This 3D point cloud data is analyzed by the 3D generative model to produce an output that corresponds to the output produced when running the simulation software. This finding was mentioned by Respondent A (Simulation and AI), Respondent B (Systems and AI), and Respondent C (CAD).

> *”One can look into replacing simulation software and simulations. One can then look at empirical formulas and try out to replace them with machine learning. ’What happens if i simulate this?’”* - Respondent A (Simulation and AI) translated from Swedish

Implementation 2 on the other hand uses the same input and encoding method as implementation 1, but produces a less certain result. Nevertheless, a less certain result can still be used as a supportive tool by indicating in advance what kind of outcome that can be expected, and potentially also provide a reasoning if utilizing XAI. Therefore, implementation 2 focuses on accelerating the use of the simulation software using 3D generative models. This finding was mentioned by Respondent A (Simulation and AI) and B (Systems and AI).

> *”[A point-cloud simulation] Can be applied by a model that understands 3D in general, that understands how a shape affects the traits of something, and explains it to the user.”* - Respondent A (Simulation and AI) translated from Swedish

Implementation 3 applies a 3D generative model capable of mutating and evaluating the 3D point cloud based on specified criteria which can be used to discover and test various different designs that are capable of meeting the criteria. This type of 3D generative model uses a reinforcement learning method as it learns and adapts its policy through trial and error. This finding was mentioned by Respondent A (Simulation and AI), Respondent B (Systems and AI), Respondent F (Simulation), and Respondent H (Management and AI).

> *"It [3D Generative Models] can support the generation of concepts..."* - Respondent B (Systems and AI) translated from Swedish

> *"It would be good with something [a 3D generative model] that is able to try its way forward to new solutions, that thinks outside of the box"* - Respondent F (Simulation) translated from Swedish

Implementation 4 is a relevant way of accelerating the process withing the simulation software on a small scale by focusing on simulation steps that are typically iterated by the software. Implementation 6 is about accelerating or replacing the simulation algorithm within the simulation software to execute a trained algorithm rather than perform accurate and computation-heavy formulas that are otherwise used by simulation softwares. This can therefore introduce an accelerated performance of the software while introducing a potentially comparable simulation quality. This method may not demand a necessarily large and deep NN for prediction, which eases the development of this kind of algorithm. This solution reads a current stage of the simulation point cloud and outputs the consecutive iterations step of the simulation cloud. What exactly this step involves would depend on the software itself. This also assumes that the applied software does in-fact use iteration steps for the simulation process, something which is common for state of the art softwares (Respondent A, Simulation and AI; Respondent F, Simulation; Respondent K, Simulation). This finding was mentioned by Respondent A (Simulation and AI), Respondent L (Simulation), and Respondent M (Simulation).

> *"Every step in the simulation can be performed by AI, maybe faster then. If one can perform one step [using AI] then one can perform the remaining steps as well, so it should work"* - Respondent M (Simulation) translated from Swedish

Implementation 5 accelerates the use of the simulation software by instead attempting to provide recommendations on adjustments before the use of the simulation software. This is done by analyzing the encoded 3D point cloud data before running the simulation, where instead of predicting the result like what is done with implementation 1 and 2, the 3D generative model returns feedback and recommendations for the employee regarding what specific modifications that can be done by the employee to produce better results. This finding was mentioned by Respondent A (Simulation and AI), Respondent F (Simulation), and Respondent L (Simulation).

> *”One can probably otherwise use it [3D generative models] to help with the simulating. If one wonders which shapes that turn out well, or to provide suggestions regarding what values I should type [into the simulation software] to get a good simulation.”* - Respondent L (Simulation) translated from Swedish

5.1.2 Innovation Processes

Five types of implementations were discovered to be relevant to innovation processes, that is processes that work past the simulation process and includes assessment of simulation result or takes an input all the way from a real-world point cloud scan. These implementations were therefore grouped into a innovation processes category. The five types of implementations, implementation 6, 7, 8, 14, and 15, are presented and analyzed in this section.

ID	Type of Automation	Implementation	Respondent
6	Accelerate Innovation Process	Read point cloud simulation data to give an indicative assessment of solution	A, H
7	Replace Innovation Process	Read point cloud simulation data to predict assessment of solution (Forecast)	A, B
8	Replace Innovation Process	Read point cloud simulation data to predict real-world performance (Forecast)	A
14	Replace Design and Innovation Process	Read real-world point cloud scan to predict a simulation outcome (Forecast)	B, H
15	Accelerate Design and Innovation Process	Read real-world point cloud scan to give an indicative outcome prediction	B, H

Table 5.1.2: This table contains a list of implementations relevant to the innovation process of new designs. These results were discovered from the conduct of this study.

The implementations found in this section focus on innovation processes which contrast to the previous section’s, section 5.1.1 about implementations focusing on Simulation Software, by encompassing analytical steps that often involve assessment by a human.

> *”’if you’re going to build an [application] in this sort of scenario, what type of [criteria] do you want to pursue then?’ and then you let an AI train forth: what is the best distribution, ’yes but with this solution you will get this advantage’ then you will [produce an optimal result]. So that you don’t just stare yourself blind on geometry, but additionally perhaps design generative AI with different and higher levels.”* - Respondent H (Management and AI) translated from Swedish

Implementation 6 reads point cloud simulation data and attempts to assess it using predefined criteria that a user would use upon completion of the simulation. In this case the analytical aspect would be the assessment of the simulation result, which is normally performed by a human who looks at the simulation outcome. The Simulation Software focuses more on producing a result that resembles the output produced by a simulation software, that does not necessarily involve any analytical assessment of the output. Implementation 6 specifically targets an indicative prediction which means that the prediction quality does not necessarily have to be of high prediction quality. A low confidence prediction should still suffice to accelerate the innovation process as long as there is a benefit for the user. The benefit in this case can be that the 3D generative model provides some sort of feedback or suggestion about what perceived properties, such as strengths and weaknesses, that a simulation can be expected to produce. Additional benefits from this type of implementation can be obtained if it is designed as an XAI that reveals why the simulation might produce certain properties. This implementation was mentioned by Respondent A (Simulation and AI) and Respondent H (Management and AI).

Implementation 7 builds upon implementation 6 by replacing both the use of a simulation software and the evaluation part of the output from the simulation software. It is different from implementation 6 by producing a prediction with very high confidence, that can be trusted to a similar level when a human would perform the same assessment task. This implementation may be very difficult to achieve, yet has the potential to replace most of, or the entire need for a user to run the simulation using the normal way. The innovative process could then jump directly into real-world testing of configured shapes that this model predicts an optimal simulation-result from. This implementation was mentioned by Respondent A (Simulation and AI) and Respondent B (Systems and AI).

Implementation 7 can then additionally be extended further into Implementation 8 which replaces the simulation process by also replacing the steps performed by the simulation software followed by attempting to predict the real-world outcome that can be expected from performing the simulation and then testing the result in real-world trials. These two step may be challenging due to the complexity and possible disconnect involved between the point cloud input data and output data forming a prediction. Additional factors extending beyond the information provided to the simulation software by default may be necessary to research for this type of implementation (Respondent H). Furthermore, quantity of standardized and relevant data could be a concern for these implementations as it could be challenging to collect a dataset with enough sample size for especially large and deep networks that may be necessary for predicting outcomes of this complexity.

> *"yes and currently we do prototypes, and then try them on, and say 'yeah but this felt good'. I wonder if an AI could be given some more liberty with its parameter-space, and think a bit outside what we currently do today, and reach something that for example feels good."* - Respondent H (Management and AI) translated from Swedish

Implementation 14 replaces the design and innovation process by reading real-world point cloud scans to predict the simulation outcome. This implementation attempts to forecast the simulation result based on a real-world scan, which cuts off the need to both generate a 3D object and perform the simulation process. This type of implementation might be very difficult however to achieve a high quality result since there are many steps in the process. The quality of the prediction may therefore be too low for a complete replacement of the regular process. A lower quality prediction could however be useful for implementation 15 since it focuses on providing an indicative outcome to the user by supporting the user with information and insights that can accelerate the regular process. Implementation 16 is more generative as it involves more creative recommendations and suggestions for modifications for the user to the regular process. Designing implementation 16 as an XAI that can explain to the user how the prediction drew a conclusion is another way of providing the user with recommendations. Implementation 14, 15, and 16 were both discussed by Respondent B (Systems and AI) and Respondent H (Management and AI). Even though implementation 16 is covered here, it belongs slightly more to the following subsection and will therefore be listed in Table 5.1.3.

5.1.3 3D Object Generation

Nine types of implementations were discovered to be relevant to the process of 3D object generation, that is processes that focus on and involve the production, generation, and optimization of 3D objects. These implementations were therefore grouped into a 3D object generation category. The nine types of implementations, implementation 9, 10, 11, 12, 13, 16, 17, 18 and 19, are presented and analyzed in this section.

There are multiple types of implementations that focus on the generation of a 3D object that replace part of or the entire process usually performed using CAD software. For implementation 9, this is done by having the 3D generative model read real-world point cloud scans as input data that can then be analyzed and used to generate resembling 3D objects as the output. The generation process can be done using methods covered in section 2.1, such

ID	Type of Automation	Implementation	Respondent
9	Replace CAD Software	Read real-world point cloud scan to generate 3D object	A, C, D, E, F
10	Replace CAD Software	Read real-world point cloud scan to generate point cloud simulation data	A, D, E
11	Replace CAD Software	Mutate the shape of 3D objects to explore new viable designs	A, B, C, D, E
12	Accelerate CAD Software	Read real-world point cloud scan to generate low-quality 3D object	A, B, D, E, F
13	Accelerate CAD Software	Read real-world point cloud scan to generate guiding/indicative point cloud simulation data	A, F
16	Accelerate Design Process	Read real-world point cloud scan and give a recommendation on design adjustments	B, H
17	Replace Design Process	Read scanned blueprint and reconstruct into accurate 3D object	D, E
18	Accelerate Design Process	Read scanned blueprint and reconstruct into less accurate 3D object	D, E
19	Reinforce Design Process	Read scanned blueprint and recommend adjustments to the design	D, E

Table 5.1.3: This table contains a list of implementations relevant to the 3D object generation process. These results were discovered from the conduct of this study.

as using voxels, boolean modeling, or using more manually made programs that have been designed using Nodes. Implementation 9 has been performed and introduced using Nodes in for example the GeoCodes example mentioned in section 2.1. Implementation 9 was mentioned by Respondent A (Simulation and AI), Respondent C (CAD), Respondent D (CAD and Simulation), Respondent E (CAD and Simulation), and Respondent F (Simulation).

Implementation 10 also replaces the process performed by CAD software Read real-world point cloud scan to generate point cloud simulation data. In this case the simulation cloud produced resembles the scanned model but is solidified and material properties already set so that minimal or no effort has to be spent before running the simulation software using this data. The goal of a 3D generative model for this specific task can therefore be seen as preparing a real-world scan into a simulation-ready counterpart. This process can be performed with a middle step of producing a 3D object that is then converted into the simulation-ready point cloud counterpart. The use of a middle-part might ease development of this kind of model, however its relative performance compared to a monolithic model intended and designed for the same purpose is not known by this study. Implementation 10 was mentioned by Respondent A (Simulation and AI), Respondent D (CAD and Simulation), and Respondent E (CAD and Simulation).

Implementation 11 is performed by replacing the use of CAD software for optimizing or exploring the shapes themselves. This is done by having the shape of the 3D object mutate. To perform this a reinforcement learning model may be optimal due to its pursuit of optimal policy, or in this case shape, to achieve a maximized score based on set criteria. This type of 3D generative model should be capable of iterating through various types of optimal and semi-optimal solutions, and should therefore be capable of discovering previously unexplored designs. Challenges associated with this type of mutation is that it does not necessarily accelerate a process as much as it is able to automate the process based on its designed capabilities. The freedom associated with the model's mutability introduces a trade-off where a employee-guided mutating model may find optimal solutions faster at the cost of risking to find less of original and unexplored shapes due to introduced bias associated with such a guidance. Implementation 11 was mentioned by Respondent A (Simulation and AI), Respondent B (Systems and AI), Respondent C (CAD), Respondent D (CAD and Simulation), and Respondent E (CAD and Simulation).

> *"...or a [3D generative] model that produces something mutating. It can be used in the manufacturing process to find new shapes to produce with."* - Respondent A (Simulation and AI) translated from Swedish

Implementation 12 Accelerate CAD Software by reading real-world point cloud scanned data that is analyzed and used to generate 3D object with the intent to make the generated 3D object look similar to the real-world counterpart. This is similar to implementation 9 however performed with a lesser expected output quality and may therefore require additional modification or fixing by a CAD user. It is able to accelerate the use of CAD softwares if the output generated is capable of providing some resource and/or time-saving advantages to the CAD-user, or give pointers to shapes worth exploring further. Implementation 12 was mentioned by Respondent A (Simulation and AI), Respondent B (Systems and AI), Respondent D (CAD and Simulation), Respondent E (CAD and Simulation), and Respondent F (Simulation).

> *"You can use generative models that adapt their shape in various ways to achieve specific purposes"* - Respondent A (Simulation and AI) translated from Swedish

Implementation 13 builds on implementation 12 by proceeding to attempt a generation or preparations for the point cloud scan that is to be used by the simulation software. This can be to for example extract material values that seem reasonable for different parts of the simulation cloud, based on analysis of the real-world point cloud scan. Implementation 12 would therefore accelerate the process of using a CAD software by designing and preparing the data to be used in the simulation. This implementation can be achieved by first performing implementation 12, followed by implementation 1 or 2. Alternatively, a generative model could be trained to skip this in-between step of generating a 3D object and instead train directly on creating a simulation-ready point cloud scan based on a real-world scan. A challenge with this method could however be a lack of manual adjustability by workers, since users wouldn't be able to take advantage of the in-between step for manipulating and adjusting from the 3D object step. Implementation 13 was mentioned by Respondent A (Simulation and AI) and Respondent F (Simulation).

> *"It [3D Generative Models] can support the generation of concepts, support the collection of requirements, and also synthetic generation of data. Generative models are good for quickly making prototypes."* - Respondent B (Systems and AI) translated from Swedish

Implementation 17 is about reading blueprints, either scanned or digital copies. These blueprints are in a 2-dimensional format but often represent something that is 3-dimensional. A 3D generative model could be trained and modeled to be able to translate this 2D blueprint data into 3D data, which can be used to produce a 3D object. If the object generated from this automated process is accurate enough it can be used to replace the manual process of reconstructing a blueprint. If it does not produce outputs that are accurate enough for the task, it can be used as a supporting system instead alongside the users regular process. Implementation 18 is about this limitation where the produced 3D object does not reach quality demands. In this case it can be used to accelerate processes by attempting to create easily adjustable work-files that might be able to benefit the user. The limitation in quality is then traded into an opportunity for the early steps of the regular design process. An alternative way to implement 18 is to apply a generative or explainable approach. A more generative approach is to design a recommendation system that suggests modifications to the regular user progress. It intends to support the designer by identifying possible mistakes by the designer and to suggest solutions or next steps in the regular design process. Implementation 19 is about analysing the blueprint itself and to suggest changes to the blueprint. This means that the generative model might either need to learn of best practices, or to learn how to construct the blueprint into 3D followed by deconstructing it and encoding it back into a blueprint after finding suggestions for improvements. The output for implementation 19 is therefore always suggestions for the blueprint itself, or an alternative blueprint. Implementation 17, 18, and 19 was mentioned by Respondent D (CAD and Simulation) and Respondent E (CAD and Simulation).

5.1.4 Data Quality Analysis

Two types of implementations were discovered to be relevant to the process of data quality analysis, that is processes that involve only analysis of data and not necessarily any automation or acceleration of any steps. These implementations were therefore grouped into a data quality analysis category. The two types of implementations, implementation 20 and 21, are presented and analyzed in this section.

ID	Type of Automation	Implementation	Respondent
20	Analyze Data	Read real-world point cloud scan and assess quality of scan	D, E
21	Analyze Data	Read scanned physical blueprint and assess quality of scan	D, E

Table 5.1.4: This table contains a list of implementations relevant to data analysis. These results were discovered from the conduct of this study.

Implementation 20 and 21 are two types of implementations of 3D generative models that focuses more on data analysis by assessing the data. Implementation 20 reads a read-world point cloud scan and assesses features such as the quality of the scan when considering properties such as the clarity and strength of features. Implementation 21 reads scanned design blueprints or sketches and also performs a data analysis process where the quality of the scan or blueprint design is assessed. These two implementations were mentioned by Respondent D (CAD and Simulation) and Respondent E (CAD and Simulation).

5.2 Technology Acceptance

RQ2 was intended to explain the underlying reasoning behind the challenges that 3D generative models could face when being implemented and adopted to the processes of an organization working in the defense industry. This was done by applying the UTAUT framework. These findings will be presented in this section. Results and analysis of each key factor is presented in more depth in this section following the structure of UTAUT using Key Factors and external characteristics.

5.2.1 Performance Expectancy

All respondents agreed that the use of AI in general was very useful and potent, and thought that AI in the context of 3D data such as 3D objects and 3D point clouds could be useful as well.

> *"It [AI] seems very exciting, one can use it [AI] for many things."* - Respondent J (CAD) translated from Swedish

> *"It [AI] has an extreme potential."* - Respondent A (Simulation and AI) translated from Swedish

As can be seen from section 5.1, there were many discovered implementations that could be used to facilitate, accelerate, support, and replace activities that users would normally do. That the respondents were aware of these implementations points at a high technology acceptance when it comes to the intention to adopt AI technology. The UTAUT framework states that performance expectancy is moderated by age only, since young people seemingly value extrinsic reward to a higher degree (Venkatesh, Morris, et al. 2003). This study did however not observe any significant links between age and performance expectancy. This could be due to the sample size not covering the full range of respondents that would reveal such a link. Instead, a link seemed to be found between performance expectancy and experience in this case.

People that knew more about AI and that had an idea of its potential often times also expected it to have a very high performance potential. This could be a phenomenon more unique to specifically AI as this technology might be difficult to comprehend while also being a popular topic of discussion that is brought up a lot for its potential. A social influence could thus be another contributing moderator that drives the performance expectancy that contributes to the use of technology. This social influence together with experience thus seem like two types of moderators that can drive user salience in the context of AI.

One difference also regarding performance expectancy was how respondents in management considered business aspects to a larger degree which introduced some scepticism toward AI as a technology that should be adopted (Respondent H, Management and AI).

5.2.2 Effort Expectancy

Effort expectancy was identified as being of less concern due to many respondents believing that AI should be pursued despite of the risk that it could involve high costs and a long time before it will be able to benefit users, The users were not so concerned about how long it could take and the costs to develop and release an AI implementation since there was a general view that AI should be invested in to not fall behind (Respondent A, Simulation and AI; Respondent B, Systems and AI; Respondent C, CAD; Respondent D, CAD and Simulation; Respondent E, CAD and Simulation).

Increased effort demanded on the user was not as much of a concern either. There was some concern from a few employees that there could be a need for greater effort if falling behind with the adoption of AI technology (Respondent C, CAD; Respondent F, Simulation).

Management had a different perspective as they perceived additional factors such as the growth of the company from stakeholders such as investors (Respondent G, Management; Respondent H, Management and AI). Expectations by investors could hence introduce barriers if the costs versus benefits were not perceived to be good enough for some AI technologies.

Findings from the interviews as a whole using the UTAUT framework provided a general picture of strong salience for the intention of adoption by the whole interviewed sample. Reasons for this were discovered to be partly explained by the experience moderator from the UTAUT framework due to effort expectancy and social influence, which will be covered in the following subsection. It was clear that the effort expectancy key factor was especially high due to all respondents already being aware to some degree of the significant benefits that AI automations could contribute with.

> *”I like it [AI] a lot, it [AI] is an emergence of new technology.”* - Respondent B (Systems and AI) translated from Swedish

This seemed likely to be traced to their shared involvement and interest in technology in general.

5.2.3 Social Influence

Social influence was identified to be very influential to the acceptance of AI technology as respondents perceived the general attitude in the organization to be open toward exploring use of AI technologies and 3D generative models. This was discovered to be especially the case after recent widespread news coverage of AI, in this case due to the release of Midjourney, Stable Diffusion, Open AI’s ChatGPT, and Google’s Bard prior to and during the conduct of this study as could be observed by the researcher.

> *”Yes but ChatGPT, it seems rather useful. One can ask it- one can be cooking food and go: [Example:] ’i have these ingredients, what [recipes] can you offer me?’”*
> - Respondent J (CAD) translated from Swedish

This increased understanding for the tools and how it worked introduced influence with seemingly independent origin from the respondent's role. The general impression of these AIs in making effort more easily achieved was spread between all the respondents due to their understanding of some or all of these mentioned AI releases. Using observed insight by the researcher as data to add to this finding, social media coverage of ChatGPT and AI had a wide and significant outreach which could be observed by the researcher throughout the conduct of this study as people in general could mention these technologies, sometimes for the purpose of entertainment, such as mentioning a fun fact or a joke linked to these AI technologies. This type of mentioning of AI technologies could be observed both within the workplace during breaks and outside the workplace. The mentioning of these technologies could therefore be observed within the organization by both the researcher and interview respondents. Hence, news coverage of AI is likely to have contributed with an increased salience toward the adoption of AI technologies due to the social influence factor.

Findings from experience which links to the social influence key factor were more subtle, yet everyone shared a perspective of the importance for them to at least attempt and pursue adoption of AI into their processes, where applicable, to stay competitive and to avoid falling behind international competition. This can be linked to the UTAUT framework's description of compliance due to pressure to adopt. In this case pressure on the organization and business. Internalization and identification was not clearly identified but still possible as the respondents all shared in common the tendency of occasionally talking about the AI topic.

When considering external characteristics' influence on the social influence key factor, the individual characteristics are likely to play a role in affecting the intention to use the technology positively toward the adoption of AI technology since the traits of daring to take risks and uncertainties and pursuing knowledge are two characteristics that can be linked to the organization, and perhaps even the defense industry in general (Respondent G, Management).

When considering the characteristics of the technology, we find that the 3D generative model is a very potent type of technology while also not being easily associated with what may be perceived to be more risky or threatening types of AI such as natural language models that can communicate like a human (Respondent F, Simulation; Respondent K, Simulation; Respondent L, Simulation). That 3D generative models are more functional by design rather than human-imitating may produce a perspective of this type of AI where it is more easily seen as a tool with a defined purpose.

5.2.4 Facilitating Conditions

Facilitating conditions is directly linked to the use of the new technology which is not so applicable in this context as the current use of 3D generative models in the organization's department was barely observed by the researcher, or observed to not be used enough to be considered by this study. However, some logic surrounding facilitating conditions was still discovered through the observation by the researcher, such as the organization already having systems for employees that enable learning and training, and also tools for contacting and reaching out to other employees for support. These two factors therefore contribute positively to the use of AI technology by the organization.

5.2.5 External Characteristics

External characteristics could be identified. People in the organization were well aware of AI as a technology and often times even familiar with its potential and risks. A reason for this could be found in how the organizational values and keywords may imply that the organization is especially open to this kind of technology (Respondent G, Management), while additionally making users more comfortable with new technology in general.

> *"...perhaps [Saab's] keywords: Knowledge, trust, and will"* - Respondent G (Management) translated from Swedish

External characteristics that may have influenced the intention to adopt specifically AI system were identified from this report. All respondents mentioned the popularity of various types of AI models that happened within a few years of the conduct of this study, that very clearly showed the potential of AI for assisting and sometimes replacing human effort. That models such as ChatGPT, Bard, Midjourney, Stable Diffusion became accessible to the general public and widely used by people meant that all respondents were well aware of the power that AI systems could introduce and could as such explain why all respondents could agree that the pursuit of AI systems was important, even if they did not always know how it would be done or how much it could cost to develop such a system. This type of characteristic can be linked to the technological characteristics. A counter argument to the influence of AI could also be found as Respondent H (Management and AI) and Respondent M (Simulation) raised the notion of exaggeration or "Hype" regarding AI technology due to it being used as a buzzword that not necessarily had any advantage in all cases over less advanced solutions. So while experience with AI increased salience toward adopting AI technology in most cases, it could sometimes also cause slightly more sceptic perspectives by people who observed exaggeration and "Hype" surrounding the technology. Also a possible link between technical expertise and eagerness to adopt AI was found as can be seen in the quote bellow (Respondent G, Management).

> *"A technically educated person probably has a more moderate picture of AI when it comes to obstacles and opportunities."* - Respondent G (Management) translated from Swedish

When considering Individual characteristics of the respondents, they perceived AI systems to be worth the perceived risks, which can be observed as some level of eagerness to adopt AI systems (Respondent B, Systems and AI; Respondent F, Simulation; Respondent L, Simulation; Respondent M, Simulation).

Environmental characteristics were discovered as the organization's values could be encouraging employees to pursue new technology that could benefit the business. The existence of a company culture that encourages pursuit of knowledge in new areas was also discovered (Respondent G, Management), which may additionally drive the individual characteristics into being open to adopt new technology.

> *"I don't think it [The organization's value's effect on employees] has to do with Saab's values, but rather with the technical experiences that influence the most... But perhaps [Saab's] keywords: Knowledge, trust, and will, which map in well as values"* - Respondent G (Management) translated from Swedish

Additional environmental characteristics were discovered as multiple respondents mentioned an ongoing war in Europe, specifically Ukraine, as a factor that increased salience for the adoption of 3D generative models (Respondent A, Simulation and AI; Respondent B, Systems and AI; Respondent C, CAD; Respondent D, CAD and Simulation; Respondent E, CAD and Simulation; Respondent F, Simulation; Respondent H, Management and AI; Respondent M, Simulation). The war in Ukraine could be observed to carry both a social and functional influence on the adoption of AI technology including 3D generative models. The social influence was the willingness to pursue short-term solutions from novel technology, such as AI, even if it could possess unknown risks (Respondent B, Systems and AI; Respondent C, CAD; Respondent H, Management and AI; Respondent M, Simulation). The functional influence was the increased investments in the defense industry which was perceived as an opportunity to explore potentially costly technologies with expected benefits (Respondent A, Simulation and AI; Respondent B, Systems and AI; Respondent C, CAD; Respondent D, CAD and Simulation; Respondent E, CAD and Simulation). This ongoing conflict has additionally increased revenue and investments in the Swedish defense industry as stated by the CEO of

Saab during an interview with him by Sveriges Radio (2023). In this interview there are multiple insightful statements such as the increased expenditures in the defense industry by many nations in Europe, as well as the acceleration of these expenditures due to the war in Ukraine (Sveriges Radio 2023).

> *"Nämen det helt klart att vi växer som företag, och det har ju börjat för flera år sedan, att se framförallt många länder i Europa som spenderar mer pengar på försvarsutgifter."* - Micael Johansson, transcribed from (Sveriges Radio 2023).

Interventions were a complex topic that was discovered and discussed as well from especially the interview with Respondent H (Management and AI), where the AI system should be weighted against other technologies that may provide a more effective solution to some problems. This showed awareness on a managerial level of the need for a business plan as well as for having a clear strategy for how to make the AI system benefit the company. Respondent H (Management and AI) was very clear on the importance of an AI system being applied where it can benefit the company and employees the most, which is an important structure of intervention when considering these external characteristics.

5.3 Perceived Technical Challenges

The technical risks that were brought up by all respondents were data-related. Due to strict security concerns. The first security concern was that the data itself had to be systematically collected and made accessible to a model. This challenge was expected to be manageable eventually but that it could still prolong the process of creating 3D generative models for the various types of implementations that were discovered.

The second data-related challenge that was discovered was the strict yet available access to the AI system implementation. Requirements on the system were that it could not be a cloud-based service that is accessible to any other external party, meaning it should run only locally within the organization's technical infrastructure (Respondent A, Simulation and AI; Respondent C, CAD; Respondent D, CAD and Simulation; Respondent E, CAD and Simulation; Respondent H, Management and AI; Respondent I, AI). This was perceived as important for security and to prevent leaks of valuable summarized knowledge that the model had learnt. 3D generative models that were trained on classified data had to therefore also become strict enough to ensure that only users who are supposed to have access would have access (Respondent C, CAD; Respondent D, CAD and Simulation; Respondent E, CAD and Simulation; Respondent I, AI).

This could be access to only some of its possible responses and capabilities, without the risk of the system leaking restricted information through deception. Another challenge was with the access to implementations, as there was a risk of declined value of the AI system from not being accessible to all types of users. Some implementations could be trained separately on especially sensitive data to solve the risk of a system leaking restricted information (Respondent C, CAD; Respondent H, Management and AI). This separate system might however not be able to benefit as many users which would affect the cost versus benefit balance negatively due to reduced availability and use (Respondent H, Management and AI). On the other hand, restricting a model from classified the data could introduce knowledge gaps in the model that could produce vulnerabilities due to the model not considering these aspects that were left out from the data set (Respondent H, Management and AI).

Development of a model that understands the level of classification of information could be challenging as well since it has to be strictly following these levels of access without the risk for leaking. A vulnerability on this regard with natural language models has been the ability to obtain filtered or normally restricted answers and information from a model that was supposed to not reveal such info, through formulation and conviction that evades the filter. An alternative solution to having the model attempt to filter or keep track of user access restrictions is to produce one model for each type of restriction level (Respondent C, CAD; Respondent H, Management and AI). This method would guarantee that correct access is given to users who have it, but also introduces a risk for extra costs if each model has to be trained and developed separately (Respondent C, CAD). The Classified data hence introduces a trade-off between security, accessibility, and cost.

A non-data related technical challenge with AI systems that was discovered was the profitability of implementing systems through specifically AI methods (Respondent H, Management and AI; Respondent L, Simulation). Some systems may not necessarily be any better than a less complex mathematical or statistical model, and the existence of hype surrounding AI technology could risk effort being spent on AI systems in areas where other types of technologies could contribute more or have a much more potent profitability (Respondent H, Management and AI; Respondent L, Simulation). The development costs and complexity of AI could thus be seen as a challenge where other technologies might be superior when considering development costs (Respondent H, Management and AI; Respondent L, Simulation), or a business perspective in general (Respondent H, Management and AI).

Chapter 6

Discussion

This chapter will begin by discussing and linking back the findings from the conduct of this study to the literature and empirical background in section 6.1. The discussion will then proceed by discussing the implications of these findings from a practical and research standpoint in section 6.2 and section 6.3 respectively. Furthermore, limitations of this study will be discussed in section 6.4. Finally, sustainability and ethical implications will be discussed in section 6.5.

This study managed to obtain three types of insight. First, this study managed to identify, sort, and discuss 21 types of implementations where 3D generative models could be applied. This specific type of finding where types of implementations of 3D generative models are listed could not be found in any previous research. Second, this study applied the UTAUT framework in a novel and unique context where it was useful to gain an understanding of acceptance from the perspective of employees who could be affected by emerging AI technology, specifically 3D generative models. Third, some additional insights regarding short-term challenges was obtained through the conduct of this study which could be useful to consider for any organization that intends to pursue this type of technology.

The purpose of this study was to contribute with sociotechnical insight into opportunities and challenges associated with the adoption of implementations of 3D generative models. This was done using UTAUT which was used for investigating the perspective of the user in regards to the factors and moderators that would predict if they seemed likely or not to want to adopt the technology. Additionally, to encompass the meaning of ”implementations” from the phrasing of the purpose, the collection of types of implementations could be used as an incrementally expanded way to build an understanding for what types of implementations that exist. The discovered types of implementations could then be used for interview discussions to further explore opinions and challenges with implementations. Hence, sociotechnical insight regarding adoption was collected and analysed for the context of this study which was able to provide insight into drivers and barriers. These drivers and barriers were grouped and sorted by the structure of the UTAUT framework after adapting it with the relevant AI-specific constructs, as covered in section 3.1.3.

Additionally, the purpose of this study had the intent of providing guidance for an organization that pursues 3D generative models into design workflows. This was done by listing types of implementations which can be used by organizations as guidance for their pursuit of the listed types of implementations of 3D generative models. It is also useful for organizations to be aware of the drivers and barriers as well as the sources of influence that were discovered from this study's interviews, and the application of UTAUT. Guidance can hence be obtained for an organization's understanding of drivers and barriers that are relevant to consider for adoption of 3D generative model, as well as a list of various types of implementations, with descriptions of their respective opportunities and challenges.

Finally, the purpose of contributing with insight for adoption and acceptance research in the context of AI and the defence industry was also obtained. This was obtained by having focused on both AI and 3D generative models, where 3D generative models is a sub-topic of AI, ML, and DL. This was done within the context of the defense industry by being directly applied in an organization that is involved in this industry. All respondents to the interview were working for the organization and had roles and tasks that were relevant to the innovation processes of the organization as well as the defense industry.

6.1 Discussion of Findings

Findings from the conduct of this study will be discussed in this section in the same order as they were presented in the results chapter. Findings from the discovered types of implementations will hence be discussed in section 6.1.1. Findings from the application of the adapted UTAUT framework will be discussed in section 6.1.2. Findings related to technological challenges will be discussed in section 6.1.3.

6.1.1 Types of Implementations

Findings from the list of implementations will be discussed and linked back to the literature in this section. All types of implementations could be linked to Industry 4.0 through either automation or increase in efficiency with the introduction of 3D generative models. The discovered types of implementations can to some degree be found in various literature in the topic of Industry 4.0. Each group of implementations will be discussed using previous literature in this section.

Simulation Software

The first group, simulation software, was found to be applicable for both automation and as support for a user's existing processes. An example of these types of implementations can be given by the notion of trying to answer what would happen if a table was hit by an object with a set amount of force. Automation could be achieved if the 3D generative model was found to perform well enough to be able to alter or replace the use or need for a simulation software. Support of a user's existing processes could be performed if the AI was capable enough to contribute and feed the user with useful insight regarding the expected outcome of the simulation. This insight would then have a potential to support or enhancing the work performed by a user in the form of time saving, reduced amount of resources, and increased consistency of production quality.

The existence of simulation as an important topic to apply AI in, such as 3D generative models, is mentioned by Cirincione et al (2019) who mentions cognitive performance simulations that can assess a human's performance under certain conditions. Latif and Starly (2020) discusses and outlines the use of simulation with machine learning capabilities for the manufacturing industry using digital twins. The use of simulation for automation is additionally mentioned by Gunal (2019) and Karlsson et al (2017) where they mention the possibility and importance of applying AI in 3D simulation settings (Gunal 2019; Karlsson et al. 2017). Karlsson et al (2017) additionally discusses intelligent decision support systems that apply AR and 3D simulation for various types of simulation-based optimizations, with a focus on digital twins of a manufacturing facility (Karlsson et al. 2017). Hunde and Woldeyohannes (2022) discusses AI based simulations as a better solution for reducing time and costs while also increasing output quality of simulation processes.

Innovation Processes

The second group of implementations, innovation processes, was found to also have a capability of replacing or supporting existing processes. 3D generative models for innovation was also found to involve so many possible parameters that could affect any outcome that it was determined to be the most complex type of implementation to pursue. Simultaneously, this type of implementation revealed promising benefits if it was to be implemented as it would be contributing through many lengthy steps of the user's process. An example of an application of 3D generative models for an innovation process can be given by the notion of asking the 3D generative model how one could make a table that can meet certain demands, or to ask the model to assess if a table would satisfy certain demands. Hence this type of implementation introduces a level of intellectual analytical assessment that a human with experience would normally perform.

The need for AI for simulation processes that are used for assessing Cirincione et al (2019) mentions applications of AI for experimentation and assessment that can learn to perform intellectual analysis, instead of or together with a human that would otherwise perform the task. David et al (2020) discusses the use of AI for analysis and assessment of simulation data in settings relevant to the defense industry for tasks such as morphological analysis, scenario building, war-gaming, and brainstorming.

3D object generation

The third group of implementations, 3D object generation, was found to have a capability of replacing CAD processes or softwares, or to accelerate CAD processes or softwares, depending on what type of input data was fed into the 3D generative model and by what the model would be looking for from the data. An example of this type of implementation can be given by the notion of wanting to add a model of a real-world table to a simulation environment, where the 3D generative model could analyse a scan to produce an accurate 3D object of the table, and potentially also assess what materials and material properties it has. This type of implementation has been well researched already, with a fast growth of new literature, and is as such one of the main applications of 3D generative models (Pearl et al. 2022; Guo, Wang, et al. 2021).

The use of point clouds and LiDAR is already in use in the car manufacture industry for the production of cars and also for the development and training of autonomous driving models (Field 2004; Liu et al. 2021). Guo and Wang et al (2021) discusses the use and potential of real-world scanned data for generation of 3D objects. This is also discussed and assessed by many other studies that express a growing potential for the use of 3D generative models for the creation of 3D objects (Pearl et al. 2022; Guo, Wang, et al. 2021; Palviainen et al. 2020; Hunde and Woldeyohannes 2022; Liu et al. 2021).

Data Quality Analysis

The fourth group of implementations, data quality analysis, was found to consist of only two types of implementations that varied depending on what type of data they were reading. One for point cloud scans and the other for 2D drawings or blueprints. A 3D generative model used in this environment would then try to predict if the data is worth using for training of another 3D generative model based on if it could be interpreted or not.

Cirincione et al (2019) mentions the use of AI as quality aware networking. Quality assurance was also mentioned as a possible application of AI in Radiation Therapy by Claessens et al (2022). Different studies that apply 3D generative models for use in generating 3D objects from point cloud data applies various types of quality inspection methods to clean their libraries, or by using libraries that are presumably already cleaned to contain data that is of a satisfactory quality. This step may become more important only if the quality of data is discovered to be a concern to the pursued model. A model that is pursued could still benefit from a quality assurance AI that is in place or in development before the development of the pursued AI model. This quality assurance model could then be used to build up a training library with satisfactory quality in advance.

6.1.2 Technology Acceptance

Findings obtained through the application of the adapted UTAUT framework as was presented in section 3.1.3 will be discussed here in the same order as in the results chapter. Findings from each key factor or construct will hence be discussed on at a time and linked to previous literature.

Performance Expectancy

This study found positive performance expectancy as respondents and observations showed an openness toward investigating and using novel technology. According to the UTAUT framework, this should contribute with a high salience (Venkatesh, Morris, et al. 2003). This study found that performance expectancy was high, which similar to the study of student use of ChatGPT, could be linked to openness toward new technology as long as it was perceived to provide clear benefits (Strzelecki 2023). In the study on the use of ChatGPT by students in higher education, performance expectancy was found to be one of the most important factors for predicting behavioural intention argued to be due to student being open to novel technologies as long as it proved useful to them (Strzelecki 2023). This openness could be a characteristic that could potentially be found in the defense industry as well. That it would be unique per industry further emphasizes the importance of investigating external characteristics of the technology, which is discussed further here in section 6.1.2 bellow.

Effort Expectancy

Effort expectancy was found to not be of much concern based on the interviews. Effort expectancy is moderated by age and experience (Venkatesh, Morris, et al. 2003).The shared notion that it was important to not fall behind with the use of AI technology in general seemingly reduced the perception that the pursuit of AI technology was a burden or that it would demand a lot of effort by the employee. This could be explained by the employees already perceiving AI as an inevitable technology that has to be pursued, and as such may have already accepted the need for additional effort in the pursuit of this technology. One fear of falling behind with the pursuit of AI technology can be linked to effort expectancy as some respondents perceived there to be less need for additional effort if pursuing the technology sooner rather than later. Interviews with management indicated that effort expectancy in the form of costs versus benefits could be a barrier depending on the perception of investors. Age difference and experience difference did not seemed to affect the responses to an observable degree, which could be due to the small sample size and the use of a qualitative method for this study.

It is good to note that the perception of effort could change once 3D generative models was pursued since the actual effort would become more evident to the respondent. This is also backed by Venkatesh et al (2003) where it was discovered that effort expectancy was most influential shortly after users had been trained to use a system. Simultaneously, some of the data collected by users of current processes could be used as input for 3D generative models, which could imply that the need of additional effort by users would not necessarily be much different. There could also be a perception that it would be worth spending extra effort now so that 3D generative models could be used later to reduce needed effort in the future which is a view observed in the acceptance of new technology in healthcare (Jayaseelan, Kadeswaran, and Brindha 2020). A study in internet banking discovered only a weak link between effort expectancy and behavioural intention (Taiwo and Downe 2013). The importance of effort expectancy may hence differ depending on the setting and external characteristics.

Social Influence

Social Influence was found to be strongly influenced by the external characteristics of the research setting as well as being somewhat influential to the user's acceptance of AI technology. The news coverage of AI technologies such as ChatGPT and Midjourney was perceived to have spread awareness of AI to the entire workplace during the conduct of the study. As these newly introduced technologies were highly practical due to being easily accessible, the general perception of the technology was positive, as it also showed potential to help users with small yet tedious tasks outside of the workplace. Even though the technology was not to be used in the workplace, the awareness of it and potential trial of it at home as well as stories and discussion that spread regarding the technology could be seen as a contributor to the general experience and expertise of AI technology overall. This could happen from various social circumstances both inside and outside of the workplace, such as with friends and family, which might have an effect of social stimulus when being and becoming more aware of the topic due to frequent discussion.

Social influence is moderated by age, experience and voluntariness of use (Venkatesh, Morris, et al. 2003). Age was once again not found to provide any clear indication of influencing the willingness to adopt the technology. Meanwhile experience was found to contribute positively toward the adoption of AI technology. An increased experience of the technology is suggested by the UTAUT framework to reduce compliance, that is perceived pressure from others, to adopting the technology (Venkatesh 2022; Venkatesh, Morris, et al. 2003). Hence an increased awareness and experience of AI technology suggests an increased acceptance of AI technology overall. Furthermore, contrary to the UTAUT framework's description of compliance (Venkatesh, Morris, et al. 2003), pressure from competition from other organizations that could attempt to pursue AI technology had an increasing effect to the willingness by users to adopt the technology. This is explained in more detail as coercive social influence, since the social influence from various types of networks affect the behavioural intention differently depending on if its coercive, normative or mimetic (Bozan, Parker, and Davey 2016). An environment that promotes the adoption of new technologies may introduce normative social influence through group pressure, where the opinion of people may be for the adoption of new technology (Bozan, Parker, and Davey 2016).

Voluntariness of use could be found to a small degree when considering specifically 3D generative models as this technology was observed by respondents as being more functional rather than human-imitating, which was seen as less of a risk. Many of the implementations that were discovered for 3D generative models may additionally not change much of the surrounding process, making it possible for the user accept the technology without having to experience a change in expectations and requirements. This type of adoption could then introduce a soft transition to the use of 3D generative models, which increases salience through voluntariness of use (Venkatesh, Morris, et al. 2003), as well as mimetic social influence (Bozan, Parker, and Davey 2016). So specifically 3D generative models may introduce more salience toward the adoption of AI technologies due to the characteristics of this technology. Hence, supporting evidence for normative compliance and mimetic compliance was discovered from this study as well as for experience and voluntariness of use as moderators that positively influence the willingness to adopt the technology.

Facilitating Conditions

Facilitating conditions was found to not be very applicable in the context of this study as the use of 3D generative models in the department was perceived as negligible. This agrees with the UTAUT framework which suggests that facilitating conditions are non-significant for predicting intention if performance expectancy and effort expectancy are used (Venkatesh, Morris, et al. 2003). However, facilitating conditions can still contribute to the later use of implementations (Venkatesh, Morris, et al. 2003), which is still useful for an organization pursuing 3D generative models for their processes. The organization's department was observed to have systems for learning and training which would facilitate the use of novel technologies such as 3D generative models.

External Characteristics

And secondly the insight and verification of the external characteristics of the technology and of individuals which influenced the outcome of UTAUT. External characteristics is moderated by gender and experience according to Venkatesh et al (2003). These external characteristics seemed to connect a lot with the experience moderator from UTAUT as well. This was explained by the perception that people who had experience with and understanding of novel AI technologies such as ChatGPT were more salient toward adopting the technology.

A finding for environmental characteristics that was discovered to likely affect employees in especially the defense industry was the ongoing conflict in Europe, specifically the war in Ukraine. The war in Ukraine was observed to carry both a social and functional influence on the adoption of AI technology through an increased willingness by employees to accept unknown risks for the pursuit of short-term solutions, and also as increased investments in the defense industry was seen as an opportunity to further explore new and costly technologies.

Lastly, the social influence factor from UTAUT was discovered to contain a lot of links to the influential external characteristics which suggests that a closer look into these dynamics could be useful for further explaining how adoption of AI technology is influenced by dynamics combining social influence and external characteristics.

Hence, regarding sociotechnical findings, the influence and importance of considering external characteristics was verified through the results from this study. Additionally links between social influence and external characteristics was discovered. These findings could be useful for future potential expansions of UTAUT as current research investigates the frameworks application and adaption for the topic of AI technology (Andrews, Ward, and Yoon 2021; 2022).

6.1.3 Perceived technical challenges

The perceived technical findings were found for data related challenges and profitability related challenges. The data related challenges focused on data security and access to the sensitive information. As the defense industry deals with a lot of sensitive data, there are a few technical demands that an AI implementation has to follow in order to reduce and prevent the risk of data leaks or breaches. The first perceived requirement on the system was to have it run locally within the organization's facilities, which means a cloud-based solution would not be an option. The second requirement was to be able to make sure users could only access data that they were supposed to have access to, which means the AI would need to either be well aware of access and restrictions, or that multiple versions of the AI would be used where each was trained on data with different levels of access. The trade-off here was the increased security of implementing multiple versions of the AI versus the increased costs associated with the extra work needed for training each model, as well as the risk of bias or vulnerabilities when a model was trained without the whole dataset.

These data-related security issues were brought up by the study by Jan et al (2022) which highlighted the challenges in industry 4.0 due to data security such as data availability, data security and return on investment. Security is highlighted as important also due to the risk of reverse-engineering attacks that can leak information about the trained dataset (Peres et al. 2020). Another threat is the tampering of the dataset if the system is able to learn from users, called personalized learning, as an attacker could attempt to control or change the behaviour of the AI (Stoica et al. 2017). This risk is most significant in cloud-based AI systems due to it being centralized. An AI that learns from the user and learns about the user will have the additional risk of containing information about individuals, which creates a privacy risk if private user information would be leaked (Stoica et al. 2017).

The profitability challenges are linked to the use of AI in areas where it may not be worth pursuing AI. Other solutions that already exist may very well be enough or sometimes even better than what an AI would be capable of for the same problem. Hence, it seems important to carefully evaluate each AI implementation for its benefits compared to other technologies and solutions before pursuing it. This aligns with what was concluded from the study by Ivanov and Webster (2017) which investigates the use of robots, AI, and automation for tourism and hospitality companies. This study discovered that the cost-benefits are complex yet have to be considered if wanting to assess if these types of technologies are worth it or not (Ivanov and Webster 2017). Challenges with assessing cost-benefits for 3D generative models was additionally found in the study by Palviainen et al (2020) where the interviewed organizations were concerned about the uncertainty in both the costs and the benefits of pursuing and implementing 3D generative models.

6.2 Practical Implications

Any organization that intends to pursue 3D generative models for their processes could find the findings from this study useful for two reasons. The first reason being that this study explores, sorts, and discusses types of implementations that may be of interest for an organization that pursues 3D generative models. The second reason being that an organization that intends to pursue 3D generative models could use the findings from this study to learn to understand some of the drivers and barriers that influence acceptance of AI technology, and more specifically 3D generative models. 3D generative models are perceived as extremely useful due to their use in simulation, such as AI simulation (David et al. 2020). Adding to the second reason, this study provides some insights into perceived technical drivers and barriers with adopting AI technology. Hence, an organization that intends to pursue 3D generative models can use these findings to try to verify if there are any areas that are especially suitable for collection and analysis of data. A few insights can therefore be found in this study that could potentially give an organization ideas in regards to data analysis and data management.

6.3 Research Implications

This study contributes to defense industry research by exploring unique and less studied applications of technology acceptance frameworks, namely the UTAUT framework. The defense industry has discovered an increased demand for user-focused development, which has contributed with a growing number of studies that focus on the perspective and experience by users in the defense industry. However, a lack in the application of technology acceptance frameworks for the context of the defense industry has resulted in the defense industry performing its own types of user-focused research using their own, less defined and less robust frameworks (Furman, Theofanos, and Wald 2014; Zielinski, Ii, and Frank 2022).

This study contributes to technology acceptance research by applying it in new environments. The UTAUT framework has this far not been applied in the context of the defense industry as was discovered in the literature review, in section 3.2.3. Additionally, while the UTAUT framework has been applied and investigated in the context of AI technology, it has not been specifically investigated or applied in the context of 3D generative models. Having a specialized focus such as this means that this study is able to contribute with insight that has not been explored before. One additional advantage that this study has when considering the application of UTAUT in an AI-context, is that the structure of the interviews were designed to ask for AI in general in the beginning, before proceeding to 3D generative models. This way, a level of insight regarding differences between AI in general and 3D generative models could be included.

This study contributes to AI research in general by introducing sociotechnical research into a field otherwise dominated by technical studies (2021). This is especially the case when considering 3D generative models, as plenty of studies could be found regarding point cloud data analysis and 3D visualization and reconstruction, while few studies could be found in sociotechnical topics, such as change management (2004; Palviainen et al. 2020). As no previous studies were found regarding

6.4 Limitations

While this study managed to gain valuable insight into the adoption of AI technology and specifically 3D generative models in the defense industry, there were areas that could have been improved as well as areas that could have been performed differently. The areas containing limitations will be separated into theoretical limitations that focuses on UTAUT how it was used in this study and data-related limitations that focuses on the data collection method.

6.4.1 Theory

When considering areas that could have been improved, this study relied on the UTAUT framework which is both considered mature and robust depending on how it is used, but that was perhaps not the most optimal or fitting for the context of adoption of AI technology. If a framework was sought for that was specifically adapted to the use for an AI context, then perhaps the insight and findings might have been different in a way that would benefit the study. A benefit from using a more specialized framework for adoption of AI could be an increased focus on the drivers and barriers that influence a user's will to adopt the technology. While the results provided insight, there were some components of the UTAUT that were less used, which could indicate that the framework indeed has some components that might not need as much of a focus for the context of this study. A more suitable framework might have avoided this phenomenon and perhaps also focus the method into areas that would provide a lot of insight, such as the social influence and the external characteristics did.

UTAUT Moderators

It would have been optimal to extend the sample size to include enough respondents with variety in regards to gender. However, this study found it challenging to obtain a representative sample size of females to be able to draw conclusions that considered the original UTAUT's gender moderator. This shortcoming would have been useful to address as this study was unable to gain any insight on this front. Another limitation that was discovered after the conduct of the study was the use of the age moderator as this moderator would have been more fitting for a quantitative and statistical analysis where a pattern between the age and quantified data could have been explored rather than the current method which only used a non-statistical observation and interpretation regarding the influence of age based on the limited sample size. The gender moderator may additionally have found use for a quantitative method as a large sample size may have supported the revelation of gender-related patterns.

Quantitative or Qualitative use of UTAUT

After the conduct of the study it became evident that some constructs of the UTAUT framework would have been more fitting to test using a quantitative method that could reveal patterns among a larger sample size. The age modifier was one such construct which was more difficult use in a qualitative study as the variance of answers seemed unrelated to the respondent's age even if that might not have been the case if inspected using statistical analysis. This was additionally argued in the study by Andrews, Ward, and Yoon (2021) where UTAUT was discovered to be most robust when applied in a quantitative method that has a proper design and execution for the setting. A more fitting design for this study could thus have been to apply a mixed-method approach for the application of the UTAUT framework, where a quantitative survey could have contributed with additional insight into the moderators that were less observable when using qualitative method. However this would also have increased the workload for the researcher who already had time constraints.

Further UTAUT Adaption

A discovery after this study was the insight that this study could have benefit from increasing the focus more on the behavioural intention early on, and even considered skipping the inclusion of predicting technology use, as the lack of existing implementations of 3D generative models limited the ability to study technology use. Therefore, it may have been advantageous to adapt the framework further by excluding the facilitating conditions and the technology use constructs from this study so that the focus would be narrowed down to the more insightful elements of the framework. Additionally, a lot of information was found regarding external characteristics that is very specific to the time in which this study was conducted, which limits the replicability of this study.

Empirical Analysis

This study could have performed a thematic analysis for the application of UTAUT rather than a narrative analysis. A thematic analysis could have revealed themes from the interviews which could be used to summarize the findings more than what a narrative analysis would have done. However, a trade-off with performing a thematic analysis could be that the researcher's unawareness of the importance between different constructs, and hence inclusion of construct with varying relevance to the study, could have resulted in themes that were biased more toward the general UTAUT framework rather than to the context of the study. Another trade-off would have been the risk of loosing valuable details when coding the data into themes. A thematic analysis for the application of UTAUTwould therefore have been a fitting alternative for this study, but that may have produced a different results depending on what details and patterns the themes would focus on.

6.4.2 Data

Another area that could have been improved is the sample size. This study managed to obtain 13 respondents in total, which is still valuable for the purpose of exploring using probing methods in a less researched topic and context. A larger sample size would however have been able to provide much more insight by discovering more possible variation of results, and also by making it possible to identify possible convergence to a larger extent. The use of the Lifecycle and Key Dimension of an AI system, which was covered in section 2.5, contributed with valuable guidance for diversifying the interviewed respondents in this study. However, since the Lifecycle and Key Dimensions of an AI system is a very novel framework, its robustness and shortcomings have been less explored, which can be a vulnerability and a risk when using such a novel framework.

Bias

The interviews themselves were conducted with a lot of care and consideration for the experience, privacy, and consent of respondents by making the interview process, use of the data, and collection of the data transparent to them. Yet, the risk of introducing bias was considered but less controlled. Since the interviews were semi-structured, the overarching structure of the interview was designed to avoid the involvement of the interviewers opinions of the topic as much as possible. This was done with the first questions being very open so that the respondent could decide on an opinion without the question emphasizing on any specific choice of answer. However, a risk for bias despite this structure was the risk of the respondent already assuming the interviewers opinion based on the topic of the study, or based on other information presented before the first question, such as information covered in the introduction. A respondent could potentially have observed a positive or negative alignment to AI in the interviewer just from introducing the topic or title of the study, as verbatim information such as sounds and reactions or body language could potentially give this information off. The risk for these type of gestures and subconscious behaviour could hence introduce a level of bias into the study that was not controlled for. A survey, interviews by more experienced interviewers, or other methods of data collection could therefore be additional measures that could be taken for future studies.

Since the sampling strategy for this thesis also used a snowball-sampling technique (Goodman 1961), there could have been a risk of respondents recommending people of a certain type, such as people who were likely to accept the offer to participate on an interview, possibly due to reasons such as them being interested in the topic already. This would then present a risk for bias which was not controlled for in this study. The combination of using a purposive sampling strategy could hence have been used further to specifically attempt to invite people who were less likely to have any previously known opinion on the topic.

Finally, this study was conducted on a focused group of people that worked in the organization. Hence, no interviews were conducted with non-employees of the organization, which could have been used as a control group or comparison group for identifying how the focused group differs from other groups of people. The analytical judgment regarding whether or not the focused group seemed especially willing to adopt 3D generative models or not was therefore not weighted against any specific value, and was instead drawn based on the perceived will to adopt technology that was experienced by the researcher when following the adapted UTAUT framework. Results regarding the general willingness to adopt 3D generative models was hence not drawn numerically, and as such can be subject to bias. Fortunately, the main findings of this study intended to explain and understand drivers and barriers for the adoption of 3D generative models, which does not need to involve any comparison between different groups of people. Hence, the results regarding insights and understanding of adoption in the context of this study are much less affected by this shortcoming.

6.5 Sustainability and Ethics

The United Nations (UN) (2015) Sustainable Development Goals (SDG) have outlined 17 goals which can be used to map sustainability aspects of 3D generative model technology as well as this study's purpose of investigating technology acceptance of such technology. SDG 8, SDG 9, and SDG 12 are areas where the use of 3D generative models can benefit sustainability. SDG 8 ”Decent work and economic growth” is contributed toward by providing technological upgrade and increased innovation that can benefit economic growth which is part of target 8.2 (United Nations 2015d). Additionally, Target 8.4 is being contributed toward by providing increased efficiency in production which can help decoupling economic growth from environmental degradation (United Nations 2015a). SDG 9 ”Industry, innovation and infrastructure” is contributed toward by upgrading technological capabilities for all countries and encouraging innovation and sustainability that is part of target 9.5 (United Nations 2015b). SDG 12 ”Responsible consumption and production” is contributed toward with this study by creating awareness and bringing up considerations of employees who could be negatively affected by the technology, which is part of target 12.8 (United Nations 2015c). Additionally, targets 12.2 and 12.5 are contributed toward due to 3D generative models being able to reduce the impact on natural resources and create more efficient use of resources overall (United Nations 2015c).

Chapter 7

Conclusions

To summarize what this study discovered, it managed to explore a wide range of different implementations that could be sorted into types and groups of implementations. It additionally managed to gain insights regarding user adoption in the context of 3D generative models in the defense industry during a time where external characteristics of AI technology may have been especially influential to the willingness to adopt AI technology. Some perceived technical challenges were also obtained and briefly discussed.

"RQ1: What types of 3D generative models are relevant to the defense industry?"

The answer to RQ1 is the listing and description of types of implementations which can be found in section 5.1 under each group and with descriptions of the implementations, and and also in the appendix in Figure A.2.1 as a summarized list of implementations. The groups consist of a total of 21 types of 3D generative model implementations for simulation softwares, innovation processes, 3D object generation, and data quality analysis. This list concludes that there are many types of implementations of 3D generative models which can be used for a lot of different purposes and implemented in a lot of different ways, sometimes even combined to form more advanced implementations. Depending on the prediction quality and explainability of the model, it could be used to support the user, or to replace and automate work by the user. Challenges with these implementations are touched upon as well and mostly boils down to obtaining relevant data that can be used to train these models on.

The second research question was answered by applying the UTAUT framework that had been adapted and defined in section 3.1.1. This framework managed to provide insight into challenges and opportunities regarding AI systems in general as well as implementations that were specifically using 3D generative models. An answer to the technology acceptance challenges for the use of 3D generative models could thus be formulated, where the users were able to see the potential of implementations of such models in areas that were relevant to their roles.

When considering perceived technical challenges of 3D generative models, it was discovered that data collection and access to data were complicated yet essential areas that had to be addressed for the use of many of the discovered types of implementations. Additionally, a business plan or strategy was seen as important before attempting to pursue implementations, since it was perceived to be important to pursue implementations with high cost versus benefit potential.

> *"RQ2: What are the drivers and barriers for adopting 3D generative models in the defense industry?"*

The answer to RQ2 is that social influence and the characteristics of the technology as well as the experience of the users were discovered as the most influential drivers and barriers of the technology. Users with a lot of awareness of AI and the capabilities of 3D generative models were very positive and salient to adopting this technology. External characteristics were found to influence the users willingness to adopt from both a social and functional perspective, as the outreach of ChatGPT seemed to increase the awareness and experience of AI technology as well as increasing the willingness to adopt AI technology such as 3D generative models. 3D generative models were additionally perceived as more functional or tool-like rather than human-like implementations of AI such as natural language models, which further increased acceptance toward 3D generative models. The ongoing war in Ukraine was seen as an influence that increased the willingness to pursue AI technology for the purpose of increasing security through advancements in the defense industry, and also due to an increase of investments in the defense industry which was seen as enabling the pursuit of new technology in general.

Overall, technology acceptance in the organization was perceived to be high based on the results of the study, and as such the intention and willingness by employees to adopt AI systems and especially 3D generative models is expected to be high as well. Technical challenges were especially found in regards to data collection and data analysis as the organization has a lot of data that could be used for automation and implementations involving AI technology. However, questions regarding access, availability, and security were discovered as the main challenges that have to be addressed for many of the identified types of implementations to be feasible.

By having answered the two research questions, this paper has managed to explain findings regarding 3D generative model that can explain the findings from the survey by Palvainen et al (2020) with a deeper explanation that considers the dynamics between multiple aspects of technology acceptance. By having conducted this research, the importance of various dynamics presented by the UTAUT have been tested and considered in the process and pursuit of qualitatively explaining how the specific technology of 3D generative models can be implemented in the defence industry, involving the perspective of employees with various different roles. The method of probing performed with this study additionally introduces a range of insight that can be used as a basis to explore more in-depth explanations. These in-depth explanations that were found by probing can be expanded upon by future studies that seek to explore more variance and similarities in a similar context as this study.

As AI is seen as an increasingly disruptive technology that can pose changes to the way employees work in various industries, the importance of having conducted this study using a user-focused perspective means the organization can now gain a perspective on what employees may think of the pursuit of 3D generative models. The opinions of employees is especially important for this type of technology as there is a risk that they could suffer if the technology replaces their current tasks. It is important to understand if employees can and want to accept change, and the extent to which they are ready to change if technology is pursued, so that the ethical aspects of introducing new technology can be considered and followed through without having to risk failure when attempting to adopt the technology.

Finally, the need for sociotechnical research is evident in general for both AI research and defense industry research. Hence, this study is expected to contribute with valuable insight into both of these topics which can be investigated further by future studies.

7.0.1 Future Work

There are many areas for future studies that are relevant to the topics of this study. The defense industry could for one use a lot more applications of mature and robust technology acceptance frameworks. The UTAUT framework could use more exploration of how it can be adapted in the context of AI and 3D generative models. It could also be explored further for adaption to a context of the defense industry as it may be able to introduce benefits to human-focused research in this industry. UTAUT may very well be capable of outperforming human-focused military standards such as MIL-STD-1472 and DEF-STD 00251 in regards to adoption of technology. It may also not be unlikely of possible incorporation of UTAUT into these military standards if discovered to be useful. A UTAUT framework adapted for the defense industry could hence be a topic for future studies. A semantic analysis could additionally be performed on UTAUT for investigating numerically if the defense industry differs in any particular way from other industries where UTAUT has been applied, such as the weight on experience that was discovered from the findings of this study.

When considering UTAUT and AI technology, the social influence factor of UTAUT was discovered to have many links to the external characteristics of AI. An in-depth analysis of how these are connected and how they can differ may yield valuable insight for future applications of UTAUT that focuses on the topic of AI technology. Additionally, the importance of the components of the UTAUT framework in the topic of AI could be further analysed using semantic analysis as well. Some of the components were not observed as being very influential in the context of this study when considering the influence of ChatGPT and an ongoing conflict in Europe. The effect of these two incidents could additionally be analysed as they may be influential factors that give this study a unique result that is only encountered near the time when this study is conducted. To repeat this study again at another time may yield different results which can provide different answers and insights, such as if opinions and perspectives regarding AI technology changes and matures, or from changes in the defense industry.

Further incorporation of AI frameworks similar to the AI RMF could additionally be used to dive deeper into managerial dimensions surrounding implementations. These other frameworks may additionally be able to provide UTAUT with new dimensions and considerations that could be useful in other contexts. One example being that this study's use of the Lifecycle and Key Dimensions of an AI system promoted the pursuit to interview people with a managerial role. The application of UTAUT on different roles is therefore something which could perhaps be explored further. Insights into how application of UTAUT could be used to investigate adoption among higher-ups of a company could therefore be another potential area to investigate. This could be especially useful for large organizations as these may have a lot of employees with managerial roles that could have unique dynamics, especially from introduction of AI for management purposes such as AI-supported decision making.

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Appendix - Contents

Appendix A

Raw Collected Data

A.1 Quotes and Translations

A.1.1 Respondent A

Quote 1

”[A point-cloud simulation] Can be applied by a model that understands 3D in general, that understands how a shape affects the traits of something, and explains it to the user.” - Respondent A (Simulation and AI) translated from Swedish

”[En point-cloud simulation] Kan tillämpas av en modell som förstår 3D generellt, som förstå hur en form påverkar något s egenskaper, och förklarar detta till användaren.” - Respondent A (Simulation and AI)

Quote 2

”One can look into replacing simulation software and simulations. One can then look at empirical formulas and try out to replace them with machine learning. ’What happens if i simulate this?’” - Respondent A (Simulation and AI) translated from Swedish

”Man kan kolla på att byta ut simuleringsprogram och simuleringar. Man kan då kolla empiriska formler och testa ersätta dem med maskininlärning. ’Vad händer om jag simulerar detta?’” - Respondent A (Simulation and AI)

Quote 3

”...or a [3D generative] model that produces something mutating. It can be used in the manufacturing process to find new shapes to produce with.” - Respondent A (Simulation and AI) translated from Swedish

”...eller en [3D generativ] modell som skapar något muterande. Det kan användas i tillverkningsprocessen för att hitta nya former att tillverka i.” - Respondent A (Simulation and AI)

Quote 4

”You can use generative models that adapt their shape in various ways to achieve specific purposes” - Respondent A (Simulation and AI) translated from Swedish

”Du kan använda generativa modeller som ändrar på formen på olika sätt för att uppnå specifika syften” - Respondent A (Simulation and AI)

Quote 5

”It [AI] has an extreme potential.” - Respondent A (Simulation and AI) translated from Swedish

”Det [AI] har extrem potential.” - Respondent A (Simulation and AI)

A.1.2 Respondent B

Quote 1

”It [3D Generative Models] can support the generation of concepts...” - Respondent B (Systems and AI) translated from Swedish

”Den [3D Generative Models] kan stödja koncept generering...” - Respondent B (Systems and AI)

Quote 2

”It [3D Generative Models] can support the generation of concepts, support the collection of requirements, and also synthetic generation of data. Generative models are good for quickly making prototypes.” - Respondent B (Systems and AI) translated from Swedish

”Den [3D Generative Models] kan stödja koncept generering, Stödja kravinsamling. även syntetisk datagenerering. Generativa modeller är bra för att snabbt få till prototyper.” - Respondent B (Systems and AI)

Quote 3

”I like it [AI] a lot, it [AI] is an emergence of new technology.” - Respondent B (Systems and AI) translated from Swedish

”Tycker om det [AI] väldigt mycket, det [AI] är en uppsjö av ny teknik.” - Respondent B (Systems and AI)

A.1.3 Respondent F

Quote 1

”It would be good with something [a 3D generative model] that is able to try its way forward to new solutions, that thinks outside of the box” - Respondent F (Simulation) translated from Swedish

”Det skulle vara bra med något [en 3D generativa model] som kan testa sig fram till nya lösningar, tänka utanför lådan.” - Respondent F (Simulation)

A.1.4 Respondent G

Quote 1

”...perhaps [Saab’s] keywords: Knowledge, trust, and will” - Respondent G (Management) translated from Swedish

”...kanske [Saabs] ledord: Kunnande, förtroende och vilja” - Respondent G (Management)

Quote 2

”I don’t think it [The organization’s value’s effect on employees] has to do with Saab’s values, but rather with the technical experiences that influence the most... But perhaps [Saab’s] keywords: Knowledge, trust, and will, which map in well as values” - Respondent G (Management) translated from Swedish

"Tror inte det [företagets värderingars påverkan på arbetare] har med Saabs värderingar att göra, utan istället med de tekniska erfarenheter som påverkar mest... Men kanske [Saabs] ledord: Kunnande, förtroende och vilja mappar väl in som värderingar." - Respondent G (Management)

Quote 3

"A technically educated person probably has a more moderate picture of AI when it comes to obstacles and opportunities." - Respondent G (Management) translated from Swedish

"En tekniskt utbildad person har nog en mer sansad bild av AI när det gäller hinder och potential. " - Respondent G (Management)

A.1.5 Respondent H

Quote 1

"'if you're going to build an [application] in this sort of scenario, what type of [criteria] do you want to pursue then?' and then you let an AI train forth: what is the best distribution, 'yes but with this solution you will get this advantage' then you will [produce an optimal result]. So that you don't just stare yourself blind on geometry, but additionally perhaps design generative AI with different and higher levels." - Respondent H (Management and AI) translated from Swedish

"'om du ska bygga ett [tillämpningsområde] i den här sortens scenario, vilken sorts [kriterier] vill du ha då?' och så låter du en AI träna fram: vad är den bästa fördelningen, 'ja men med den här lösningen har du denna fördelen', då kommer du att [producera optimalt resultat]. Så att man inte bara stirrar sig blind på geometri, utan även kanske gör generativ AI med andra och högre nivåer." - Respondent H (Management and AI)

Quote 2

"yes and currently we do prototypes, and then try them on, and say 'yeah but this felt good'. I wonder if an AI could be given some more liberty with its parameter-space, and think a bit outside what we currently do today, and reach something that for example feels good." - Respondent H (Management and AI) translated

from Swedish

"Ja och i dagsläget så gör vi prototyper, och så prov-bär vi dem, och säger 'ja men det här kändes bra'. Undrar om en AI skulle kunna ge sig lite friare parameter-space, och tänka lite utanför det vi gör idag, och komma fram till något som exempelvis upplevs som bra." - Respondent H (Management and AI)

A.1.6 Respondent J

Quote 1

"It [AI] seems very exciting, one can use it [AI] for many things." - Respondent J (CAD) translated from Swedish

"Det [AI] verkar spännande, man kan använda det [AI] till många olika saker." - Respondent J (CAD)

Quote 2

"Yes but ChatGPT, it seems rather useful. One can ask it- one can be cooking food and go: [Example:] 'i have these ingredients, what [recipes] can you offer me?'" - Respondent J (CAD) translated from Swedish

"Ja men ChatGPT, det verkar ju ganska användbart. Man kan fråga, man kan laga mat liskom och bara: [Exempel:] 'ja har de här ingredienserna, vad har du [för recept] att erbjuda?'" - Respondent J (CAD)

A.1.7 Respondent L

"One can probably otherwise use it [3D generative models] to help with the simulating. If one wonders which shapes that turn out well, or to provide suggestions regarding what values I should type [into the simulation software] to get a good simulation." - Respondent L (Simulation) translated from Swedish

"Man kan nog annars använda det [3D generativa modeller] för att hjälpa till med simulering. Om man undrar vilken form som blir bra, eller för att ge tips om vilka värden jag borde skriva [in i simulationsprogrammet] för att få en bra simulation." - Respondent L (Simulation)

A.1.8 Respondent M

"Every step in the simulation can be performed by AI, maybe faster then. If one can perform one step [using AI] then one can perform the remaining steps as well, so it should work" - Respondent M (Simulation) translated from Swedish

"Varje steg i simulationen kan göras av AI, kanske snabbare då. Kan man göra ett steg [med AI] så kan man göra resterande steg också, så det borde gå" - Respondent M (Simulation)

A.2 Table of Discovered Implementations

ID	Type of Automation	Implementation	Respondent
1	Replace Simulation Software Point Cloud	Reads simulation data to predict an outcome (Forecast)	A, B, C
2	Accelerate Simulation Software	Reads point cloud simulation data to give an indicative outcome prediction	A, B
3	Reinforce Simulation Process	Optimizes the properties of a point cloud simulation data by mutating it and testing results, applying reinforcement learning method	A
4	Accelerate Simulation Algorithm	Reads point cloud simulation data to incrementally simulate steps within the software faster or with less cost of resources or computation power	A, B, L, M
5	Accelerate Simulation Software	Reads point cloud simulation data to give recommendation on adjustments	A, F
6	Accelerate Innovation Process	Read point cloud simulation data to give an indicative assessment of solution	A, H
7	Replace Innovation Process	Read point cloud simulation data to predict assessment of solution (Forecast)	A, B
8	Replace Innovation Process	Read point cloud simulation data to predict real-world performance (Forecast)	A
9	Replace CAD Software	Read real-world point cloud scan to generate 3D object	A, C, D, E, F
10	Replace CAD Software	Read real-world point cloud scan to generate point cloud simulation data	A, D, E
11	Replace CAD Software	Mutate the shape of 3D objects to explore new viable designs	A, B, C, D, E
12	Accelerate CAD Software	Read real-world point cloud scan to generate low-quality 3D object	A, B, D, E, F
13	Accelerate CAD Software	Read real-world point cloud scan to generate guiding/indicative point cloud simulation data	A, F
14	Replace Design and Innovation Process	Read real-world point cloud scan to predict a simulation outcome (Forecast)	B, H
15	Accelerate Design and Innovation Process	Read real-world point cloud scan to give an indicative outcome prediction	B, H
16	Accelerate Design Process	Read real-world point cloud scan and give a recommendation on design adjustments	B, H
17	Replace Design Process	Read scanned blueprint and reconstruct into accurate 3D object	D, E
18	Accelerate Design Process	Read scanned blueprint and reconstruct into less accurate 3D object	D, E
19	Reinforce Design Process	Read scanned blueprint and recommend adjustments to the design	D, E
20	Analyze Data	Read real-world point cloud scan and assess quality of scan	D, E
21	Analyze Data	Read scanned physical blueprint and assess quality of scan	D, E

Table A.2.1: This table contains a list of all the implementations that were discovered from the conduct of this study.

Appendix B

Additional Figures

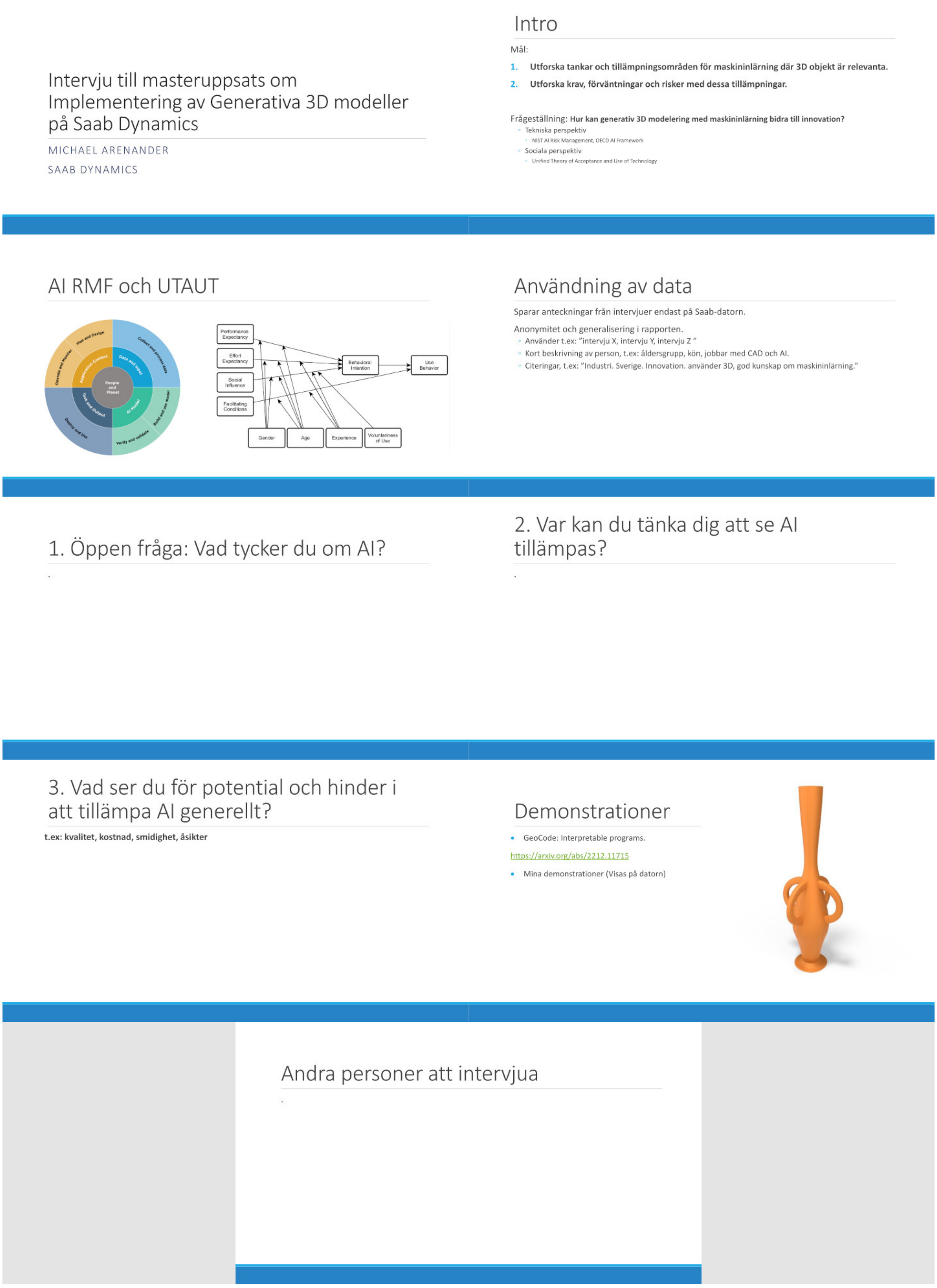

Figure B.0.1: This is an example of how the power point used for the presentations looked like before the insertion of any responses by respondents.