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A Framework of Critical Success Factors for Implementation of Industry 4.0 in Aerospace and Defense Industries

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A FRAMEWORK OF CRITICAL SUCCESS FACTORS FOR IMPLEMENTATION OF INDUSTRY 4.0 IN AEROSPACE AND DEFENSE INDUSTRIES

by

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ABSTRACT

The fourth industrial revolution, or Industry 4.0, is essential to the success of Aerospace and Defense (A&D) organizations as it showcases the ability to adapt, innovate, and remain competitive. Industry 4.0 technologies such as cyber-physical systems (CPS), big data, cognitive computing, smart factories, connected manufacturing, and the Internet of Things (IoT) focus on revolutionizing manufacturing through embedding digital and physical systems, with the goal to maximize the desired output(s) while using minimal resources (Sony et al., 2020). Although there are numerous advantages, there are challenges associated with implementation of these complex systems. This doctoral research investigates the critical factors needed for successful implementation of Industry 4.0 in A&D. A systematic and Thematic Analysis (TA) of the applicable literature revealed this area of research has significant opportunities for advancement and further examination. The review identified 12 initial factors and an implementation outcome. These factors were further assessed through conducting a survey with industry experts. The ten emergent factors, their interrelationships, and impacts on the outcome variable were examined using multiple linear regression and correlation analyses. This assessment revealed interaction amongst emergent factors is essential and resulted in three Critical Success Factors (CSFs): Documentation & Governance, Resource Allocation, and Workforce Involvement. These factors reiterated embedding documented strategic guidance for implementation, ethical standards, and updated uniform policies across all organizations is crucial. Further, ensuring resources such as funding for required items and adequate time to perform associated tasks, is also vital for success. The research also showed involvement of the workforce in implementation efforts, including participation in decision-making activities and being knowledgeable about the overall implementation plan, is another critical component. Following this framework and noting the

resulting CSFs, the potential benefits and successful implementation of Industry 4.0 technologies is more accessible to the A&D industries.

This dissertation is dedicated to my family for their continuous encouragement, support, and love.

To Allah (SWT), the sustainer of the Earth and Heavens, without your blessing, nothing is possible.

To my father, who provided me with this life which has given me endless opportunities, thank you for showing how far faith, dedication, good character, hard-work, and a pure heart can take you.

To my mother and sister, I became a strong woman because strong women raised me. Thank you for showing how it is possible to achieve high levels of professional and personal success. Watching you both earn the “Dr.” title while effortlessly supporting and loving your families was awe-inspiring.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

Aerospace and Defense	A&D
Artificial Intelligence	AI
Business Process Management	BPM
Cronbach's Alpha	CA
Confirmatory Factor Analysis	CFA
Continuous Improvement	CI
Cyber Physical Systems	CPS
Critical Success Factors	CSFs
Defense Advanced Research Projects Agency	DARPA
Department of Defense	DOD
Data Security/Privacy	DSP
Defense Technical Information Center	DTIC
Employees Acceptance	EA
Ethical Guidelines	EG
Employees Involvement	EI
Enterprise Operations	EO
Future Vertical Lift	FVL
Human Machine Interactions	HMI
Implementation Approach	IA
Intelligence Advance Research Projects Agency	IARPA
Internet of Things	IoT
Joint Artificial Intelligence Center	JAIC
Kaiser-Meier-Olkin	KMO
Model Based Engineering	MBE
Model Based Systems Engineering	MBSE
Management Commitment	MC
Missiles And Fire Control	MFC
Machine Learning	ML
Management Training	MT
Naval Air Warfare Center	NAVAIR
National Defense Authorization Act	NDAA
National Mission Initiatives	NMI
On the Job	OJT
Opertaional Research Model	ORM
Principal Component Analysis	PCA
Policies for Development	PD
Performance Measurement	PFM
Policies for Usage	PO

Preferred Reporting Items for Systematic Reviews and Meta-Analysis	PRISMA
PricewaterhouseCooper	PwC
Research and Development	R&D
Resources Allocated	RA
Rotary And Mission Systems	RMS
Research Objective	RO
Return on Investments	ROI
Research Question	RQ
System Configuration	SC
Systems Engineering Transformation	SET
Systematic Literature Review	SLR
Smart Manufacturing Coordination Group	SMCC
Small Medium Enterprises	SME
Thematic Analysis	TA
Technical Compatibility/Readiness	TCR
Training and Education	TE
University of Central Florida	UCF
United Kingdom	UK
United Nations Industrial Development Organization	UNIDO
United States	US
United States Air Force	USAF

CHAPTER ONE: INTRODUCTION

Overview of Industry 4.0

The implementation of more complex and autonomous systems stems from the Industry 4.0 concept of integrating human-and-machine interfaces to develop intelligent processes and faster solutions. Industry 4.0 components such as cyber-physical systems (CPS), big data, cognitive computing, smart factories, connected manufacturing, and the Internet of Things (IoT) focus on revolutionizing manufacturing through embedding digital and physical systems, with the goal to maximize the desired output(s) while using minimal resources (Sony et al., 2020). Such revolutions include using Artificial Intelligence (AI), Machine Learning (ML), and other transformative solutions which emphasize the importance of interconnectivity and real-time data.

This fourth industrial revolution is essential to the success of an organization as it showcases the ability to adapt, innovate, and remain competitive within specified industries. In addition, Industry 4.0 solutions can be used for prediction and pattern recognition, optimization of opportunities, and risk management - all of which result in revenue gains, reduced downtime, and increased operational efficiencies. Specific to manufacturing environments and the supply chain lifecycle, these transformative technologies result in improved decision-making by providing greater insight, control, and visibility of data.

Industry 4.0 in Aerospace and Defense

In A&D applications, there has been limited deployment of Industry 4.0 advancements due to funding constraints, security concerns, and changing fiscal policies. Because of this, research, development, and innovation are often slower in A&D sectors than commercial environments. However, recent efforts following advancement of Industry 4.0 technologies and the Third Offset Strategy have allowed for quicker and less expensive developments in A&D industries. This is due to the strategic goal of the Pentagon, which ensures warfighters are connected with experts to incorporate innovations derived from commercial domains into applicable military usage (Knox, 2020).

The implementation of these emerging technologies within A&D industries enhances model based engineering and digital transformation, resulting in increased scale and speed of military actions and product development, more informed decision-making (Sigala, 2019), and reduction of the cognitive burden on the warfighter (Williams & Lawson, 2020). Other potential benefits include achieving overall military, information, and economic superiority through Industry 4.0-based transformative technologies within nuclear, aerospace, cyber, and biotechnology fields (Allen & Chan, 2017). This superiority can be accomplished through using Industry 4.0 solutions to manage complex systems, rapidly analyze and incorporate required changes, transfer applicable knowledge, and enhance collaboration across boundaries.

However, there are also challenges with implementation, including acceptance of new technologies, obtaining the optimal interaction between the human and machine, security and privacy reservations, and difficulty in defining Industry 4.0 ethical codes due to the constantly evolving definition of acceptable behavior. Additionally, although data can be considered a strategic asset, there are concerns relating to the ethical data collection, consent, and privacy, as algorithms within smart machines require large amounts of data.

With the difficulty to generalize Industry 4.0 military products and systems, there is paralleled difficulty in defining generalized ethical codes for development and use (Lewis et al., 2016). Because of this, there is agreement these advance systems are comprised of both threats and promises and will require a globally accepted set of ethical codes. In 2020, the

United States (US) Department of Defense (DOD) adopted a set of ethical principles for the use of AI and was adopted to develop ideas on ethics and Industry 4.0 solutions within this dissertation. These guidelines apply to combat and non-combat functions and were built on the pre-existing ethics initiative. This existing framework provides the foundation for ethical behavior, while the new guidelines also address the recent challenges through ensuring responsible use of AI military systems (DOD, 2020). These standards encompass the following five areas: responsible, equitable, traceable, reliable, and governable. The most recent additions include requirements for inclusion of personnel within the intelligent decision-making process to ensure successful and ethical implementation of Industry 4.0 technologies (Lawless et al., 2020).

Statement of Problem

General deployment of Industry 4.0 has been limited because of organizations not fully understanding the respective smart technologies, their importance, and their applications. There are also challenges with acceptance of the cyber-physical technologies and difficulties involving quality management, funding, and security. Furthermore, there are both ethical and societal concerns regarding the implementation of some Industry 4.0 solutions, such as those involving the integration of the human and machine (Hellstrom, 2013). This is also a challenge due to the lack of globally accepted ethical guidelines for development, implementation, and usage as well as the varying opinions on whether humans or the machine should be considered the responsible agent (Allen & Chan, 2017).

In both commercial and A&D sectors, deployment of Industry 4.0 has been limited due to the increased vulnerabilities within the cyber-physical domain, such as theft, hacking, and cybersecurity susceptibilities (Knox, 2020). Similarly, there are concerns with privacy and security involved with the collection and data analysis needed for the smart systems used in

Industry 4.0. Although the availability of data provides additional opportunities, there are also potential challenges in analyzing, drawing conclusions, and finding importance within the collected data (Maher & Orlando, 2019). The data can also be difficult and time-consuming to obtain in the required quantities due to the data space being too large (Li et al., 2017) which can lead to inefficiencies with the smart machines. In addition, there are limitations with potential bias, the quality of data acquired, and dependence on input parameters (Meyer et al., 2020) for these data-driven models. Because of these challenges, organizations will need to develop appropriate strategies for implementation as well as methods of prevention and countermeasures to help lessen these potential obstacles and risks.

As these advancements become more prevalent, it is essential to resolve the concerns related to applying Industry 4.0 technologies. This dissertation aims to achieve resolution through development of a framework based on identification and analysis of CSFs for effective Industry 4.0 implementation in the A&D domain, where CSFs are defined as “the limited number of areas in which results, if deemed satisfactory, will ensure successful competitive performance of the organization” (Rockart & Bullen, 1986).

Research Objectives (ROs)

To ensure the problem statement is properly addressed, the following research objectives were established:

RO 1: Provide organizations awareness of the challenges of implementing Industry 4.0 in A&D

RO 2: Provide organizations awareness of the goals of implementing Industry 4.0 in A&D

RO 3: Provide organizations awareness of the benefits of implementing Industry 4.0 in A&D

RO 4: Provide organizations with CSFs to implement Industry 4.0 in A&D

RO 5: Provide organizations with a framework to implement Industry 4.0 in A&D

Through statistical analysis, each of these research objectives were verified and resulted in an established framework for successfully implementing Industry 4.0 technologies in the A&D sector. This research can be used to determine new methods of conducting business, new areas to perform further research, and will increase operational efficiencies when followed.

Dissertation Overview

This research focuses on identification of CSFs for effective implementation of Industry 4.0 technologies within the A&D domain. The resulting developed framework evaluates the hypothesized CSFs, using a structured questionnaire and statistical analyses, and provides empirical evidence on the variables needed for successful implementation of Industry 4.0 technologies.

This dissertation includes a four-phase research design. The first phase involves investigating RO1, RO2, and RO3 using a thorough Systematic Literature Review (SLR) and bibliometric analysis. The SLR also addresses RO4 through emphasizing the importance of developing a comprehensive set of factors, where the chosen publications were used to support a TA of Industry 4.0 implementation success in A&D. Next, a survey questionnaire was developed to address RO5. The questionnaire allowed for integration of the selected experts' experience and helped to evaluate the individual factors and their potential associations. To determine which factors are significant predictors for implementation success, regression modeling and correlation analyses were used.

The resulting comprehensive framework can be used to support current and future implementation of Industry 4.0 in A&D environments. The findings can also be used to guide future research.

CHAPTER TWO: METHODOLOGY

Introduction to Methodology

The mixed-method approach that is used in the development of this dissertation begins with assessing the literature to understand the current state, goals, and challenges of Industry 4.0 in A&D. This information was then synthesized to provide further insight into the various factors needed for successful implementation.

Following the identification of potential CSFs, a structured questionnaire was developed. The generated questions were based on identified CSFs found in the studied literature. The results of the questionnaire, including the relationship amongst these identified factors, were statistically analyzed using the linear regression method to quantify the importance of each CSF on the successful implementation of Industry 4.0. The resulting comprehensive framework, supported by empirical evidence and expert experience, provide an Industry 4.0 implementation success model for A&D settings.

Research Questions (RQs)

To address the objectives previously outlined in this dissertation, the following RQs were generated:

Main RQ: What are the critical success factors for successful implementation of Industry 4.0 technologies in A&D industries?

Sub RQ 1: What are the goals of Industry 4.0 implementation in A&D?

Sub RQ 2: What are the challenges of implementing Industry 4.0 in A&D?

Sub RQ 3: What factors are most significant for successful Industry 4.0 implementation in A&D?

Sub RQ 4: What significant inter-relationships exist amongst the determined factors?

To answer the above RQs, this study used both evidences found in the literature as well as expert experience to empirically assess the relationship between the hypothesized CSFs and implementation success.

Key Terms and Definitions

To provide a baseline for future research and a general understanding of this study, Table 1 provides the operationalized definitions which were adopted. It is important to note there are many variations in defining Industry 4.0; these will be discussed in a later section.

Table 1: Operational Definitions

Industry 4.0	Fourth Industrial Revolution focused on interconnectivity, intelligent machines, real-time data, and autonomous solutions; requires integration of the physical and cyber worlds.
Implementation	Execution or incorporation of a model, specification, standard, framework, plan, or design to improve a process, system, or product.
CSF	"The limited number of areas in which results, if deemed satisfactory, will ensure successful competitive performance of the organization" (Rockart & Bullen, 1986).
A&D Industry	Organizations which focus on design, development, testing, usage, maintenance, and repairing of space crafts, aircrafts, vessels, weapon systems, and various related equipment.

Overview of the Research Approach

Figure 1 visually depicts the approach used to conduct the research detailed in this dissertation. For each phase outlined below, the respective dissertation chapter is referenced.

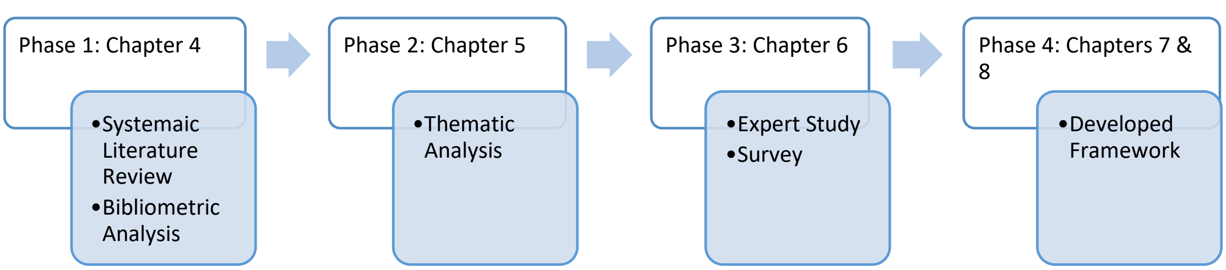

Figure 1: Overview of Research Design

The research started with a SLR to identify the relevant publications within this research area and to investigate the current state of this literature. To ensure a thorough and methodical review was conducted, a systematic approach was incorporated (Tranfield, et al., 2003). The review focused on studies that specifically address Industry 4.0 implementation in A&D domains. To analyze the resulting publications and provide a robust evaluation of the papers, a bibliometric analysis was then conducted (De Bellis, 2009).

The SLR and follow-on bibliometric analysis reiterated there is minimal current research related to Industry 4.0 implementation, especially in A&D sectors. In addition, there were numerous factors mentioned and many variations in terminologies found within the literature. Therefore, the next phase involved generating a comprehensive list of factors, or essential constructs, defined in the literature through performing an inductive synthesis of the included publications. This qualitative approach extracts specific statements from the literature to further define key terms and interrelations; it also ensures key findings are effectively transferred into industry or general practice. The software used to support this analysis was Microsoft Excel and NVivo Pro 12. More information regarding the TA conducted in this phase is provided within Chapter 5.

To further investigate the identified potential factors, the next stage involved using a survey questionnaire as an additional tool to collect data. This method offers many benefits including the ability to assess multiple variables within one study, investigating relationships or potential trends in data, and allowing the use of statistical methods to quantify information. Additionally, survey methods are often used to collect large amounts of data in a short time frame and used to help generalize findings (Saunders & Lewis, 2012). The resulting data was then used to perform regression and correlation analyses to gain insight into the factors and their inter-relationships. More detailed information regarding the survey content and dissemination is included in Chapter 6.

Overview of the Research Synthesis

The resulting data from the questionnaire was analyzed using Microsoft Excel and IBM SPSS Statistics 28 software packages. Regression models were developed and used to evaluate the model fit's assumptions and to investigate noteworthy relationships amongst the significant factors. The identified CSFs, their significant relationships, and their effects on implementation were used to develop the final framework for Industry 4.0 implementation success in A&D organizations. More information regarding the statistical validation is provided within Chapter 7.

Finally, the resulting comprehensive framework, supported by empirical evidence and expert experience, to provide an Industry 4.0 implementation success model for A&D settings. More information regarding the framework is provided in later sections.

CHAPTER THREE: BACKGROUND INFORMATION ON A&D

Findings on Current Efforts

This section and the following subsections address the goals (Sub RQ1), challenges (Sub RQ2), and current applications of Industry 4.0 technologies in the A&D domain. To provide essential background information, it is important to begin with understanding the working definition of autonomy in this domain.

Definition of Autonomy

Multiple studies reiterate the lack of a uniformly accepted definition of autonomy, especially involving intelligent systems used in A&D applications. A 2018 Brookings Institution provides a definition by describing essential characteristics: intentionality, which relates to the design of algorithms to make human-like decisions, intelligence, referring to using data and ML to make more informed decisions, and adaptability, or the ability to learn as decisions are made or as information is compiled (Knox, 2020). The National Defense Authorization Act (NDAA) offered another definition through providing concepts and features of smart systems, including the capability to actively learn and improve through experiences and to perform tasks with human-like perception without human oversight (Knox, 2020). Although there is no agreed-upon definition, the Pentagon released a more succinct definition by providing a more singular characterization that can be implemented across the US armed services. This 2019 Pentagon definition describes smart machines as being capable of experiential learning (Nian, et al., 2020), pattern recognition, predictability, decision-making, concluding, and taking affirmative action. Furthermore, the decision-making capability of stems from data analytics (Bouanna et al., 2020) where there are three distinct classes of decision-making - operational, tactical, and strategic

(Dixit et al., 2020). This is executed through four major stages: determining the high-level objective, collecting appropriate data, identifying the model architecture, and choosing the optimum strategy. In each of these phases, human intelligence and collaboration are critical (Brunton, et al., 2021).

Goals of Industry 4.0 Implementation in A&D

This section addresses Sub RQ 1. The literature suggests many goals of implementing Industry 4.0 in A&D including improved decision-making, increased efficiency and agility of processes and operations, decreased overall costs, and less cognitive burden on personnel. In addition to the goals on the battlefield, the incorporation of model-based systems engineering (MBSE) and digital transformation efforts in development also have key advantages. The goals for incorporating Industry 4.0 technologies into design, test, and development of A&D systems include the time and cost savings associated with performing tasks and the reduction of human error. For example, the US Army has saved over $100 million per year due to implementing tailored maintenance schedules and algorithm-based logistics plans for the Stryker fleet (Knox, 2020). Further, following the launch of Project Maven in 2017, there was a decrease in the amount of time human analysts dedicated to filtering drone footage due to increased automation (Knox, 2020).

Studies have shown using smart algorithms can reduce testing and operational times through discovering fundamental relationships (Brunton et al., 2021) while surpassing human performance in more complex tasking (Nian et al., 2020). A&D industries provide a driving force for technology development and advancement due to their applications. With respect to the design and production of military assets, ML-enabled systems can aid in reduction of human error and increased ergonomics when functioning as intended. In addition, Industry 4.0 solutions, such as digital threads or digital twins, provide organizations with essential metrics and real-time visibility that enhance agility. The US Air Force (USAF) added, "modeling and simulation tools will optimize manufacturability, inspectability, and sustainability from the outset. Data captured from legacy and future systems will provide the basis for refined models that enable component and system-level prognostics. Archived digital descriptions of new systems would greatly facility any subsequent re-engineering required in the future" (USAF, 2013).

Both on the battlefield and in manufacturing environments, Industry 4.0-based technologies in A&D increase operational efficiencies through interconnectivity and real-time analysis which improves the speed, accuracy, safety, and quality of critical decision-making (Huan et al., 2018).

Industry 4.0 Applications in the Defense Domain

Although mission-specific use of Industry 4.0-enabled machines, such as those which use ML or AI, may be classified, or held by the DOD (Wei et al., 2020), there are several publicly known research initiatives in progress. Current applications include surveillance, target acquisition, weapons delivery, intelligence, reconnaissance, command and control, cyberspace, logistics, information operations, and autonomous or semi-autonomous vehicles (Slayer, 2020). Studies have also shown ML can be used for communication amongst various robotic systems (Alshamhi et al., 2020), aid in fraud detection (Bastian, 2021), and can be applied to real-time remote sensing to assist in object classification, and object recognition (Aziz et al., 2020). Efforts in a few of these domains are farther along due to the availability of larger datasets from human-gathering, drone reconnaissance, or satellite imagery (Knox, 2020).

Examples of other applications on the battlefield include Industry 4.0-enabled autonomous or semiautonomous vehicles used to identify objects, recognize obstacles, learn their surrounding environments, communicate and collaborate amongst one another, and aid in navigation planning (Wang et al., 2020). The Industry 4.0 technologies also help to minimize errors and aid personnel in environments deemed more challenging. The DOD is also actively testing the concept of swarming, which involves the collaboration of various-sized autonomous vehicles. Specific to the intelligence and reconnaissance sector, the US Army uses the Gray Eagle as a multipurpose platform for multi-domain operations, and the Pentagon's Project Maven utilizes ML algorithms to collect, analyze, and organize footage from UAVs with the intent to determine hostile activity for targeting (Buoanna et al., 2020).

In production environments, studies have shown ML can be implemented into A&D logistics and planning (Ajakwe et al., 2020). For example, predictive maintenance involving the F-35 employs predictive algorithms to help maintenance personnel determine which aircraft components to inspect or repair, and the Army Stryker uses algorithms for tailored maintenance where a time-versus-cost analysis is conducted prior to scheduling work (Knox, 2020). The US Navy has also used ML to support vessel scheduling and obsolescence management (Rainey & Harguess, 2018). All these efforts have resulted in increased operational efficiency, minimized downtime, and the inclusion of more advanced systems.

Funding Organizations and Considerations

The DOD leverages Research and Development (R&D) from various research-based and academic organizations, as well as agencies such as the Intelligence Advance Research Projects Agency (IARPA) and Defense Advanced Research Projects Agency (DARPA) (Slayer, 2020). In the 1960s, DARPA developed a program to begin researching the early stages of ML. By the 1970s, DARPA was the main supporter of ML research in the US and established a multitude of intelligent programs tied to military actions (Wang et al., 2020).

Due to the high cost of innovation (Foster & Arnold, 2020), R&D efforts estimating more than 15 million dollars annually require coordination with the Joint Artificial Intelligence Center (JAIC) – an organization stemming from the Third Offset Strategy framework (Knox, 2020). In addition, projects directly related to addressing military operational challenges must be overseen by the National Mission Initiatives (NMI) (Slayer, 2020).

In 2018, following the generation of the Third Offset Strategy, DARPA planned to invest two billion dollars over the next five years to support the US armed forces' implementation of Industry 4.0 AI/ML (Wang et al., 2020). In 2019, the US Army contributed 72 million dollars in collaborative projects involving battlefield Industry 4.0 AI concepts and universities (Wang et al., 2020). In 2020, an 800-million-dollar contract was awarded to the JAIC with the intent to further increase Industry 4.0 AI/ML in battlefield domains (Slayer, 2020), and an expected 16.5 billion dollars is expected to be spent on military robotics by 2025 (Allen & Chan, 2017). In an investigation by PricewaterhouseCooper (PwC), it was estimated around $907 billion will be invested across nine industries between 2018 to 2023, with $15 billion of this allocation being invested in the A&D sector (PwC, 2016).

Challenges Associated with Using Industry 4.0 Technologies

In conjunction with Chapter 3, this section addresses Sub RQ 2. Following the Third Offset Strategy of using commercial Industry 4.0-enabled systems for A&D use, there will be barriers and challenges preventing a smooth transition of developed intelligent systems into the DOD. For instance, standards relating to ethics, safety, performance, accountability, and acquisitions rarely align in civilian and defense realms. In addition, there are apprehensions regarding human integration and collaboration with Industry 4.0 solutions, particularly involvement in the decision-making (Wei et al., 2020), where there is concern of potentially replacing human judgment with algorithmically derived choices (Lewis et al., 2016). There are also concerns associated with not trusting and over-trusting Industry 4.0-enabled machines stemming from the unpredictable or inexplicable features of the system.

Another societal challenge is the fear of the machine eventually developing its own agenda after initially behaving ethically. Researchers found this fear stems from concerns about innate human behavior and the survival mechanisms which cause humans to act unethically. However, others have argued that Industry 4.0 allows for the opportunity to create systems that do not include this predisposition and can perform even more ethically than humans (Novak, 2021). Another challenge with implementation is the number of cultural years of manned processes, operations, and systems. This results in more resistance to change due to the learning curve and desire to continue to use traditional systems.

Specific to information operations, Industry 4.0-enabled technologies have allowed for more realistic imagery, audio, and video forgeries. While this can help with quicker detection and evaluation of vulnerabilities, such tools can be used against the US and US allies to promote societal discourse, erode public trust, blackmail officials, or generate false news reporting (Knox, 2020). Although there are DARPA initiatives to identify Industry 4.0-produced falsifications, these systems are capable of being trained to outsmart forensic tools (Knox, 2020). Further vulnerabilities within these systems include data-poisoning attacks, hacking or gaining access for malicious purposes, and intentional attacks on the system intended to trick the algorithms into functioning in unanticipated ways. Particularly in A&D applications which utilize the wireless capabilities for essential communication, such susceptibilities pose great risks.

Although Industry 4.0 methods, such as ML, can serve as countermeasures in the realm of IoT threats, there must be useable data to determine the effectiveness of such protection systems.

Researchers found most of the above risks are a result of inconsistency in data collection methods, the quality of data, and the quantity of data (Zaman et al., 2021). Other resolutions include using defensive algorithms (Liu et al., 2018), decentralized technologies (Miglani & Kumar, 2021), or establishing a well-defined security assessment standard (Liu et al., 2018). Decentralized frameworks, such as Blockchain (Miglani & Kumar, 2021), aid in sharing secured information across networks.

There are also limitations, as well as benefits and drawbacks, related to Industry 4.0 technologies requiring larger data sets. For example, there are opportunities due to the availability of data but potential challenges in analyzing, drawing conclusions, and finding importance within the collected data (Maher & Orlando, 2019). The data can also be difficult and time-consuming to obtain in the required quantities due to the data space being too large, which can lead to ML inefficiencies. In addition, there are limitations involved with potential bias, the quality of data acquired, and dependence on input parameters (Meyer et al., 2020) for these data-driven models.

CHAPTER FOUR: LITERATURE REVIEW AND ANALYSIS

Introduction

This SLR thoroughly investigates the existing literature related to the successful implementation of Industry 4.0 technologies in A&D settings. The review also focused on understanding current and future usage of these smart solutions in defense or military environments. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol was used for this systematic review; the PRISMA guidelines include 27 items that aim to reliably examine and detail applicable scientific evidence (Moher et al., 2009).

Following identification and review of the available literature, a bibliometric analysis was conducted to further investigate this area of research in terms of maturity and development. Through evaluating the current status of factors and implementation, a more strategic framework can be developed to improve the possibility of successful incorporation. This approach allows for a qualitative and quantitative investigation of the current state of this topic as well as provides a core set of publications that can be used for future research.

Abstract

In recent years, technologies have made significant progress due to increased availability of larger data sets, more powerful computing performance, and greater budget allocations. However, many implications and concerns related to successful global implementation of A&D Industry 4.0 solutions remain. This study provides a systematic review of published material on Industry 4.0 in A&D to develop a list of CSFs needed for successful implementation of smart technologies. The review also included investigating Industry 4.0 definitions, technologies, implementation factors, and empirical studies on the usage of Industry 4.0 solutions in A&D.

Records from 2015 to 2022 were found using multiple databases and showed ample research in organizations working toward digital transformation and model-based engineering, specifically in areas related to manufacturing, research and development, logistics, surveillance, reconnaissance, intelligence, and command and control. The results also emphasize the need for empirical evidence related to the implementation of Industry 4.0 and the lack of papers studying Industry 4.0 in A&D settings. The literature review includes a bibliometric analysis to assess the maturity of the topic and papers, and a TA to investigate the CSFs identified in the literature. These identified CSFs were then used to perform an expert study to assess their role in Industry 4.0 implementation success.

Methodology

The SLR approach minimizes research bias by ensuring a comprehensive and organized review of current literature related to Industry 4.0 and potential implementation success factors. The six-step process is shown in Figure 2 (Tranfield et al., 2003).

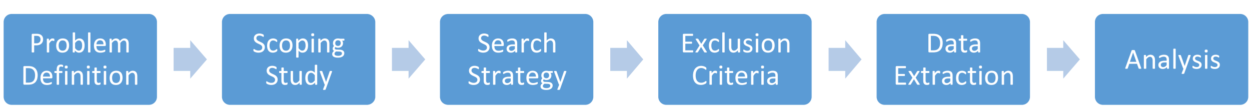

Figure 2: Overview of the SLR Process

Alongside following PRISMA guidelines and the above six-step process, the main objective of this section is to discuss efforts related to the incorporation of Industry 4.0 solutions in A&D as well as known issues and challenges for successful implementation. This SLR is organized as follows: the next section explains the search terms and strategy, followed by lists of the exclusion criteria, a description of the results, and follow-on analyses of the chosen material.

Search Terms and Strategy

Because developing a search strategy is an iterative process, the use of a scoping study aids in refinement of the scope through identification of terminology applicable to the chosen research area. Therefore, during this exploration stage, various sets of keywords were used to discover relevant articles within multiple academic databases, including Compendex, ProQuest, Web of Science, and EBSCOhost. Because the research topic is multi-faceted, using appropriate keywords is crucial to identify applicable articles. Therefore, the capture rate for each potential search string of keywords or concepts was evaluated during this scoping study phase.

This preliminary review of the available literature reiterated the minimal research of Industry 4.0 in A&D environments and the need for more thorough investigations on the implementation of such technologies.

The final search terms are shown in Table 2. Although other terms were considered and tested, these terms were found to not be applicable to the topic and were not considered for inclusion in this study. For example, words such as “incorporate” and “apply” were tested in place of “implementation” but did not yield results related to the scope of the study.

Table 2: Search Terms

A&D	**Industry 4.0**	**Factor**	**Implement**
Defense Industr*	Industry 4.0	Obstacle	Deploy*
Aerospace Industr*	Quality 4.0	Framework	Adopt*
Aerospace and Defense	Smart Manufacturing	Challenge	Implement*
Department of Defense	Smart Industr*	Factor*	
Defense Contractor	Digital Transformation	Barrier	

Table 2 displays four main concepts, one in each column, each with multiple related terms shown in the respective rows. The use of Boolean operators, such as AND and OR, were utilized to search for publications using the Compendex, ProQuest, Web of Science, and EBSCOhost platforms. The databases were chosen to increase the reach and potential of finding more applicable literature; EBSCOhost and ProQuest were chosen due to the broad platforms and inclusion of industry sources while Compendex and Web of Science were selected due to the inclusion of engineering-related research.

Within each concept (column), all search terms were combined using the OR operator; the AND operator was then used between each concept (column). This allowed for all search terms and concepts to be included within the Boolean phrase. The search scope was limited to "everywhere except full text" and papers written in English. This assisted in noise reduction and removal of captures that did not include these terms in the abstract or title. The results from executing the search are shown in Figure 3.

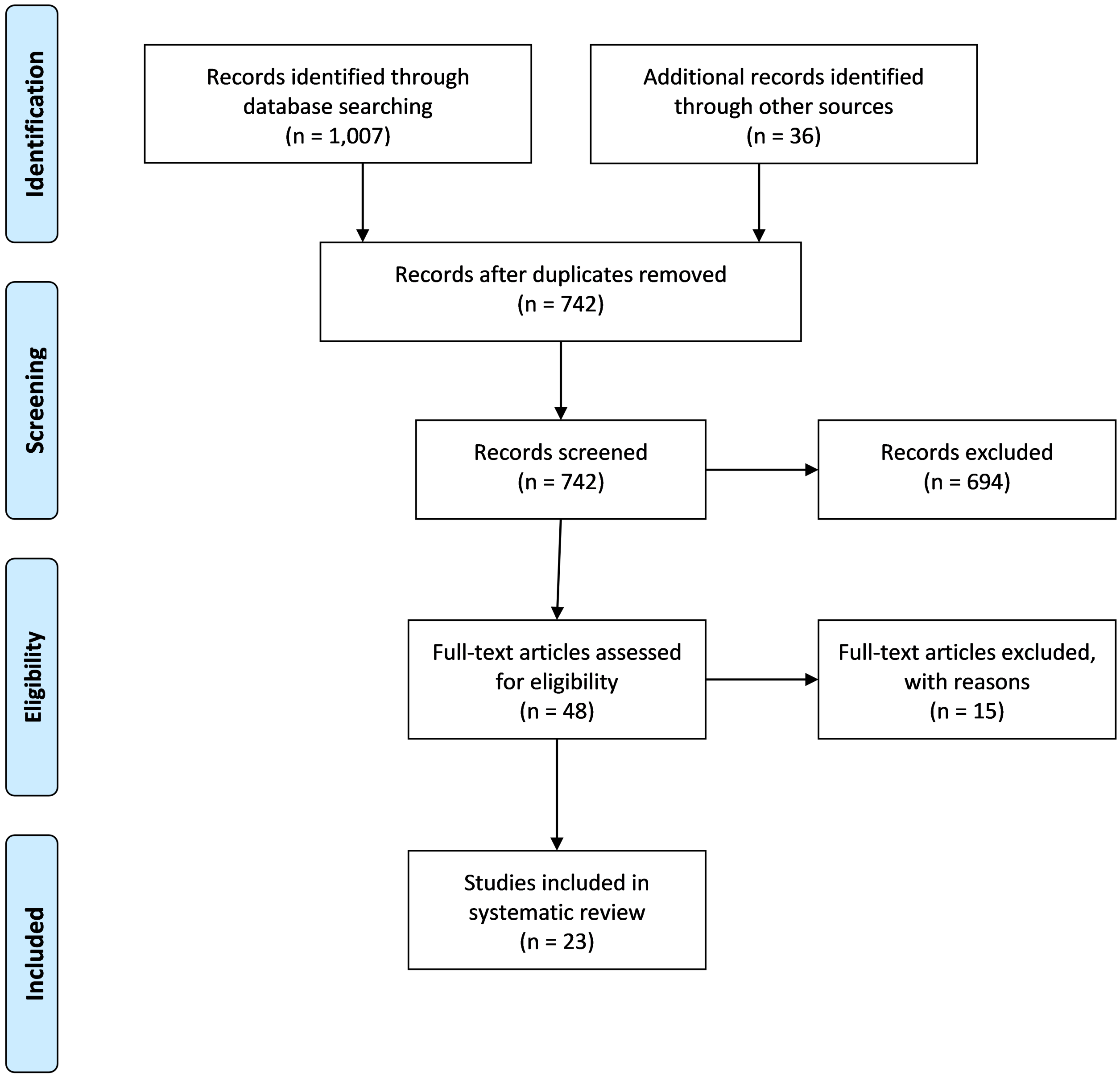

Figure 3: PRISMA Literature Flow

Data Extraction and Results

The initial search resulted in 1,007 publications being identified from the above academic databases. An additional 36 records, such as published theses and DOD technical reports, were also identified through the Defense Technical Information Center (DTIC). All these sources provided ample information regarding Industry 4.0 or advances in A&D. Duplicate records were removed, which resulted in 742 titles remaining. A formal screening process was then used to narrow down the literature with the goal of identifying information relevant to the defined RQs. This screening process included applying the following criteria:

Exclusion criteria:

- Papers, upon review, were found to be unrelated to the RQs
- Letters, posters, newspaper articles
- Papers written in other languages
- Papers which were classified or For Official Use Only (FOUO)

Inclusion criteria:

- Papers written in English
- Papers related to the RQs
- Papers published from 2015 to 2022
- Papers identifying or describing Industry 4.0 in A&D
- Papers which were open access, unclassified, and not FOUO

The above criterion was then applied and the abstracts for the remaining papers were read for applicability. After removing irrelevant titles, 48 were analyzed by reading the entire text. Irrelevance includes if the paper explored the design or use of Industry 4.0 but did not focus on the implementation portion or applicable factors. A total of 23 records met all eligibility requirements and the inclusion criteria. These records, which were chosen for the review, were published between 2015 and 2022.

It is important to mention the risk of bias in the selection of relevant papers. In this review, bias could occur through the application of the exclusion and inclusion criteria, or when determining applicability to the systematic review. To address the potential bias, clear and objective RQs were considered throughout the selection process.

Bibliometric Analysis

Bibliometrics uses both qualitative and quantitative techniques to assess the content and maturity of available literature (McBurney & Novak, 2002). Using the core set of publications identified through the SLR, the 23 papers were evaluated based on specific standards (Tranfield et al., 2003). The chosen criteria help to provide valuable insights about the development of Industry 4.0 in A&D. The information collected include characteristics of publication, the author(s), and the research design used; this section addresses RQ3.

Characteristics of the Publication

To understand the trends in the paper set, the number of studies per year was identified. The SLR searched for papers published between 2015 and 2022, with the final set including studies from 2017 to 2021, as shown in Figure 4.

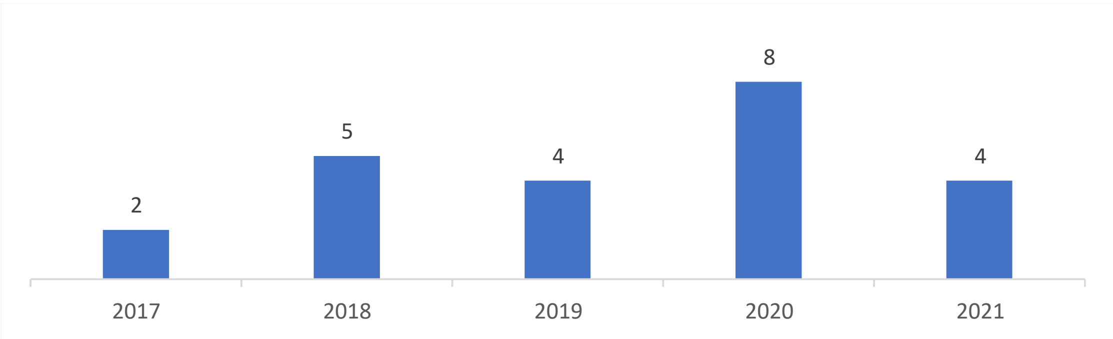

Figure 4: Publications Per Year

The earlier studies used descriptive methods based on literature reviews to provide insight into elements needed for success. These papers focused on providing theoretical frameworks and qualitative assessments regarding implementation challenges. More recent studies, including those from 2020 and 2021, use case studies and structured questionnaires to gain more insight into implementation in the field. This evolution reflects the modernization of techniques to synthesize evidence and the need to understand Industry 4.0 in practice. The results also provide more confidence in the recent studies to help understand the current state of Industry 4.0 implementation challenges and impacts. In addition, although not consistent, the increase in research since 2017 is shown with the most papers being published in the 2020 timeframe. This reiterates the research area of Industry 4.0 is growing as more organizations are attempting to utilize the advancing systems.

Within the paper set, there were two types of studies – journal articles and conference proceedings. Figure 5 visually summarized these findings and showed most of the studies were journal articles.

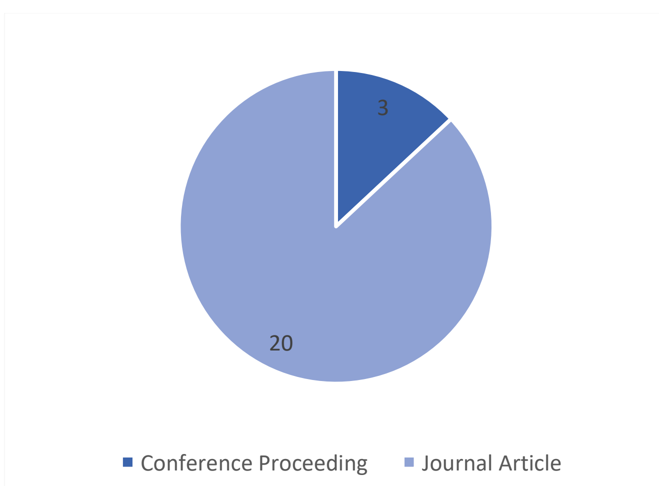

Figure 5: Study Types

This result emphasizes the emergent nature of the Industry 4.0 research area in A&D as most studies are categorized as academic, descriptive, or exploratory investigations. In addition, there are very few examples from conferences or books which focus on industry best practices or lessons learned.

Characteristics of the Author(s)

To further understand the publications, the characteristics of the authors were investigated to highlight the perspectives contributing to the research topic. This also includes understanding the disciplines of the contributors and the location of the research being performed. Using the 75 total authors included in the 23 papers, Figure 6 depicts whether the author represents academia or industry.

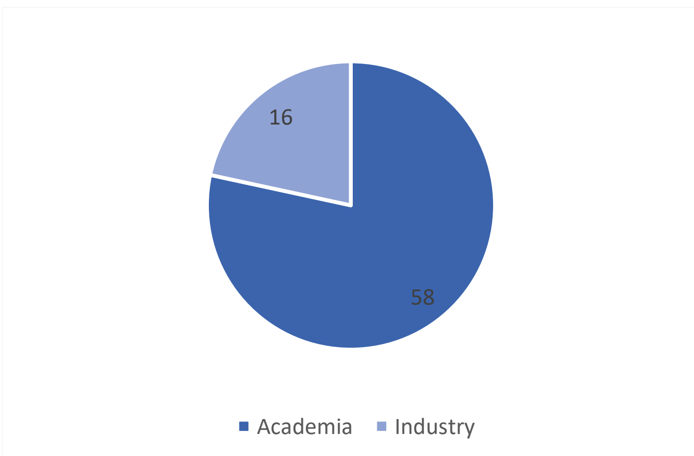

Figure 6: Author Representation

It can be suggested there are few experts within the field of A&D Industry 4.0 as no two others have more than one study included in this data set. However, there is collaboration amongst authors as there was an average of 3.26 authors per study. This result emphasizes the need for more practical and empirical studies investigating the integration of Industry 4.0 within the field. Expanding on this, Figure 7 summarizes the academic or professional associations of the authors.

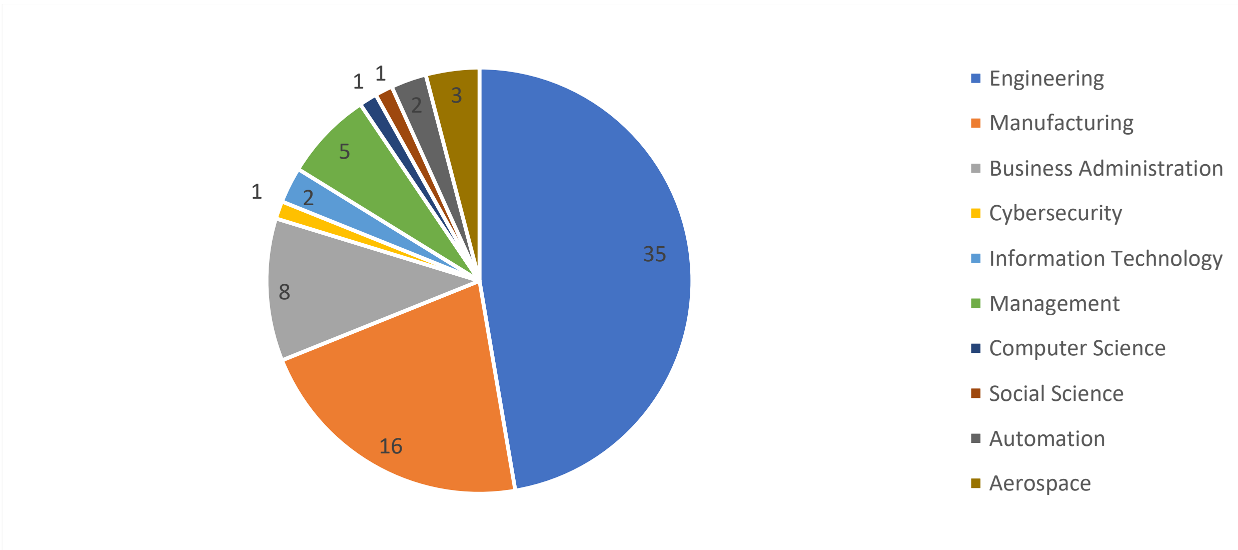

Figure 7: Author's Discipline

The above analysis shows most of the research is being conducted from an engineering perspective, followed by manufacturing and business approaches. The multitude of disciplines found in the set of publications echoes the multifaceted topic of Industry 4.0 and the interdisciplinary nature required for successful implementation. Moreover, the international interest and preliminary collaboration efforts in this area are evident with 19 countries being represented in the papers.

Characteristics of the Research Design

The classification of methodologies in terms of data collection and the data analysis approach was also investigated. The results, summarized in Figure 8, show over 56% of the studies used the traditional literature review method and 26% used the SLR approach to collect information. This indicates there is ample data from the conceptual or theoretical standpoint related to industry 4.0. On the other hand, three studies used case studies to collect data while one paper utilized a survey. This reiterates the lack of practical research related to Industry 4.0 implementation, particularly in the A&D domain, and the developing or emergent theories during this time.

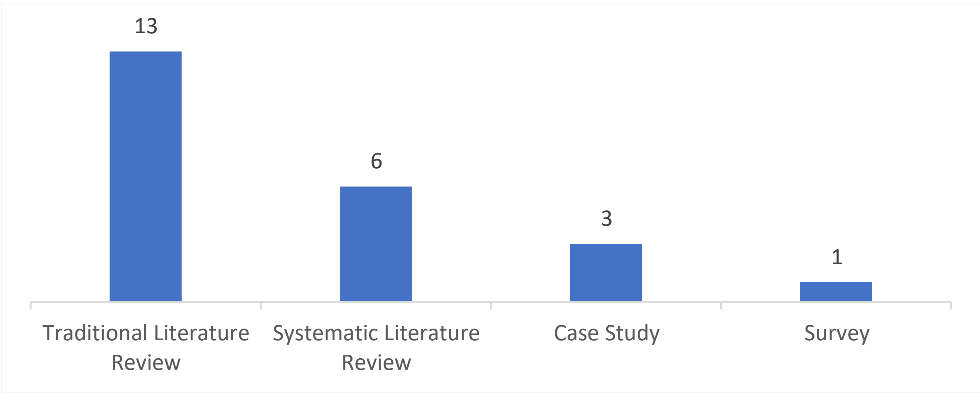

Figure 8: Data Collection Method

To further understand the maturity, development, and rigor of the research related to Industry 4.0 in A&D, the methodologies used in the selected set of papers were also examined; these results are shown in Figure 9.

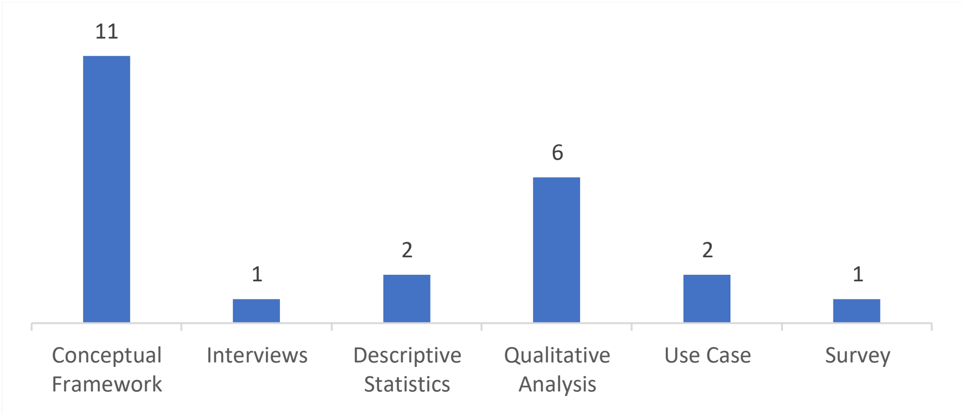

Figure 9: Data Analysis Method

The most common approach for data analysis was to provide a conceptual framework followed using qualitative analysis. These methods highlight the exploratory nature of this research topic and the need to further explore implementation models. Other utilized methods include generating descriptive statistics following case studies, conducting an interview to understand the challenges of Industry 4.0 implementation in manufacturing environments, using a survey to investigate the applicable factors for using augmented reality, and evaluating digital twin environments via the use case method.

These data collection and analysis methods were mainly exploratory in nature and showed the need to further develop empirical research in this domain.

Content Characteristics

The content, in terms of identified keywords and the specific Industry 4.0 technology mentioned, was explored. The exploration began with compiling the keywords provided by the authors to understand the most frequently used and to also identify the variations in terminology amongst the papers. A total of 109 keywords were gathered with each paper using approximately four keywords per article. Figure 10 displays the most frequent keywords found in the SLR.

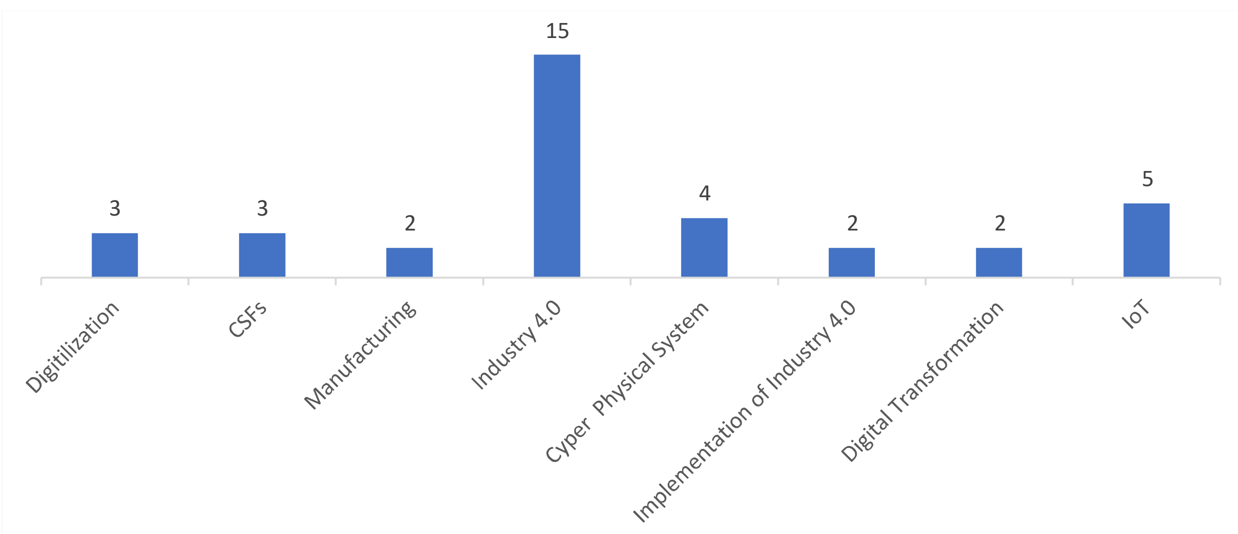

Figure 10: Most Frequent Keywords

This analysis helps provide insight to the topic of the study, aids in learning variations in terminology within the research field and assists in expressing significant constructs. The most common keyword used in the set of papers was Industry 4.0, with a significant number of occurrences compared to the remaining set of words. In addition to this list, more than 15 other keywords were mentioned once in the data set. This emphasizes the variations amongst the terminologies in this research domain. For example, terms such as “smart factory” and “smart manufacturing” were mentioned in different articles. Further, the “workforce” and “management” keywords also had dissimilarities but indicate these are important categories of factors to consider during Industry 4.0 implementation.

The specific types of Industry 4.0 technologies mentioned within the papers were also studied. The results can be seen in Figure 11.

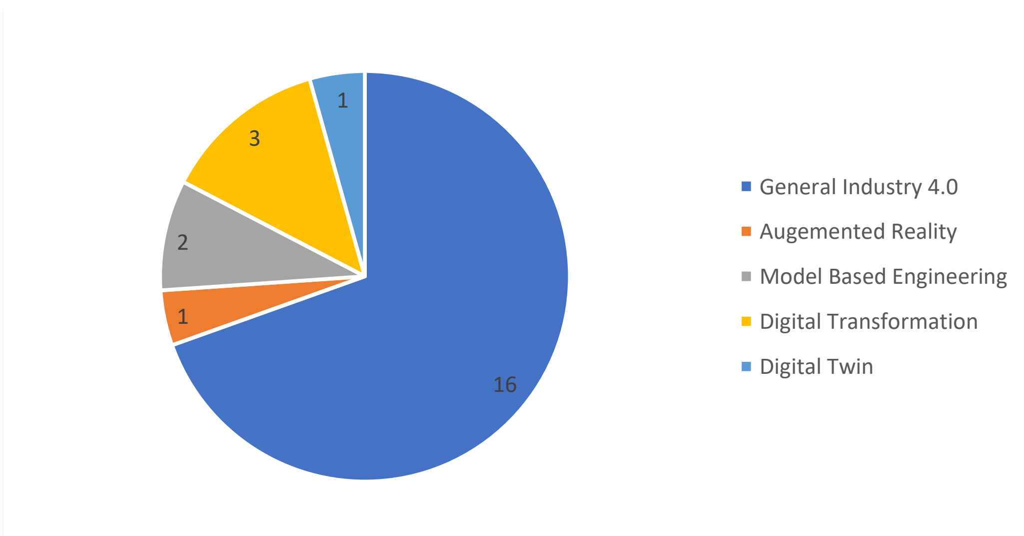

Figure 11: Industry 4.0 Technologies

The majority of the papers did not specify the type of Industry 4.0 solution which the study was focused on. These papers did provide a high-level summary of increasingly popular smart technologies but used a more system level approach to discuss the overall challenges, benefits, and key factors for use. Three of the papers focused on digital transformation techniques, which is another variation in effort and terminology to the digital twin concept studied in another article; augmented reality and using model-based approaches were less popular topics of the studies. This result proves that increasing research related to the general concept of Industry 4.0 solutions is needed prior to elaborating on each specific smart technology. This initial background can be applied to future efforts, including those involved with improving the methods for implementation.

Table 3 expands on the technologies mentioned in the paper and provides a list of the cited technology, and the application or definition.

Table 3: Industry 4.0 Technologies from the SLR

Source	Technology	Application or Definition
Havle & Ucler, 2018	Advanced/Smart Robots	Autonomous robots with integrated sensors and standard interfaces
Havle & Ucler, 2018	Additive Manufacturing	For manufacturing prototypes and spare parts
Masood & Egger, 2019	Augmented Reality	Digital enhancements with display devices; positioned between physical and virtual reality with broad applications such as training or assembly operations
Havle & Ucler, 2018	Simulation	Represents optimization using real-time data
Havle & Ucler, 2018	Horizontal and Vertical System Integration	Integrated value chain from supplier to customer
Havle & Ucler, 2018	IoT	Networked machines, products, and communication
Havle & Ucler, 2018	Cloud Computing	Real-time communication for production using large amounts of data
Havle & Ucler, 2018	Cybersecurity	Intelligent machines managing security risks for systems and products
Havle & Ucler, 2018	Big Data Analytics	Analyzing data from various digital measures
Bécue et al., 2020	Digital Twin	Aids in monitoring and controlling through replication physical assets
Abollado et al., 2017	Digital Workflows	Management tool to improve, automate, improve organizational performance, and streamline processes

Source	Technology	Application or Definition
Da Silva et al., 2019	CPS	Unification of digital environment with the real world through multidisciplinary engineering systems
Papke et al., 2020	MBSE	Project captures and maintains system design information in a system modeling toolset and data repository
Bibby & Dehe, 2018	e-Value Chains	Connect the entire supply network from suppliers to distributers to end customers
Bajic et al., 2020	Fog and Edge Computing	Decentralized service for storage and processes; can act as the interface between end users and cloud data centers
Bajic et al., 2021	Semantic Web Technologies	Allow humans and computers to work collaboratively

Lastly, NVivo 12 Pro was used to perform an assessment on the most frequent words within the paper set to provide insight into the key concepts associated with the research topic. Figure 12 depicts the 30 most frequent words used in the articles but excludes words with less than four letters to reduce nuisances in verbiage or common acronyms.

Figure 12: Most Common Words from SLR

The results show words such as management, performance, support, information, and improvement are all components of Industry 4.0 and should be studied as potentially influential constructs. Other attributes include challenges, engineering, digital, and integration.

Review of the Literature

Defining Industry 4.0

The included literature reaffirmed the lack of a uniformly accepted definition of Industry 4.0. Furthermore, although there is agreement that the revolution started in Germany, there are variations in the attributes which comprise this approach. Havle and Ucler (2018) stated Industry 4.0 is a transformation of technologies and organizations which requires physical components to integrate and communicate with the digital environment. Becue et al. (2020) added that digitalization results in economical and societal changes as well. One study suggested there are six principles of Industry 4.0 related to virtual replicas of physical processes, interoperability, decentralization, real-time capacity, service orientation, and modularity (Da Silva et al., 2019). Another article added three more attributes to this list including cost reduction, mass personalization, and convergence (Pollak et al., 2020).

Although this paper utilizes the definition of Industry 4.0 mentioned in Table 1, further definitions of Industry 4.0 mentioned in the paper set are included below, in Table 4.

Table 4: Definitions of Industry 4.0 from the SLR

Definition	Source
"A new value chain organization and management throughout the products life cycle."	Kagermann & Helbig, 2013
"A collective term for technologies and concepts of value chain organization."	Hermann et al., 2016
"Fusion of technologies that is blurring the lines between the physical, digital and biological spheres."	Unido, 2017
"A complex communication network between various companies, factories, suppliers, logistics, resources and customers."	Qin et al., 2016
"The new technological developments that the Internet and support technologies form the backbone of integrating physical objects, human players, intelligent machines, production lines and processes across organizational boundaries."	Shaif et al., 2015
"Fostering strong customization of products under the conditions of highly flexible production, introduction of methods of self-optimization, self-configuration, self-diagnosis, cognition and intelligent support of workers in their increasingly complex work."	European Commission, 2017
"Designated the digital networking of people, products and machines, and moreover the closely related intelligent data processing, digital value-added services and business processes."	Sony & Naik, 2020
"An integrated digital approach that uses authoritative sources of systems' data and models as a continuum across disciplines to support lifecycle activities from concept through disposal."	Zimmerman et al., 2019

Definition	Source
"Horizontal integration of networks to facilitate intercorporation collaboration, vertical integration of hierarchical systems inside a factory…and end-to-end engineering integration across the entire value chain."	Pollak et al., 2020

Challenges and Benefits of Implementation

Chapter two of this paper detailed the challenges of using Industry 4.0 solutions in A&D settings. This section is focused on discussing the challenges and benefits of implementing Industry 4.0 technologies mentioned in the SLR papers. Both these sections address Sub RQ 1 and Sub RQ 2.

There are challenges associated with the prevention of large-scale implementation, which can be considered barriers or obstacles to Industry 4.0. The main barriers include the lack of government regulations, the need for high financial investments, the poor technological infrastructure, the complexity of the technologies, organizational issues, and lack of human capital (Da Silva et al., 2019).

There are also challenges associated with the process of Industry 4.0 integration. Managerial, security, technological, and financial are categorical groups that encompass multiple implementation concerns (Da Silva et al., 2019). For example, due to the resulting social changes (Rahanu et al., 2021) and modifications of the role of human workers (Becue, et al., 2020), there are many managerial issues dealing with the lack of human resources, such as various levels of skilled workers, a clear strategic vision, differing definitions, and financial resources. There is also the resistance to upgrade knowledge and the uncertainty involved with personnel data protection (Bajic et al., 2020) as there are new categories of risks and vulnerabilities increase in parallel with the amount of real-time data and connections to cyberspace (Tupa et al., 2017).

Financial uncertainties such as the return on investments (ROI) and technological challenges including the integration of machines and newfound dependencies on automation (Da Silva, 2019) are additional challenges that need to be addressed to incorporate Industry 4.0 in A&D. There are also potential obstacles associated with the strategy of implementation; Sony & Naik (2020) stated an organization can lose its sense of purpose and generate chaos if the approach involves quick adaptation and integration without proper planning.

To resolve concerns, there needs to be ethical guidance for developers and users (Rahanu et al., 2021), assurance of integrity and positive human-machine interactions (Elkaseer et al., 2018), standardization of policies, data governance, an assessment of the transformation process, and knowledge of the technologies prior to incorporation. Adoption requires understanding the potential benefits of the technologies to help alleviate these barriers and challenges (Masood & Egger, 2019). Potential benefits are categorized as economic, environmental, social, technological, or a combination of these. Economic advantages include real-time decision-making, improvements in quality, increased competition, reduction in processing times, and transparency between organizations. In terms of environmental impacts, Industry 4.0 can aid in failure prevention, reduction of waste, and increased energy savings. There are also social advantages, including more uniformed processes for workers and reduction of high-risk tasks performed by personnel, (Da Silva et al., 2019) because of overall advances in systems and advancements in systems due to using smart technologies.

These technologies, if effectively integrated, can establish new types of services, products, or more value-added business models. In addition, mass customization of parts, automatic or flexible production chains, product optimization, enhanced communication channels, and increased human-machine interactions all result from using these approaches

(Havle & Ulcer, 2018). The inclusion of complex machines can help to simplify processes while reducing costs, increasing the quality of the service or product, developing green solutions such as sustainable manufacturing, and enhancing competitiveness and innovation (Pozzi et al., 2021) within organizations.

A&D Industry 4.0 Readiness and Adoption Models

Understanding the benefits and challenges of implementing Industry 4.0 in A&D is essential for successful execution. The DOD mandate of modernizing systems and capabilities to streamline processes and improve practices (Wang, 2020) is driven by the 2018 DOD Digital Engineering Strategy and Systems Engineering Transformation (SET) initiatives (Zimmerman, 2019). The transformation is needed to sustain complex systems in an environment with constantly changing threats and evolving mission requirements. To deliver agile capabilities and speediness in results, Wang (2020) emphasized that transformation involves more than tools or infrastructure but also encompasses changes in processes and people, where the latter is considered the hardest issue to tackle.

Zimmerman referenced recent and ongoing initiatives such as the Submarine Warfare Federal Tactical Systems, Naval Air Warfare Center (NAVAIR) SET, and Future Vertical Lift (FVL), to discuss the enablers and readiness of Industry 4.0 in A&D. Enablers include the strategies, policies, continuous improvement (CI) initiatives, workforce culture, and employee training. These constructs are needed to assess the readiness of integrating smart technologies in the defense sector with the goal to transform the design, development, delivery, and operations of complex A&D systems (Zimmerman et al., 2019).

Bibby & Dehe (2018) assessed Industry 4.0 readiness and maturity in the United Kingdom (UK) defense sector by performing an assessment using a focal firm and 14 experts. The results emphasized three key areas for assessment – factory of the future, people and culture, and strategy. Wang (2020) also summarized lessons learned from recent DOD efforts. These include the need for an overarching vision, development of priorities, using an incremental approach, adherence to the vision, and needing support from executive management.

Bibby & Dehe (2018) described two maturity models from two different consulting firms; the first gives feedback on the organizational opportunities and provides advice for improvement. The second model, by PwC, gives an assessment of the organization's current Industry 4.0 status before giving advice on how to proceed. Pacchini et al. (2019) studied the readiness of a Brazilian diesel engine manufacturing company, where the results stressed the importance of understanding the current status of an organization prior to implementing Industry 4.0. Fitsillis et al. (2018) identified the need to recognize personnel competencies to assess readiness as the skills required are numerous and diverse. This paper recommended learning the different work segments, product life cycles, and technologies within an organization to calculate the required skills and training needs for Industry 4.0 readiness.

There are multiple adoption models mentioned throughout the literature as well; Butt (2020) recommended using a modified Business Process Management (BPM) method to ensure that all applicable business processes are effective. On the other end, Masood & Egger (2019) acknowledged four models which are not ideal for the implementation of Industry 4.0. For example, the Diffusion of Theory (DOR) is not preferred as it does not incorporate the environmental aspect of Industry 4.0, which is a component that can be categorized as an essential barrier or driver. The Technology Adoption Model (TAM) and the Unified Theory of

Acceptance and Use of Technology (UTAUT) focus on the individual user, which is not preferred due to the narrow scope and not focusing on the potential organizational changes with larger impacts. The suggested approach follows the TOE method (Technology, Organization, Environment) where each measure can either promote or impede implementation success (Masood & Egger, 2019). This method was used as a basis to further develop the constructs described in Chapter 5, as it can be used to assess the readiness of an organization to transform and incorporate Industry 4.0 solutions in A&D.

Conclusion

Using the PRISMA approach, 23 publications were selected to investigate CSFs for implementing Industry 4.0 in A&D. To assess the maturity of this literature, a bibliometric analysis was performed. The bibliometric analysis reviewed metrics that show the diversity of disciplines researching Industry 4.0. Although the authorship revealed a minimal number of industry experts empirically testing data, a multitude of countries and technologies were discussed. The number of studies and research growth per year were also evaluated, as well as the approaches for data collection and analysis.

Although A&D manufacturers are expected to lead the transition of smart factories and Industry 4.0 implementation (Minnick, 2017), the articles describe the challenges of acceptance and barriers to integrating these technologies. This includes variations in defining the associated terminologies and different assessment models being used to propose requirements for Industry 4.0 in the field. Due to the lack of empirical testing in the articles, as well as the factors and the approaches not being unified, a more detailed analysis of the existing evidence is needed to develop a comprehensive framework. The next chapter focuses on a TA to uncover common themes and identify CSFs within the publications, as the multitude of factors mentioned in the papers requires categorizing and prioritizing to improve chances of success.

Limitations and Future Work for the SLR

Although beneficial, the SLR method also includes limitations and biases in the selection process. During the initial review phase, the researcher may lose some potentially relevant work when searching with the "everything but full text" feature of the database. However, this approach was used to limit capturing papers that mentioned the search term once within the article. Further, if the article mentioned the term within the title, abstract, subject line(s), or in the keyword(s), the chance for relevance to the topic increased.

There are also limitations in terms of the variations of terminologies used across publications. This can inhibit inclusion of all related work. While the use of iterative searching can aid in this limitation, there is still the possibility of missing applicable research. Similar to search methods, there are limitations with the various platforms. Indexed publications are limited depending on the database. To address this, multiple platforms were used to increase the capture rate of the search. Other methods which were included involved strategic development of the inclusion and exclusion criteria to establish a specific scope and identify the range of terminology related to a single concept.

Future efforts can use more search iterations and multiple knowledgeable researchers to further refine and improve the overall research approach while minimizing limitations. The research can also be extended through further investigation of the interrelationships amongst the factors, more in-depth analysis of the identified factors within A&D and operationalizing the factors to better comprehend the constructs. In addition, field studies can be performed to provide validation approaches for empirical testing.

CHAPTER FIVE: RESEARCH SYNTHESIS

Introduction

This portion of the dissertation uses the publications selected from the SLR and conducts a TA of the articles. The intent of the analysis is to further categorize and describe the identified factors while providing an operationalized definition of implementation success in A&D environments. Because the 23 included papers showed inconsistencies with definitions, constructs, and lack of a comprehensive assessment of factors, this analysis helps to address these gaps and variations. Through inductively synthesizing the implementation factors noted in the papers, an initial conceptual framework was generated.

The set of papers identified by the SLR provides evidence of implementation factors for Industry 4.0 in A&D. This initial review found three main categories of factors: organizational, technological, and strategic. Because these groups are considered broad, the TA helped to determine a comprehensive set of factors that were further investigated in later sections.

Critical Success Factors

Critical Success Factors, CSFs, is a term first introduced in 1960 and was later defined as "the limited number of areas in which results, if they are satisfactory, will ensure successful competitive performance for the organization. They are the few key areas where things must go right for the business to flourish" (Rockart & Bullen, 1986).

CSFs also incorporate approaches and strategies on how to accomplish goals. The organization must properly identify CSF to ensure success within the system, process, or enterprise. Therefore, CSFs, or factors, are theorized to significantly impact the success of an implementation process (Aquilani et al., 2017). Furthermore, the efforts of the organization will be less than ideal if results in the areas of success factors are not deemed adequate.

Following the bibliometric analysis and a brief review of the publications, multiple studies report success factors for implementing Industry 4.0 in various manufacturing and defense environments. Each study presented numerous factors, such as executive management involvement, being required for implementation. Within these factors are more descriptive constructs. For example, management training and management funding is encompassed by executive management involvement. The papers also provided variations in defining successful implementation, which is further discussed in a later section of this chapter. Each of the sections within this chapter elaborates on the findings from the literature, summarize the definitions of success, and investigate the mentioned CSFs.

Overview of TA Process

Thematic Analysis (TA) is considered a qualitative approach that consists of six stages shown in Figure 13: (1) reading papers (2) extracting and coding key statements (3) identifying themes (4) addressing differences in interpretation (5) identifying common themes (6) preliminary review of results (Braun & Clarke, 2012).

Figure 13: TA Process

Stage (1) focused on becoming more familiar with the 23 peer-reviewed articles from the SLR. The results from this stage can be seen in the previous bibliometric analysis. Stage (2) extracted and coded statements based on importance and through multiple iterations. Initial codes are determined, and themes are generated while revisiting the data to discover applicable statements. There was no limit to the number of themes or codes applied to a given paper. Stage (3) helps consolidate the data by bringing common components, ideas, or experiences together to generate themes. Stage (4) reviews the coded data for each theme and elaborates on differences in interpretations. Stage (5) further uses these identified themes to understand the patterns and to explain how the theme related to the applicable RQ(s). Stage (6) extracts raw data from the publications to illustrate the themes and further answers the appropriate RQ(s) or RO(s).

TA Findings

The preliminary review of the Industry 4.0 and A&D literature emphasizes the benefits of using advancing technology and potential factors which influence implementation success to obtain the intended benefits. However, the implementation of factors has not been emphasized in the A&D realm. To help discover themes and trends within the 23 papers, the TA was conducted using the Nvivo Pro 12 software package and Excel spreadsheets, as required. This qualitative data analysis tool helps ensure the data management process is accurate, inductive, and iterative through coding and organizing statements in the literature to evaluate themes, definitions, interrelationships, and potential factors.

The first stage of the TA process, shown in Figure 12, was performed and the results are shown in the previous bibliometric analysis. To conduct the second stage of extracting and coding statements, Nivo Pro 12 software was used and focused on coding statements relating to Industry 4.0 definitions, factors or aspects related to implementation, details of implementation, results or goals of implementation, as well as challenges, benefits, and future efforts. In the third stage, these identified statements were consolidated based on common themes or ideas. The final two stages further identify these themes and review the coded data to assist in determining the set of CSFs which will be used for the questionnaire. The next section provides detail on coding, resulting themes, and results.

Discussion of TA Results

To determine the critical factors needed for successful Industry 4.0 implementation in A&D and to answer the defined RQs, the TA focused on three main themes: (1) language related to key constructs, such as implementation success, (2) factors for successful implementation, (3) the results or impacts of successful implementation. The findings from the TA align with the defined ROs and RQs, which address the current and future state of A&D Industry 4.0 while providing a comprehensive set of factors and noting potential outcomes.

Defining Implementation Success and Outcomes

The literature shows the constructs of implementation on successful implementation are not specifically defined in the A&D realm, although there are goals associated with the implementation of Industry 4.0 in this sector. Further, the papers reiterate that the definition of success depends on the application and organization. This section addresses TA themes (1) and (2).

Havle & Ucler (2018) state the outcome of Industry 4.0 implementation is higher competitiveness of the organization through increased sustainability and profitability. There is also a goal to fulfill customer needs, provide more innovative solutions at lower costs, and increase flexibility and production of high-quality products. Other papers suggested improving performance is an indicator of success, where there can be quantifiable terms of efficiency improvement (Masood & Egger, 2019). Following this concept of achieving higher operational efficiencies is the outcome of greater levels of automation (Sony & Naik, 2020).

Pozzi et al. (2021) emphasizes there are no explicit definitions of success or agreed-upon measures for defining success, but indirect definitions can include companies creating more products, reaching new target audiences, and creating new business models. Effective implementation can also be including Industry 4.0 technologies in the process or adhering to the schedule and delivery measures when using these smart technologies (Pozzi et al., 2021). Masood & Egger (2019) parallel this by defining implementation success as the willingness of the organization to increase Industry 4.0 solutions in terms of applications and locations.

The involvement of stakeholders in the improvement and incorporation processes as well as enhanced personnel performance was also found to be indicative of success. This is reiterated by Havle & Ulcer (2018) emphasizing the need for strategic actions to implement Industry 4.0 into all business processes and disciplines. Zimmerman et al. (2019) further elaborates on the importance of human involvement in both acceptance of technologies and participation in work culture transformations within defense sectors. This study further implies successful implementation by describing the usage of these tools to drive programmatic decision-making, provide an authoritative source of truth, and establishing an infrastructure to support activities and collaboration across all stakeholders (Zimmerman et al., 2018).

An analysis using Nvivo 12 Pro software was performed using these definitions of implementation success in the 23 publications retrieved by the SLR. The results from the iterative coding process are summarized in Figure 14.

Figure 14: Defining Industry 4.0 Implementation Success

These indications help to understand the framework of how implementation success is viewed within this topic area. The change or incorporation of Industry 4.0 solutions aims to improve the performance and processes of an organization and is measured through metrics in the main categories of operational impacts, individual gains, and organizational impacts. Successful implementation is guided by factors, which were based on the literature and assessed by determining common themes, codes, and groups of factors. For this dissertation, successful implementation is defined as total improvement, where the above results (Figure 14) are indicative of success.

Factor Groups Impacting Implementation Success

Although there are minimal empirical studies performed in this topic area, the resulting SLR paper set included articles that detail the proposed categories of constructs, specific factors, and tested implementation of such in various fields. The approaches, focuses, and methods differ amongst the studies, but all papers provide insight into essential criteria and groups of constructs for implementation success while reiterating the need for empirical studies on understanding CSFs.

For example, Masood & Egger (2019) emphasized the TOE approach where technology, the organization, and the environment are essential categorical groups that can impede or promote successful Industry 4.0 implementation. Becue et al. (2020) stated the need to address more than the technical constructs of Industry 4.0, such as adaptation concerns and security reservations. Papke et al. (2020) reiterated this by highlighting implementing Industry 4.0 solutions involves the evolution of goals and capabilities. Transformation also involves an understanding of the required resources, the current organizational environment, and the enterprise-wide vision. The remaining literature discussed factors, definitions, and constructs that were distinct across the papers. However, some studies did not include a comprehensive list within the same publication or only identified high-level groups of factors.

Because of the multifaceted implementation approach, the studies revealed three main categories of factors: organizational, technological, and strategic. The 12 factors within these groups were found within the 23 papers and coded using NVivo 12 Pro software and Microsoft Excel. This helped to list and group the constructs based on the most common factor name or applicable category. The results, shown Table 5, detail the main category of the factor, the identified factor, and sub-factors.

Table 5: Identified Factor Categories and Factors

Factor Category	Factor	Sub-Factors
Organizational	Management Commitment	Management Involvement/Engagement
		Leading Change Management/Motivational
		Updated Vision
		Clear Expectations

Factor Category	Factor	Sub-Factors
	Management Training	Management Flow Down
		Knowledge of Industry 4.0
	Employee Involvement	Awareness of Industry 4.0
		Involved in Process Changes
	Employee Acceptance	Understanding New Roles (Ex: HMI)
		Employee Satisfaction
		Feedback Role
		Resistance to Change
	Training and Education	Gap Assessment
		Quality Education
		Strategic Hiring
		Competency Assessments
	Communication	Communication Across Organizations
		Collaboration Across Organizations
		Customer Focus
		Customer involved
	Resource Allocation	Support from Leadership
		Funding
		Required Staffing
		Proper Time Constraints
Technological	Technical Readiness	Technical Compatibility
		Process Compatibility
		System Configuration/Interoperability
	Governance	Policies for Usage
		Ethical Considerations
		Cybersecurity Framework Established
		Protection of Personnel Data
	Procedures and Processes	Identification of Process
		Updating Processes
		Evaluation of Updated Processes
Strategic	Strategic Approach	Strategic Planning
		Implementation Approach
	Performance	Continuous Improvement
		Performance Measures

Factors Impacting Implementation Success

This section addresses TA theme (3) and provides more details provided by the authors in the paper set regarding the factors influencing successful implementation of Industry 4.0. The following subsections, separated by factor category, discuss each factor in more depth and provide additional evidence found in the literature.

Organizational Factors

Many of the authors emphasized the importance of executive and leadership commitment to ensure effective Industry 4.0 implementation in their organization. Pozzi et al. (2020) conducted a case study involving nine Italian manufacturing companies which have already incorporated at least one Industry 4.0 technology in their respective industrial segments. After multiple interviews with management, direct observations, and reviewing documents, the results of this study defined top management support as a crucial factor. The support and commitment of management are essential for change management in terms of highlighting the importance of the transformation, accepting the need to introduce new technologies, reinforcing the mission, and proactively being involved with the change. Masood & Egger (2019) followed this by stating leadership plays a pivotal role in innovation. Managerial commitment can be shown through integration of the organizational goals with strategic planning, providing proper resources to stakeholders, and practicing the same methodologies which are being flowed down. To accomplish this, management training is also a critical component of successful Industry 4.0 incorporation. Certain competencies, training, and understanding of Industry 4.0 concepts are required of managerial personnel to lead the organization and the transformation (Sony & Naik, 2020). Further, for managers to create and maintain this influence, proper resources must be allocated to directly influence and achieve the mission of the organization. Examples of resource allocation include providing funding, political support, and employee training (Sony & Naik, 2020).

In terms of the workforce of A&D organizations, the papers prioritized the overall employee perspective. Butt (2020) added these human-centric factors are often overlooked in

Industry 4.0 implementation where this is an overreliance on technological tools rather than organizations in transformations.

Employee involvement begins with the identification of the Industry 4.0 solution, followed by recognition of the humans within this system and their respective task scenarios. This helps to assess the human impacts of task changes (Neumann et al., 2021) and allows employees to be included in the integration process. Neumann et al. (2021) stated this involvement from the human dimension is essential for optimization, safe implementation, and employee acceptance. In addition, being involved allows employees to directly observe the potential benefits and become more educated on Industry 4.0 solutions (Masood & Egger, 2019).

The literature revealed that human-machine interactions can be considered a significant barrier for implementation if the optimal interaction between humans and the machines is not obtained. Sony & Naik (2020) added this integration of the human and machine is needed to ensure extensive connectivity and digitization of the organization. The interrelationship between these factors is seen through the importance of human involvement in guiding the acceptance of technologies through participation in work culture transformations and human-machine operations.

To encourage employee involvement and increase chances for acceptance, proper knowledge and training are vital. Pozzi et al. (2020) focused on determining factors using experts within a specified field and concluded employee training is essential to promote success. Furthermore, the case study involving Italian manufacturing companies reiterated success was found in organizations that focused on knowledge gaps and established training activities, such as On The Job (OJT) or formal training, to develop proper skillsets. Sony & Naik (2020) suggested creating customized training programs for current employees and developing a strategic recruitment process for specific skills of new employees Overall, without the commitment of the workforce, implementation will fail (Abollado et al., 2017).

Multiple papers report organizational culture as a barrier to success. Pollak et al. (2020) studied 39 Polish companies to understand organizational perceptions during the implementation stage. The results found lack of experts, lack of technical knowledge, and poor human attitude toward Industry 4.0 to be the main observations. Because work culture serves as a foundation for all business decisions (Sony & Naik, 2020), it is imperative to foster an environment of innovation and motivation. An example of how this can be accomplished is through the organizational vision, where senior management is encouraged to drive change through the updated vision, creating an inspired culture, and forming alliances within an organization (Sony & Naik, 2020).

Industry 4.0 adaptation influences all stakeholders within an organization including the customer, end-users, employees, and leadership. Therefore, communication and collaboration amongst these groups is essential. Clearly communicating the rationale for change and engaging key stakeholders in the transformation provides personnel with a sense of responsibility and control while increasing their willingness to accept the change. Further, communication and collaboration techniques result in a mutual understanding across all roles while the landscape of traditional business shifts to a more complex environment (Sony & Naik, 2020).

Because Industry 4.0 encourages change throughout all processes and systems, the papers stress the importance of the work environment needing to be agile, flexible, and adaptable to the changing needs of the customer. Understanding the customer requirements during implementation, such as design criteria or mandatory testing, is essential to ensure the proper Industry 4.0 technology is being implemented in the proper process, system, or stage of the lifecycle. Therefore, organizational success is accomplished through proper communication, adherence to the vision, and helps to integrate all required stakeholders during the transformation process.

Technological Factors

Integration of new digital workflows with current systems is essential during the implementation stage. If the new systems being introduced are not compatible with the current systems, or if the new systems are unable to replace all required capabilities of the current systems, there will not be successful integration of Industry 4.0 solutions (Masood & Egger, 2019). This idea of interoperability sets the frame for the readiness assessment through understanding the adaptation, modification, or replacement needed of current technologies used. Sony & Naik (2020) stressed the importance of transforming all products or services into automated and flexible processes which are capable of interaction and communication amongst numerous devices and machines. Therefore, process compatibility is a critical component to ensure successful implementation as using Industry 4.0 solutions in certain processes may not be considered value-added. Process identification and understanding can aid in this assessment prior to updating the procedure to include cyber-physical systems. It is also necessary to revisit the updates and evaluate the resulting performance data.

In addition, understanding the system configuration and the benefits of using the specific Industry 4.0 are essential to accomplish TCR (Abollado et al. 2017). The interrelationships between factors can be seen here as well, as the workforce knowledge of the Industry 4.0 solution is required to understand the benefits of usage, and therefore impacts the integration of the smart technologies. This is also evident in the use case involving Czech manufacturers, where it was determined Industry 4.0 technologies are not always an ideal replacement, and their appropriateness in a process, system, or product should be evaluated (Nwaiwu et al., 2020) prior to considering implementation.

From the technology perspective, Industry 4.0 solutions require large data sets which increase vulnerabilities within these systems. These susceptibilities include data-poisoning attacks, hacking or gaining access for malicious purposes, and intentional attacks on the system intended to trick the algorithms into functioning in unanticipated ways. From the human acceptance viewpoint, many of the publications state the core issue involves DSP during the data collection and data analysis processes. Prior to or during the initial phase of implementation, certified or accredited policies should be established or modified to help with data, personnel, and product protection (Sony & Naik, 2020).

To further address these concerns, these regulations should include a standardized cyber security policy, risk mitigation framework, and discuss established controls. Following the notion of controls and the need for protection, data should also be reviewed for quality, timeliness, and availability prior to being utilized for decision-making purposes. In addition, the adequacy of the data retrieval system should also be monitored (Masood & Egger, 2019).

Specific to information operations, Industry 4.0-enabled technologies have allowed for more realistic imagery, audio, and video forgeries. Suggestions from the authors include implementing defensive algorithms (Liu et al., 2018), decentralized technologies (Miglani & Kumar, 2021), or establishing a well-defined security assessment standard (Liu et al., 2018) for prevention.

The need for established policies for usage of Industry 4.0 solutions was another mentioned gating element. Villagran et al. (2019) stated regulations can either be created or modified to include the latest business transformations involved with Industry 4.0. For example, standards for the smart manufacturing coordination group (ISO-SMCC) can be modified and updated to include regulations needed to protect the privacy of personnel.

Whether generated or modified, “standardization is the key to the connected world” (Villagran et al., 2019) and is required for implementation to ensure interoperability, uniformity, and compliance across all developers and users. Furthermore, standardization across industries and locations of practice allows for a globally accepted definition of cyber-physical environments, including its components, personnel, processes, resources, and projects (Papke et al., 2019), and can promote smoother implementation of advancing tools.

Examples of governance include designing and implementing Industry 4.0 solutions based on established standards, policies that require a common language across all components to allow for effective information exchange, and the incorporation of a globally accepted security assessment. There should also be general recommendations for organizations implementing Industry 4.0, such as the creation of working groups or establishing committees to resolve various issues (Villagran, et al., 2019). This alignment across organizations can aid in a smoother implementation process, including in defense sectors where performance, reliability, safety, accountability, and ethics rarely align with the civilian realm.

Although most industries have organization-specific ethical guidelines, such as the DOD framework adopted in 2020, standardization in the definition of ethical development and usage contributes to the generation of policies and global implementation of Industry 4.0. While the guidelines for machine ethics and Industry 4.0 in defense industries are constantly evolving, there is agreement on the overall need for future research focusing on designing ethical intelligent systems and ethically using such systems. This construct also reiterates the multifaceted topic of Industry 4.0, as the included papers explain if machines are developed with ethics in mind, there is more trust and human acceptance of using Industry 4.0-enabled systems. Further, the concept of HMI and ethical guidelines aligns with the goal of machine ethics and the DOD initiative – for machines with ethical components to share the responsibility and consequences of decisions with their human counterpart while precluding harm to personnel. In addition, the DOD requires the inclusion of personnel within the intelligent decision-making process, to ensure the successful and ethical implementation of AI/ML (Lawless et al., 2020).

Strategic Factors

A clear strategic approach from executive management is needed to promote and incorporate Industry 4.0 in all business practices and across all organizational disciplines (Havle & Ulcer, 2018). The strategic plan and implementation were found to be related factors that are essential for this smooth implementation as stakeholders, finances, and resources should be addressed. Butt (2020) recommended preparation activities prior to executing the strategic plan. This begins with the identification of processes or business practices that need to be improved, followed by analyzing the process to understand key metrics, such as performance indicators or associated risks. From there, the change can be acknowledged, and the Industry 4.0 technologies can be included to streamline or enhance the business process, product, or service (Butt, 2020). Butt added that the plan also involves risk management and contingency planning, as these constructs are often overlooked during implementation. The strategy should clearly define the current state of the organization and where it needs to be based on the Industry 4.0-based vision and the evolution of the goals and capabilities of the organization (Papke et al., 2020).

Sony & Naik (2020) also endorsed performing strategic planning on a project level, as Industry 4.0 implementation can be considered a series of strategically executed initiatives where the project management lifecycle can be applied. For example, the strategic plan can parallel the project management sequence of initiation, planning, execution, control, and closeout. Additionally, Kohlberg & Zuhlke (2015) and Tortoerlla and Fetterman (2018) found through empirical studies the benefit of adopting Industry 4.0 in organizations that use lean production practices. This is due to the reduced essential work being less complex and the ability to support direct implementation.

The strategic approach should follow the updated vision of the organization and should encompass every aspect of an organization, not only the production component (Sony & Naik, 2020). For example, digitalizing the supply chain using Industry 4.0 solutions, such as IoT or transforming logistics processes using cloud computing, helps to further promote incorporation as the entire organization will dynamically transform (Sony & Naik, 2020) together. The interrelationship of factors is evident in this construct as well; as an example, transparent communication increases the chances of effective incorporation following the dissemination of the strategy.

Abollado et al. (2017) found it challenging and costly to implement Industry 4.0 across all disciplines and levels in an organization and recommended starting with a limited number of activities and select stakeholders. The initial activities chosen should be well known and clearly understood prior to transforming. In addition, the papers acknowledged two types of approaches for the implementation. The implementation plan can be incremental and evolutionarily in nature or can be radical and considered revolutionary (Pozzi et al., 2021). The former approach is deemed an extension of the business model while the latter approach is categorized as an innovation in the business model. Cordeiro et al. (2019) recommended using the incremental approach through conducting a small-scale pilot study to further define, modify, and execute the plan and implementation method.

The papers emphasize the importance of the organization's metrics and recommend using performance measures to obtain data and modify the strategy needed. This interrelationship will be explored in later sections. Measures can also be used as a form of sustainability through monitoring the success of the updated processes or services while identifying positive or adverse trends (Abollado et al., 2027). If modifications are required, performance metrics can guide decision-making and provide evidence to alter approaches or processes.

Sustainability of Industry 4.0 involves maintaining the defined vision through reduced resources, such as raw materials or energy consumption (Sony & Naik, 2020). It promotes a balance between the current and future organizational, economical, technological, and social needs. Resource efficiency and sustainability influences the implementation of Industry 4.0 due to the impacts on local communities, the interfaces with personnel, and the overall value chain. Sustainability is an influential factor in implementing Industry 4.0 but is also essential in maintaining the benefits following implementation. To aid in sustainment, CI initiatives should be conducted to evaluate areas of concerns and modify systems as needed.

Alongside the use of sustainable processes and systems, CI can be achieved through frequent performance measures and the appropriate modifications to the strategy. Enterprises committed to CI were found to have already adopted lean principles (Pozzi et al., 2021) prior to implementing Industry 4.0 technologies and acknowledged lean productions allowed organizations to exploit the effectiveness from Industry 4.0 tools.

Conclusion of TA

Despite the abundance of factors noted in the literature and synthesized through the TA, there is a strong need to perform an empirical analysis to compile the success factors. The literature provided a large group of factors, which were investigated and coded using Nvivo 12 Pro and Microsoft Excel software packages. This allowed for proper categorization and compilation to enable the expert study. All the factors found in the literature are detailed below with a brief summary of the definitions provided by the authors in the paper set. The grouping of the factors in the description is based on these definitions and explanations found in the literature.

It is important to note the interrelationships between these factors. These relationships will be further explored in later sections. These factors will be used to conduct an expert study to understand the CSFs needed to implement Industry 4.0 technologies in A&D.

A summary of the identified factors, a brief description, and additional notes for each construct are shown below, in Table 6.

Table 6: Summaries of Factors Found and Applicable Notes

Factor(s)	**Factor Summary**	**Additional Notes**
Management Involvement Manager Training	Support and active involvement from leadership are essential. Leaders need to understand Industry 4.0 concepts to provide key resources to stakeholders, transform and lead organizations through change, and maintain this influence	Acceptance/support of new technologies, reinforce the mission, proactive in change management
		Need to understand the skill set of employees and create cross-functional teams
		Provide funding, political support, and employee training

Factor(s)	Factor Summary	Additional Notes
Employee Involvement Employee Acceptance Training and Education	Involving personnel is essential for safety and optimization. Identify humans in the system, assess human impacts of task changes, and perform outcome analysis. Customized training plans are needed as well as recruiting for specific skills and anticipation of new ways of working	Included in the integration process and determining which technologies or systems are impacted Earlier involvement and understanding of the benefits lead to increased acceptance Needed to ensure extensive connectivity and digitization of the organization Focus on knowledge gaps and establishing training activities
Communication	Drive change through the vision, foster open communication and transparency, provide a sense of responsibility, and adapt to changing customer requirements	Foster open communication and transparency Be flexible to adapt to changing customer requirements Adherence to the vision through proper communication channels
Technical Readiness	Technology readiness ensures all systems are ready to transform. Technologies should be flexible, automated, and facilitate communication through integrating physical products and the cyber world. To increase chances of success, systems must be compatible, be able to communicate, and be configured properly. There is also a need to manage cyber security during implementation with methods to protect data and personnel	Provides insight into where the organization currently is with technology and where it needs to be Can result in theft, hacking, or data-poisoning attacks; data should be reviewed for quality purposes New systems must be compatible with current systems if being integrated and allow for positive interactions Entirety of system should be transformed and allow for devices to communicate
Governance	Regulations need to be established prior to implementation which include policies, standards, and ethical guidelines for development and usage of Industry 4.0 technologies. Standardization across industries promotes uniformity in all aspects of processes and can promote smoother integration	Development guidelines can include designing machines with a common language Usage guidelines can include AI systems in defense requiring a human component prior to execution Guidelines should include rules for ensuring advanced

Factor(s)	Factor Summary	Additional Notes
		systems are developed to benefit society
		Global regulations allow for smoother implementation
Strategic Approach Procedures and Processes Performance	The strategic approach involves developing a plan, based on thorough preparation, to incorporate the technologies. Identification of processes needing to be re-engineered should be completed prior to developing the plan Recommendation to initially implement in phases with limited stakeholders and fewer activities to ensure the approach is thoroughly planned and properly executed. Use metrics to identify trends and modify approaches as needed to promote improvement	The plan should include incorporation of Industry 4.0 in all business practices and across all organizations
		Incremental/evolutionarily in nature or can be radical/revolutionary
		Modify or adapt approaches based on data received
Resource Allocation	Reduction of resources but inclusion of Industry 4.0 technologies is essential to promote sustainability. The regular use of organizational data can aid in this through understanding the benefits of using Industry 4.0 technologies and allowing a balance between resources used and those required. Systems and processes should be frequently assessed through improvement initiatives and modified as needed	Maintaining the vision through reduced resources
		It is recommended to incorporate Industry 4.0 in organizations that already practice CI through the adoption of lean practices

Initial Operational Research Model (ORM)

The initial ORM was generated based on the factors found in the literature and the sub-factors which more accurately represent and refine the construct. The preliminary 12 factors are modeled in Figure 15, with the sub-factors denoted in parenthesis. Overall, a total of 25 items are included in the assessment. Alongside the definitions for implementation success shown in Figure 14, these findings will be incorporated into the survey-based research.

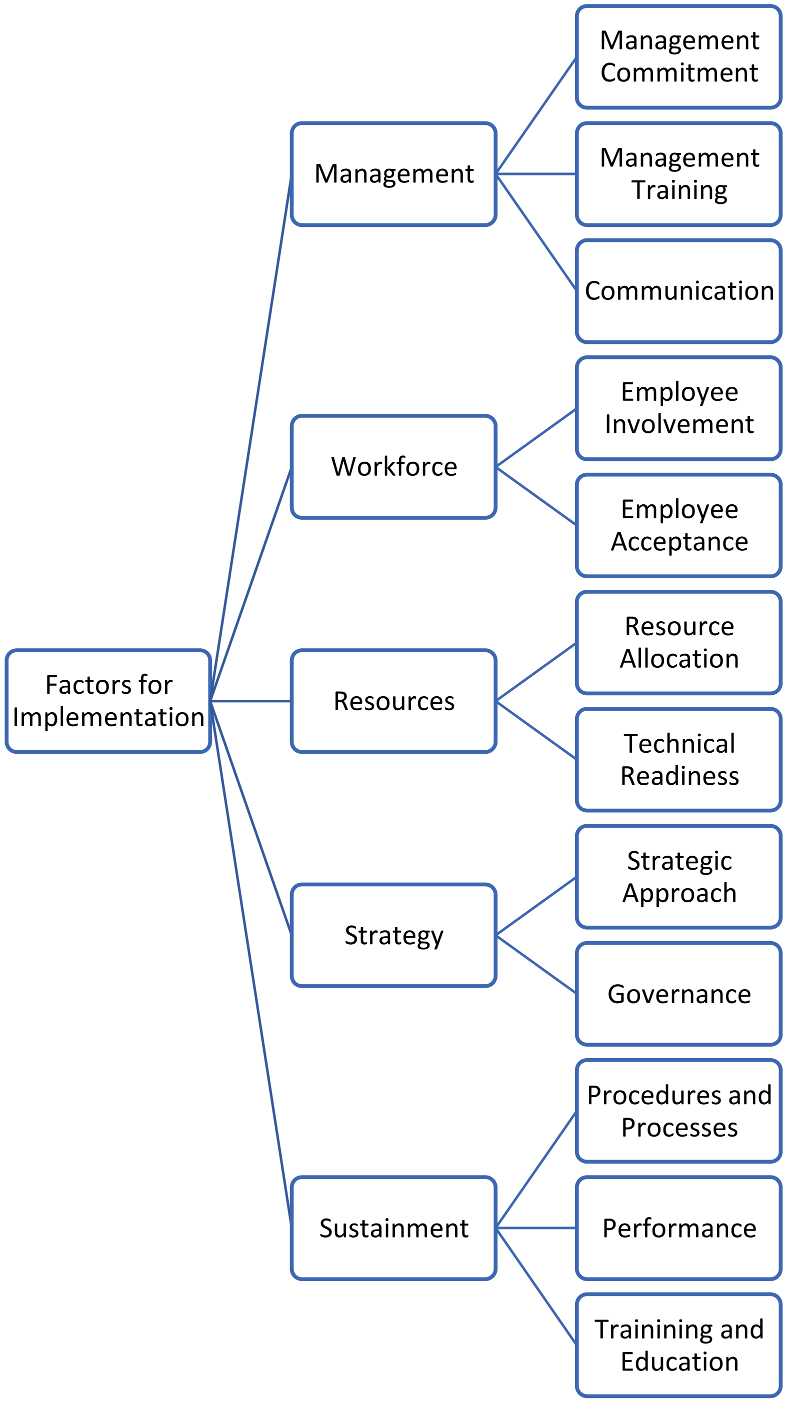

Figure 15: Initial ORM

CHAPTER SIX: SURVEY STUDY

Overview of Survey Approach

Following the identification of CSFs, a structured questionnaire was developed. This expert study aimed to investigate the views of professionals within the A&D sector regarding the implementation of Industry 4.0 using the survey approach. The questionnaire was limited to a single A&D independent contractor (the name of the contractor will not be disclosed in this dissertation). Participants were surveyed via a series of questions administered through an online system. The results were then analyzed using multiple software packages in addition to using descriptive statistics and linear regression to draw conclusions.

Questionnaire Structure

The validity of data heavily depends on the structure and design of the questions (Sanders & Karr, 2015). Because of this, the wording of the questions was strategic to prevent confusion or respondent inattention. Methods such as the reverse word approach were investigated but were found to be challenging with no empirical evidence to prove its benefit or ability to prevent bias. Therefore, this reverse word method which involves incorporating statements consisting of straightforward or reverse-worded items was not implemented in the survey (van Sonderen et al., 2013). To help ensure the questionnaire resulted in reliable responses, the questions were based on the outcomes from the SLR and the inclusion of the resulting factors.

The structure of the questionnaire included two sections; the first section focused on obtaining background information on the respondent to confirm the participant had the proper experience to be in the study. This section had nine questions and aimed to obtain the following data: the position (or title) of the participant, years of experience, estimated size of the organization, their role in Industry 4.0 implementation, the specific Industry 4.0 technologies used, team performance, time of involvement, and the general level of implementation success. The second section portion of the questionnaire consisted of 13 main questions based on the identified factors with additional sub-questions based on the related sub-factors, resulting in a total of 77 statements within the second section of the survey. The respondents were asked to rate their agreement, using the Likert scale, to the 77 statements, with the purpose to ask about the participant's experience and identifying the presence of factors during Industry 4.0 implementation. To prevent participants from determining theoretical constructs, the questions were shuffled resulting in no specific order.

As mentioned above, to measure the extent of agreement concerning the significance of the factors, an agreement scale was used in the questionnaire. In addition, an odd number scale was chosen due to its ease for respondents to remember the categories, the convenience of the scale length, and to allow for a midpoint response to choose when not certain (Krosnick et al., 2002). Each response used the Likert scale, from 1 to 5, which allowed participants to quantify their level of agreement with the statement provided. Responding with "1" indicated strong disagreement from the participant while responding with "5" indicated a strong agreement with the provided question or statement. The bipolar scale also includes a "zero-point" which allows the questions to be measured in the positive direction or the negative direction. This scale also allows for more control by asking the respondent about observations rather than opinions. Therefore, the respondents can use the scale to provide input on the existence of factors or the impact of the factors.

Development of Questionnaire

This section discusses each factor based on the ORM in Figure 15, where the sub-factors represent sub-concepts amongst each factor. These sub-codes, alongside the definitions noted in Figure 14, were used to create the Likert-scale items for each construct. These 77 statements included in the questionnaire are detailed below and separated by factor for clarity and comprehension. The final formatted survey can be found in Appendix B.

Management Commitment

The first factor identified in the ORM is Management Commitment. This variable includes four sub-factors: management involvement/engagement, leading change management/motivational, updated vision, and clear expectations. The following items were developed for this construct:

MC1: Management was involved with implementation activities.

MC2: Management was engaged in implementation activities.

MC3: Management used motivation tools to engage the team.

MC4: Management showed commitment through effectively leading the change.

MC5: Management gave clear expectations as far as improvement plans.

MC6: Management provided a clear vision detailing the results of implementation activities.

MC7: Management plays an important/active role in implementation activities.

Management Training

The second factor identified in the ORM is Management Training. This variable includes two sub-factors: management flow down and knowledge of Industry 4.0. The following items were developed for this construct:

MT1: Management communicated implementation plans with the team.

MT2: Management flowed down applicable information to help the team with implementation activities.

MT3: Management showed knowledge regarding the systems being implemented or the processes being changed.

Employee Involvement

The next factor identified in the ORM is Employee Involvement. This variable includes two sub-factors: awareness of Industry 4.0 and involvement in the change process. The following items were developed for this construct:

EI1: I was aware of the implementation objectives of my role.

EI2: I understood the benefits of using Industry 4.0 technologies.

EI3: I was involved in implementation activities.

EI4: I was included in decision-making activities.

EI5: I am knowledgeable about the overall implementation plan.

EI6: I am aware of and understand the corporate mission and vision to use industry 4.0 technologies.

Employee Acceptance

The next factor identified in the ORM is Employee Acceptance. This variable includes four sub-factors: understanding new roles, employee satisfaction, feedback role, and resistance to change. The following items were developed for this construct:

EA1: Employees understand their work scope once implementation is complete.

EA2: Employee satisfaction with using Industry 4.0 technologies was measured.

EA3: Employee feedback was a part of the decision-making activities.

EA4: Employees easily adopted Industry 4.0 principles and processes.

EA5: Employees agreed with the decision to incorporate Industry 4.0 technologies in their work processes.

Training and Education

The next factor identified in the ORM is Training and Education. This variable includes four sub-factors: gap analysis, quality education, strategic hiring, and competency assessments. The following items were developed for this construct:

TE1: There is an understanding of the gap between employees’ current skill set and skill set needed for Industry 4.0 technologies.

TE2: Learning and education were evaluated, and training was planned.

TE3: Education or training was provided.

TE4: Experienced Industry 4.0 employees were hired.

TE5: Employees performed a competency assessment of required skills.

TE6: My team members have the required experience.

Communication

The next factor identified in the ORM is Communication. This variable includes four sub-factors: communication across organizations, collaboration across organizations, customer focus, and customer involvement. The following items were developed for this construct:

C1: There was communication between different levels of management.

C2: There was communication between affected organizations.

C3: There was collaboration across affected organizations.

C4: Team members communicated well with each other.

C5: The organization considered customer needs in implementation activities.

C6: Complaints were used to improve the implementation process.

C7: Different disciplines collaborated to improve the results of Industry 4.0 implementation.

C8: My team can easily reach out to individuals as needed.

C9: I received updates from the project/program management office.

C10: The team welcomed and encouraged customer input throughout implementation.

Resource Allocation

The next factor identified in the ORM is Resource Allocation. This variable includes four sub-factors: support from leadership, funding, required staffing, and proper time constraints. The following items were developed for this construct:

R1: There were sufficient resources to support implementation.

R2: There was adequate funding for Industry 4.0 implementation purposes.

R3: There was adequate staffing to support implementation.

R4: There was adequate time for staff to perform tasks associated with implementation.

R5: My team was able to purchase items needed to make implementation more efficient.

R6: My team received leadership support from management.

Technical Readiness

The next factor identified in the ORM is Technical Readiness. This variable includes three sub-factors: technical compatibility, process compatibility, and system configuration or interoperability. The following items were developed for this construct:

TR1: There was technical compatibility with the new Industry 4.0 technologies and current processes.

TR2: The process was changed to include Industry 4.0 technologies only if it was deemed value-added.

TR3: A system configuration assessment was performed prior to implementation.

TR4: Technical compatibility assessments were performed prior to implementation.

TR5: Systems were ready to transform and use Industry 4.0 technologies.

Governance

The next factor identified in the ORM is Governance. This variable includes four sub-factors: policies for usage, ethical considerations, cybersecurity framework, and protection of personnel data. The following items were developed for this construct:

G1: Policies have been adopted to include the use of Industry 4.0 technologies.

G2: There are ethical guidelines in place prior to implementation.

G3: There are standards in place to be used across organizations for implementation.

G4: There are policies in place to protect the privacy of personnel when using data-vulnerable systems.

G5: There is an updated cybersecurity framework addressing Industry 4.0 technologies.

Procedures and Processes

The next factor identified in the ORM is Procedures and Processes. This variable includes three sub-factors: identification of processes, updating processes, and evaluation of updated processes. The following items were developed for this construct:

PP1: Processes or systems which are impacted by Industry 4.0 implementation were identified and defined.

PP2: Processes and protocols being updated with Industry 4.0 implementation were evaluated.

PP3: My team developed high-quality processes for implementation (documented, repeatable, mistake-proof).

Strategic Approach

The next factor identified in the ORM is Strategic Approach. This variable includes two sub-factors: strategic planning and implementation approach. The following items were developed for this construct:

SA1: The organization pursued long-term organizational goals and policies.

SA2: The strategic plan was known and clear prior to implementation.

SA3: The policies and strategies were developed according to current and future needs.

SA4: The implementation approach was understood and shared.

SA5: My team has dedicated time for project planning.

SA6: My team first implemented Industry 4.0 technologies in smaller-scale projects or processes.

SA7: My team has realistic schedule expectations for implementation.

Performance

The last factor identified in the ORM is Performance. This variable includes two sub-factors: continuous improvement and performance measures. The following items were developed for this construct:

P1: Performance metrics were obtained.

P2: Performance data and information was analyzed.

P3: Data generated from the performance measures were used in decision-making or implementation activities.

P4: The organization regularly updated its policies and protocols.

P5: The organization continuously improves processes to implement Industry 4.0 technologies.

P6: Performance indicators are compared across organizations to identify opportunities for improvement.

P7: My team uses principles of continuous improvement (lean manufacturing, etc.).

Outcomes of Implementation

The outcomes, detailed in Figure 14, were used to develop the following constructs:

O1: There was an improvement in organizational performance following implementation.

O2: There was an improvement in organizational efficiencies following implementation.

O3: There was an improvement in processes and procedures following implementation.

O4: There was an increase in stakeholder satisfaction following implementation.

O5: There was an improvement in quality following implementation.

O6: The organization is now in a competitive position following implementation.

O7: The implementation of Industry 4.0 technologies was successful.

Data Source and Participants

The team was identified based on their related work with Industry 4.0 and having active A&D industry experience. Participants must have current or previous experience with Industry 4.0 technologies (examples include Artificial Intelligence, Digital Transformation, Model-Based Engineering, Model-Based Systems Engineering, Machine Learning, etc.), be currently employed by the chosen A&D contractor, and be of at least 18 years of age.

A two-step approach was taken to ensure the solicited experts reflected the target population and had experience regarding the problem statement. First, the survey invitations were restricted to the members within the selected A&D company. Second, the filtering questions in the first portion of the questionnaire confirmed if the respondent was actively involved in Industry 4.0 implementation in aerospace or defense domains. If the participant did not have a participation nor observation role, the survey and respective responses were omitted from the study. This approach of purposeful sampling was used to ensure qualified participants can provide relevant information while representing the target population of interest (Etikan et al., 2016).

All members of this study are considered employees of the independent A&D contractor, did not receive additional compensation beyond their standard annual salary, and were selected due to their involvement with Industry 4.0 technologies. In addition, participants were selected based on conversations with various levels of management, and the study was approved for dissemination by the corporation’s Communication and Human Resources teams. The University of Central Florida (UCF) Institutional Review Board (IRB) also determined the study is exempt from regulations.

Because the sample size influences the estimation and interpretation of the statistical analyses, considerations were taken when determining the sample size. Various studies offer differing suggestions; Hair et al. (1998) determined a minimal sample size of 100 is recommended while Reisinger & Turner (1999) concluded valid results for estimation result from samples as small as 50. Since the target population has an undefined quantity, this survey aimed to obtain at least five responses for every factor identified; this ratio of the number of replies per variable (N:p) varied in recommendations as well, but a 5:1 relation was selected for this survey. Therefore, the study aimed to obtain a minimum of 60 responses.

Data Collection and Procedure

The questionnaire was administered using UCF Qualtrics, where invites for eligible participation were sent via e-mail. Eligible participants from the chosen A&D contractor (the name of the contractor will not be disclosed in this dissertation) were selected based on their current role and discussions with upper management. This survey creation webpage allowed for the questionnaire to be administered electronically. Participants were able to complete the survey online in a location and time of their choosing. The 13 main questions within the survey were designed to investigate the expert's experience or knowledge of Industry 4.0 implementation in A&D settings.

An e-mail invitation was sent to eligible participants and included information regarding the purpose, benefits, and risks associated with the study. This information was shared in a clear and simple manner to ensure proper understanding. The e-mail also included contact information, the estimated time to complete the questionnaire, and the two-week deadline. If participants did not respond to this first e-mail within one week, a built-in reminder was sent to the same distribution. If neither e-mail received a response, the participants were removed from the study. The invitation did include an option to forward the request to other professionals within the chosen A&D contractor.

Once the participant clicked the option to "complete survey", the consent to participate in the research study was confirmed. Respondents also had the ability to skip or return to any question prior to submitting responses. Following the two-week deadline and once all the data was collected, the information was extracted from the Qualtrics system. However, if respondents did not complete the survey in its entirety, their responses were removed from the study.

Pilot Test

To ensure content validity and reliability, a pilot test was conducted to test the generated survey prior to disseminating it to the sample population. The recommendation on the number of participants included in a pilot study varied throughout the literature; Connelly (2008) suggested 10% of the sample population while Isaac and Michael (1995) recommended between 10 and 30 subjects for pilot studies. It has also been recommended to include at least 10 subjects (Saunders et al., 2007) to further aid in refining statements by obtaining feedback from the tester's experience.

The responses of these testers helped to evaluate the reliability of the factors and the questions through the calculation of the coefficient alpha. Table 6 details the scale for alpha and the resulting internal consistency.

Table 7: Scale for Cronbach's Alpha (CA)

CA	**Internal Consistency**
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

If the resulting value was above the threshold of 0.7, the construct was considered reliable for this study. If factors had a reliability score less than 0.7, items within the questionnaire were refined or clarified, but content was not removed. Items were not removed as the constructs were developed from empirical evidence and found within the literature.

Pilot Test Results

The sample for this pilot study was considered representative of the target population. Invites for the pilot study were sent to 15 participants with 10 responses after the one-week deadline. However, three of these 10 participants did not complete the entirety of the survey and therefore, their responses were omitted from the study. Therefore, the analysis from the pilot test used the responses from seven respondents.

The analysis for internal consistency was performed with two different scopes. The first involved examining the entirety of the 77 statements for overall reliability based on the seven completed surveys. This calculation was performed in Microsoft Excel and resulted in an alpha value of 0.986. Because the resulting value was above the threshold of 0.7, the entirety of the second section of the survey was considered reliable for this study and the alpha-value indicates the survey is a consistent measure of the Industry 4.0 concept.

To further examine the internal consistency of each construct, the second analysis calculated Cronbach’s alpha for each independent variable, or factor, and the dependent variable, the outcome of implementation. This investigation used IBM SPSS Statistics 28 software package. The results are shown in Table 7.

Table 8: Pilot Test Reliability Analysis Results

Factor	CA
Management Commitment	0.892
Management Training	0.811
Employee Involvement	0.808
Employee Acceptance	0.815
Training and Education	0.939
Communication	0.865
Resource Allocation	0.947
Technical Readiness	0.840
Governance	0.856
Procedures and Processes	0.833
Strategic Approach	0.566
Performance	0.932
Outcome	0.907

The dependent variable, or *Outcome*, had an alpha value above 0.90, showing there is high strength in the consistency measure of this concept. 11 factors had a reliability score above the threshold of 0.7, indicating the construct is reliable for the study. Of these 11, three of these factors were deemed “excellent” for internal consistency due to having an alpha value above 0.90; the remaining eight factors were deemed “good” for having an alpha value between 0.80 and 0.90. One factor, *Strategic Approach*, was considered to have “poor” reliability as a result of having an alpha value between 0.50 and 0.60. This allowed for the opportunity to refine items within this factor.

Because the small sample population from the pilot study included seven active participants, it is not recommended to remove items on this basis. Further, the items were developed from expert studies and empirical evidence found in the literature. Therefore, The pilot test results were used to refine items and make procedural improvements. The sample population was also representative of the target population for the formal survey. Because of this, respondents were also asked to provide feedback, via e-mail, for recommendations to improve the overall survey experience and to refine the survey as necessary. This peer review by industry experts resulted in improvements related to updating unclear wording, including the option to "go back" to unanswered questions, and the inclusion of a progress bar to show survey completion status. Respondents also requested instructions be included which tell the participants to focus on one Industry 4.0 effort and to note the survey is written in past tense; if the respondent is currently in an Industry 4.0 related role, the instructions stated to answer the questions based on current experience. These updates were implemented prior to the distribution of the formal survey to the target population.

CHAPTER SEVEN: SURVEY RESULTS

Formal Survey Results

This section presents the results from the formal survey including the number of responses and the quantity of usable responses. Data exploration was then performed and discussed based on the usable sample.

Survey Responses

Despite using various strategies to encourage participation, such as reminder e-mails and automatic notifications, the overall response rate was low. A total of 118 e-mail invitations were sent requesting participation. Following the two-week deadline for completion, 54 responses were received. Since the target population had an undefined quantity, the survey aimed to obtain at least five responses for every factor identified; this ratio of the number of replies per variable (N:p) varied in recommendations as well, but a 5:1 relation was selected for this survey. Therefore, the study aimed to obtain a minimum of 60 responses. Although 54 responses were received, Reisinger & Turner (1999) concluded valid results for estimation result from samples as small as 50.

The low response rate can be a result of the specific scope of the research and the requirement for participant involvement. The scope required a certain set of respondents who participated in or directly observed Industry 4.0 implementation in A&D, which did not apply to the entirety of the population within the A&D contractor. In addition, the limited number of responses can stem from the lack of compensated academic research being performed in A&D industrial environments. However, the literature does allow for the acceptance of low response rates after ensuring the responses are adequate and exclusion criteria were applied appropriately (Baruch & Holtom, 2008).

Data Exploration

Fincham (2008) stated the average response rate when using e-mail surveys is between 25% and 30%. This survey had a response rate above 45% because of receiving 54 responses from the initial 118 e-mail invitations. Of these 54 responses, 42 were deemed usable after the screening process. The screening process evaluated missing data and determined if straight-lining occurred (Hair et al., 1998). Screening for straight lining included looking for signs of survey fatigue by noting the lack of variation in responses. Responses were also removed if the respondent did not consent to participate, did not participate nor observe Industry 4.0 implementation, or did not complete the questionnaire in its entirety.

The adherence to basic statistical assumptions was assessed prior to (Field, 2018), and exploring the distributional characteristics of each factor in the second portion of the questionnaire. Each response in this section used the Likert scale, from 1 to 5, which allowed participants to quantify their level of agreement with the statement provided. Responding with “1” indicated strong disagreement from the participant while responding with “5” indicated a strong agreement with the provided question or statement.

Between all the factors, the mean responses from the Likert statements ranged from 2.34 to 4.30. The most frequent response was “3” and “4”, with 905 and 1024 occurrences, respectively. The minimum responses, in terms of frequency, were “1” and “2” with 144 and 413 occurrences between the 77 statements. Further, the mode for each statement was calculated and reiterated the previous result through showing 34 statements had “4” as the most common response, while 27 statements were answered with “3”. There were no items that had a mode equal to the low scale value of “1”. Therefore, the response of “1” was not a value that appeared often in the data set. This indicates respondents did not “strongly disagree” with many of the items, but rather the majority of respondents “somewhat agreed” with the Likert statements. The average response between all the statements was 3.56, indicating many participants responded with “neither disagree nor agree” and “somewhat agree”. Table 9 shows the mean response per factor, with the Likert legend being referenced.

Table 9: Mean Survey Response Per Factor

Factor	Mean Response	Between the Following Likert Scale Items
Management Commitment	3.68	Neither Disagree Nor Agree & Somewhat Agree
Management Training	3.62	Neither Disagree Nor Agree & Somewhat Agree
Employee Involvement	4.10	Somewhat Agree & Strongly Agree
Employee Acceptance	3.40	Neither Disagree Nor Agree & Somewhat Agree
Training and Education	3.38	Neither Disagree Nor Agree & Somewhat Agree
Communication	3.84	Neither Disagree Nor Agree & Somewhat Agree
Resource Allocation	3.42	Neither Disagree Nor Agree & Somewhat Agree
Technical Readiness	3.29	Neither Disagree Nor Agree & Somewhat Agree
Governance	3.32	Neither Disagree Nor Agree & Somewhat Agree
Procedures and Processes	3.62	Neither Disagree Nor Agree & Somewhat Agree
Strategic Approach	3.53	Neither Disagree Nor Agree & Somewhat Agree
Performance	3.31	Neither Disagree Nor Agree & Somewhat Agree
Outcomes	3.59	Neither Disagree Nor Agree & Somewhat Agree

Further, the histograms revealed the distribution for each factor was relatively symmetric with some factors showing a negative skew and having clustered values toward the right. Additional analysis of factors, normality of data, and interrelationships is detailed in later sections.

Demographic Analyses

The nine questions in the first section of the survey were used to gather demographic data on the participants. This information was also used as a filter to ensure the participant met the established criteria while also giving context to the included population. The responses provided foundational perspectives and experiences of the experts included in the study, which gave further insight into the results detailed in later sections.

Prior to these questions, the exclusion question was asked. If respondents did not observe nor participate in Industry 4.0 implementation, the survey automatically concluded, and participants could not complete the remainder of the questionnaire. If the participants participated or observed implementing Industry 4.0 technologies in A&D, the following questions were answered. If data were missing, the responses were excluded from this study.

Participants were asked to provide their current title to give insight into positions that have participated or observed implementing Industry 4.0 technologies in A&D and those which have not. Figure 16 visually displays the number of responses, per position, included in the study.

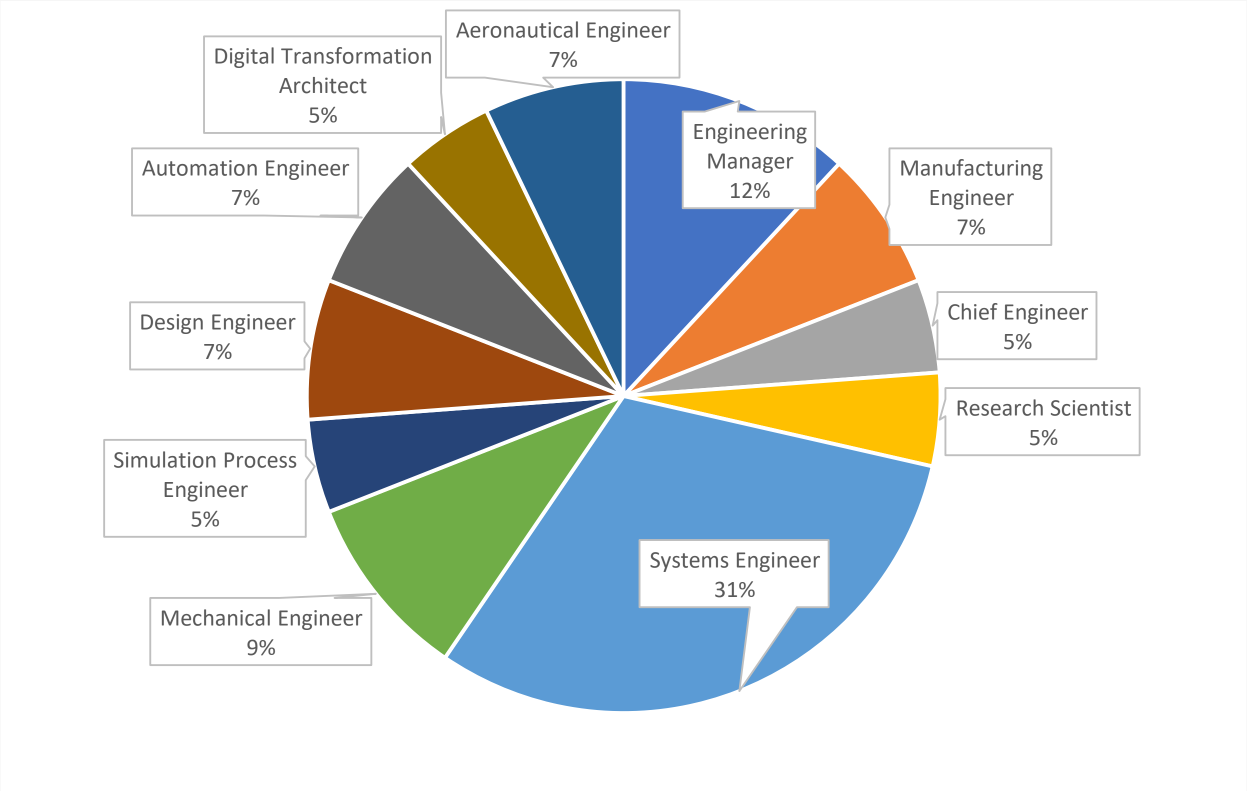

Figure 16: Survey Participant's Current Title

The respondents all have a technical background based on their positions being within engineering or a similar technical discipline. Most of the participants (31%) are currently in a Systems Engineer role or are in a managerial position (12%). The titles span various knowledge backgrounds including Automation, Aeronautics, Mechanical Engineering, and Simulation Processes. These roles also perform their respective work in different lifecycles of product development. For example, Design Engineering roles are more prominent during preliminary and critical design phases while Manufacturing Engineering roles are seen during the production phase. This variety parallels the literature which echoes the multifaceted topic of Industry 4.0 and the interdisciplinary nature required for successful implementation. Later sections further explore these relationships and investigate whether this result can be correlated with specific factors.

The next demographic question asked respondents the number of years spent in their respective Industry 4.0-related role. This information was used to provide a baseline for the knowledge, involvement, and experience levels for the provided response responses. The results showed most of the participants have been in their role for 0-5 years, about one-third of participants have been in their position for over 10 years, and very few mid-level employees participated. This spread of knowledge levels shows the included sample provided an adequate representation of the workforce, where entry, mid, and senior-level A&D contractors are included within an organization.

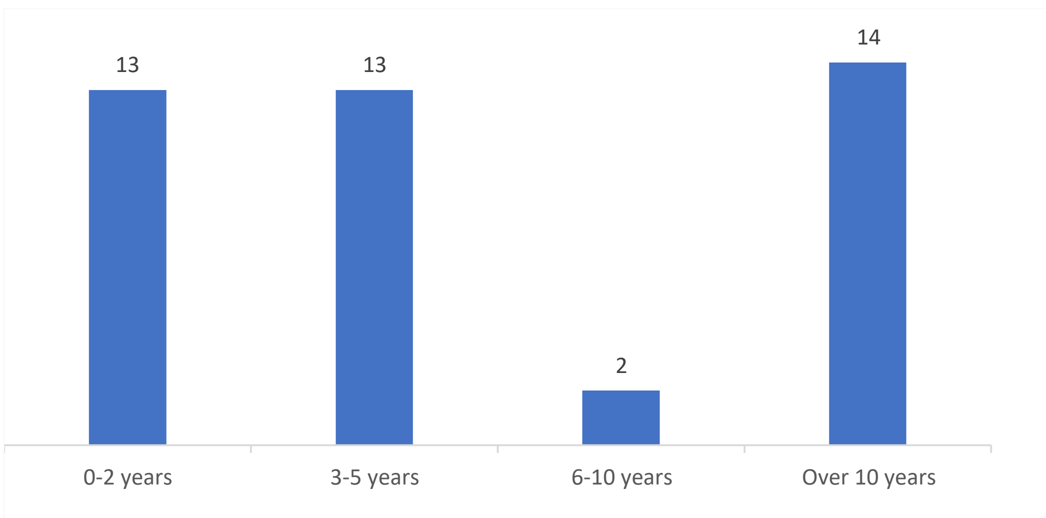

Figure 17: Years in Current Industry 4.0 Role

Following this question, Figure 18 represents the Industry 4.0 technologies participants have experience with, after selecting options from a pre-populated list.

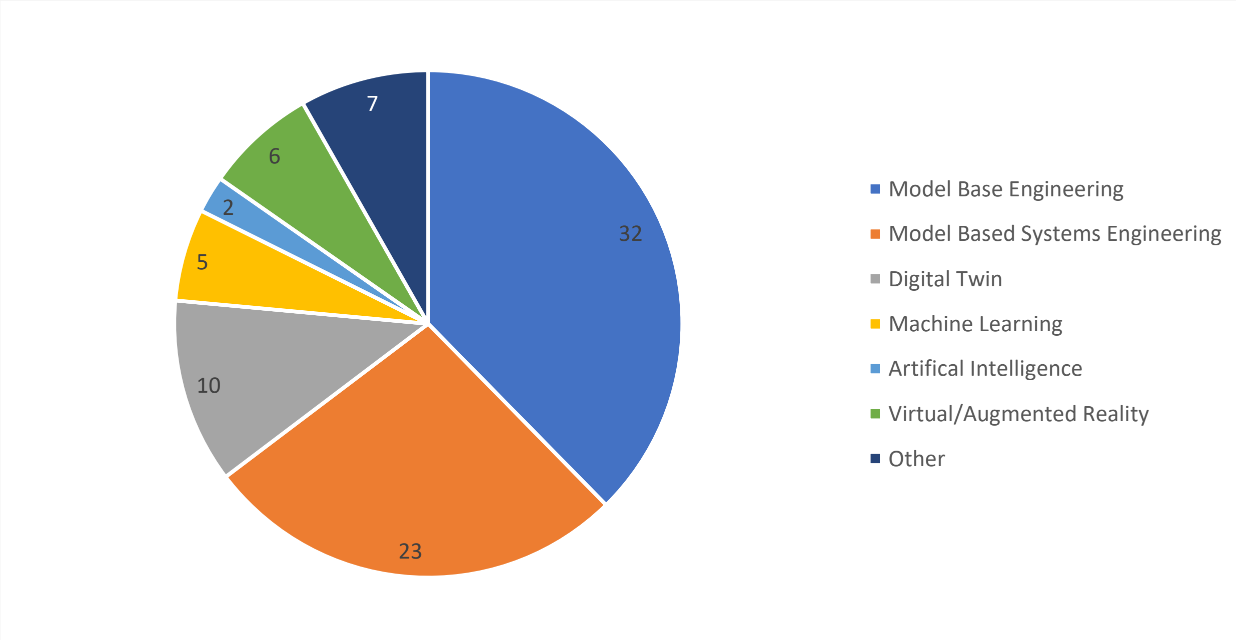

Figure 18: Survey Participant's Industry 4.0 Technologies

This question aimed to understand the different Industry 4.0 tools, applications, and processes currently in the A&D domain. MBSE and Model-Based Engineering (MBE) are the two most common applications, with Digital Twin, ML, AI, and Virtual/Augmented Reality also being included in the A&D Industry 4.0 tool suite. Seven of the respondents selected the "other" category, showing there are additional technologies being implemented. The literature reiterated the variety of Industry 4.0 technologies; therefore, this question was essential to give context to the results and detail the current technologies associated with A&D fields.

The time since the last implementation experience was questioned to ensure the responses were based on more recent experience and recollected accurately. Figure 19 summarizes these findings.

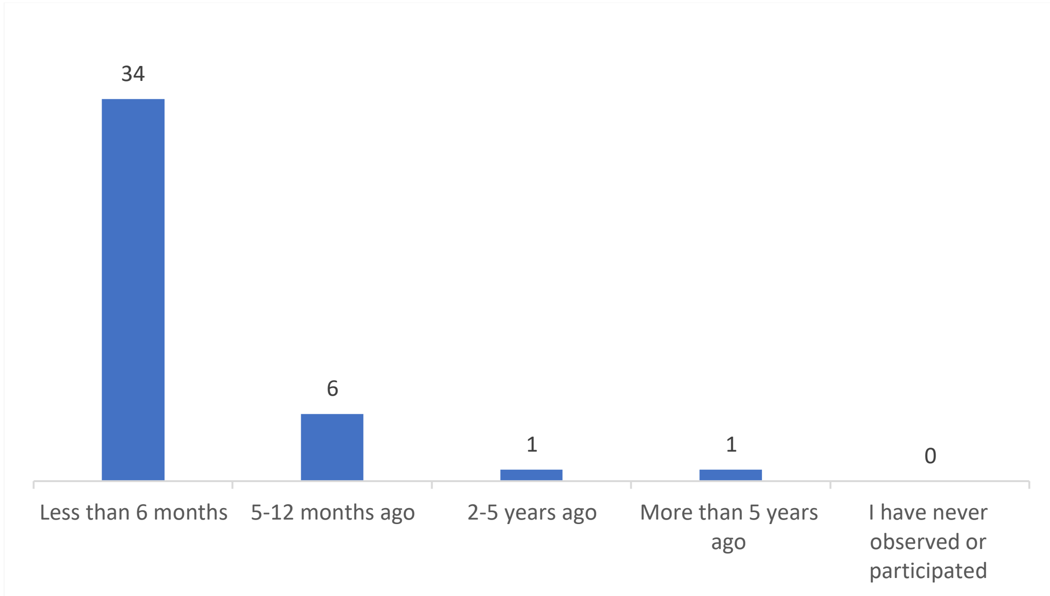

Figure 19: Time Since Last Implementation

Over 80% of respondents were involved with Industry 4.0 implementation within the last six months. This provides a positive indication of implementation activities being ongoing and increasing as these technologies become more prominent in A&D. This question was also used as exclusion criteria if participants had never observed or participated in implementation activities. The result for this option in Figure 19 shows zero, as a confirmation that the included data has correctly applied the exclusion criteria and the responses from these participants have been removed.

While a previous question was used to assess how long the participant has held their current Industry 4.0-related role, understanding the total years of experience beyond the respondent's current position is essential. Figure 20 represents the total years of experience each participant has with Industry 4.0 technologies.

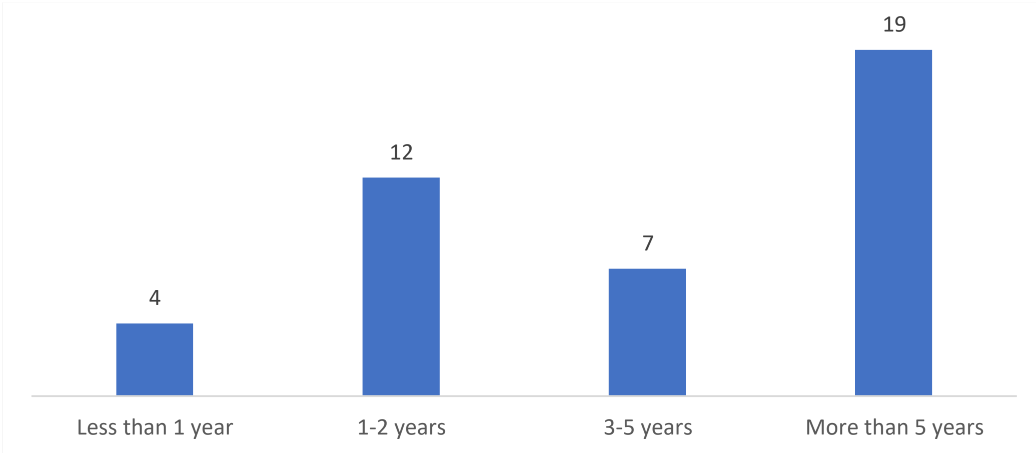

Figure 20: Total Years of Industry 4.0 Experience

Although most of the respondents have more than five years of experience with Industry 4.0 technologies, there is evidence of A&D contractors having less than one year of experience as well. This re-affirms the concept stated in the literature of Industry 4.0 concepts and advancements becoming more prevalent in the near term. Further, there are ongoing efforts to allow for continuous and quicker developments in the A&D domain through proper training and education. Later sections further explore these relationships and investigate whether those with greater experience state the importance of knowledge sharing to those with less Industry 4.0 experience and if this is a means to successful implementation.

The next question in the demographic portion of the survey asked participants to categorize the size of the organization which will be using the Industry 4.0 technologies.

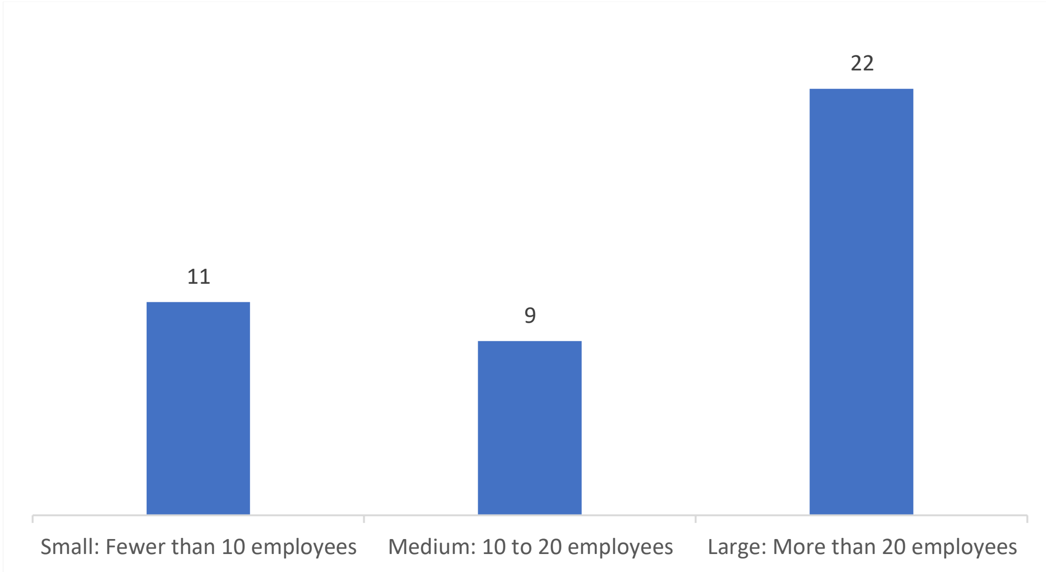

Figure 21: Size of Organization Using Industry 4.0

Figure 21 summarizes these results and aligns with the literature findings which state larger organizations more often use advanced systems and processes because of their enhanced structure and need for effectiveness. These structural factors, such as processes, procedures, governance, and strategic approach, are further explored in later sections to investigate if these have an important role in implementing Industry 4.0.

Figure 22 indicates the respondent's role (or roles) during implementation. The question aimed to understand if there are specific roles not represented in this study, which were discussed in the literature, as this could affect the representability of the sample.

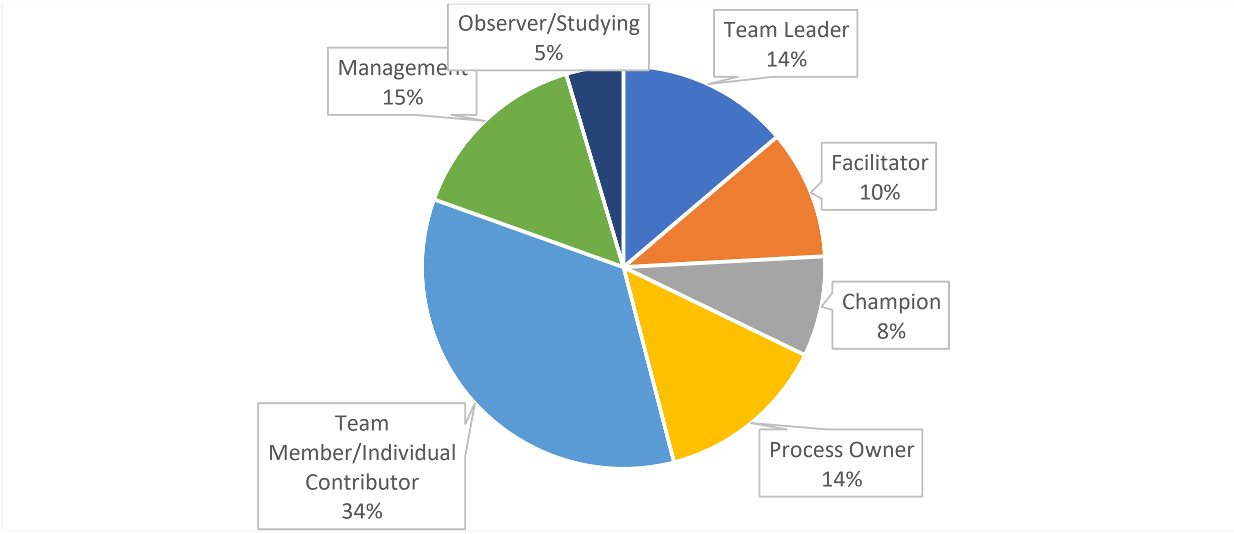

Figure 22: Role (or Roles) During Industry 4.0 Implementation

Most respondents reported their role in the implementation process as team members or individual contributors. Following this, 15% held management roles and 5% reported an observer or learner role, which indicates these professionals were not actively involved in the process. Similar to the findings in the literature, this question reiterated personnel can hold multiple roles during implementation efforts. Later sections further explore these relationships and investigate whether this result can be correlated with specific factors.

To gauge general levels of performance, Figure 23 represents the employee's perspective of their organizational performance, in terms of the ability to meet cost, schedule, and quality targets.

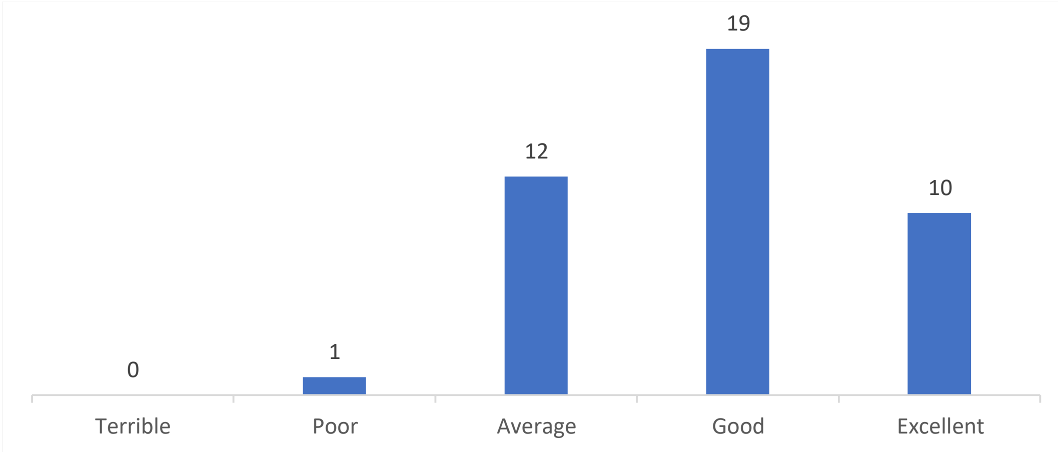

Figure 23: Organizational Performance Rating

The above 5-point Likert scale was used to understand the expert's perspective, with most respondents coding a "4" for "good" organization performance by the team and none indicating "terrible" performance. Because the literature states successful implementation of Industry 4.0 technologies should result in improved organizational performance and overall efficiencies, this question was used to provide a baseline and will be further investigated in later sections. The exploration will investigate if implementation can be connected to technical readiness or performance factors.

The final question in the demographic section asked respondents to use the 5-point Likert scale to assess the success of the overall implementation of Industry 4.0 in A&D. This question provided additional insight into the experiences of the survey respondents.

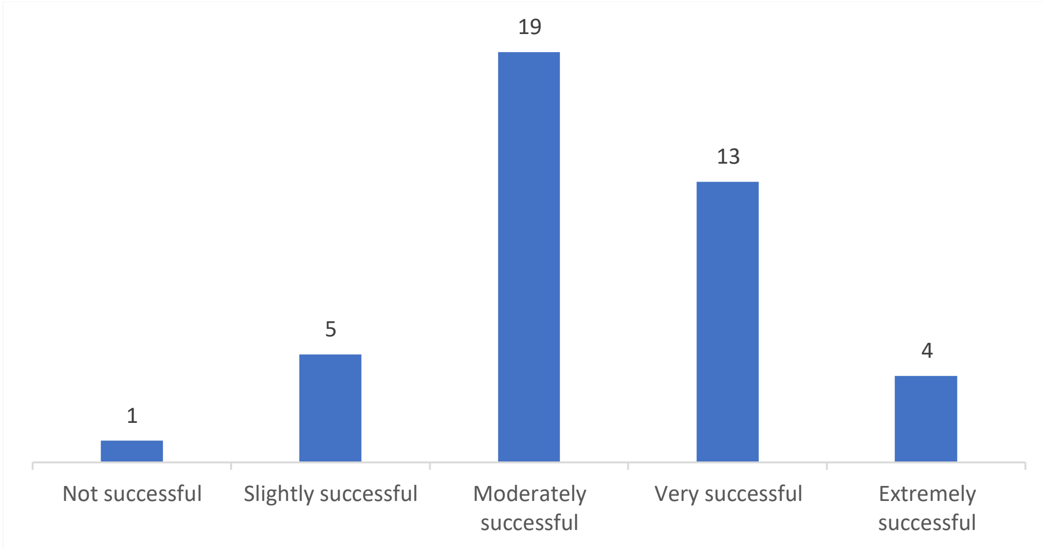

Figure 24: General Success Rating

The results show most respondents evaluate their implementation success as “moderately successful”. All but one participant stated experiencing a successful implementation at certain levels. Further evaluation of this rating is performed using Crosstabulation methods.

The Chi-square test and Crosstabulation were performed using six nominal background questions and compared with the overall Industry 4.0 success experience. Crosstabulation is used to provide insight into the two variables while the Chi-square test states whether the results from the Crosstabulation are statistically significant. To utilize this testing method, two assumptions were checked and validated. The assumptions include the two variables should be categorical and these variables should consist of two or more independent categorical groups (Statistics, 2020, 2021). Seven of the total nine demographic questions met this criterion and were used in this assessment, including the success question. Appendix C provides the full results for the Chi-square test and Crosstabulation performed using IBM SPSS Statistics 28 software package.

For the *current title of the participant*, 45% of the total sample stated implementation was “moderately successful” while 31% claimed it to be “very successful”. Of those in management positions, 20% said the effort was “not successful.” Compared with the other disciplines, personnel involved with automation or simulation processes more often rated the outcome as “extremely successful”. Although the Chi-Square test concluded there is no association between these two variables, the results suggest management is less satisfied with the outcome. This could stem from leadership having higher expectations of Industry 4.0 implementation due to the nature and visibility of their work.

For *years the participant has held their current Industry 4.0-related position*, most of the different levels varied between “very successful” and “moderately successful”. Of those with more than three years experience, 29% concluded the implementation activities were “extremely successful” while 7.7% of personnel with 0-2 years of experience claimed efforts were “not successful”. Although the Chi-Square test concluded there is no association between these two variables, the results suggest those with more experience are more optimistic. This could stem from this group having more background, involvement, and knowledge of Industry 4.0 and experience with its implementation.

Similar to this result, for the *time since the last implementation*, most respondents agreed the implementation was “moderately successful”, with 2.9% of respondents with less than six months since the last implementation disagreeing. The Chi-Square test concluded there is no association between these two variables and the results appear to parallel this result through 100% of the respondents who experienced implementation more than five years ago expressing similar degrees of success as those who have experienced implementation activities within the last six months.

Regarding the *years of experience with Industry 4.0 technology (or technologies*), for each experience level, the average response was “moderately successful” for Industry 4.0

implementation efforts. However, 8.3% of those with 1-2 years experience stated the effort was, "not successful". The results show higher acceptance (15.8%) of implementation success from those with five or more years experience who claimed "extremely successful" outcomes.

For the *size of the organization*, 100% of the small (less than 10 personnel) and medium (10-20 personnel) stated some level of success following implementation while 4.5% of the large organizations (more than 20 personnel) disagreed. However, 50% of the large organization claimed activities were "very successful" while only 18% of the small organization stated the same. This assessment aligns with the literature which states larger organizations tend to implement more successfully due to displaying more agility and greater drive. However, following these conflicting results and the conclusion from the Chi-Square test indicating there is an association between these two variables, more evidence is needed to determine which organization size implements Industry 4.0 more effectively.

Regarding the *performance rating for the organization*, 40% of those who rated the organizational performance as "excellent" also concluded the implementation of Industry 4.0 was "extremely successful". Disregarding specific levels of performance, most agreed implementation was "moderately successful" or "very successful". However, 100% of respondents who claimed "poor" performance also claimed "slightly successful" implementation activities. The Chi-Square test concluded there is an association between these two variables and the results appear to parallel this through higher performance ratings being indicative of implementation success. This correlation is echoed in the literature which states that organizational performance and operational efficiencies will improve following successful Industry 4.0 incorporation.

Summary of Demographic Questions

The first section of the questionnaire included nine questions used to understand the demographics of the survey participants. The follow-on demographic analysis provided significant information and insight into the survey sample by obtaining the following data: the position (or title) of the participant, years of experience, estimated size of the organization, their role in Industry 4.0 implementation, the specific Industry 4.0 technologies used, team performance, time of involvement, and the overall level of implementation success.

Further evaluation in the form of Chi-Square tests and Crosstabulation explored the environment of the participants and gave perspective to the responses provided. Crosstabulation was used to provide insight into the selected two variables while the Chi-square test states whether the results from the Crosstabulation were statistically significant. The Crosstabulation testing concluded statistically significant associations between general success and organizational performance, as well as an association between general success and the size of the organization.

Analysis of Factors

The initial ORM shown in Figure 15 provided a preliminary list of factors based on the studied papers. Figure 14 also detailed the implementation outcomes. This section uses the 42 usable questionnaire responses to refine these structures based on empirical evidence. Exploratory Factor Analysis (EFA) and CA approaches are used to refine the 12 preliminary factors into a final set of factors. This set of factors addresses Sub-RQ 3.

Exploratory Factor Analysis (EFA)

EFA allows for further exploration of the initial ORM through determining the inter-relationships among the factors included in the survey.

Confirmatory Factor Analysis (CFA) is a similar method that investigates latent patterns within data. However, CFA is used to test hypotheses of existing theories or concepts (Fawad, 2021). For these reasons, EFA was selected for this study to measure constructs and summarize the information contained within the large number of variables using a smaller number of factors. This approach can also develop new constructs based on the existing items when applicable. Because the variables, or survey questions, can be correlated to a lesser or greater extent, the EFA statistical procedure groups variables which have high correlations. The strongly correlated groups of variables represent an underlying theme or construct (Tabachnick & Fidell, 2013). Determining this relationship allows for model reduction and results in a smaller subset of factors which can be used to refine the ORM based on empirical data.

Six separate EFA models were developed based on the main categories of factors outlined in Figures 14 and 15. The use of separate models allows for a more effective EFA process and ensures adequate statistical power. Table 10 shows which items are included within each model.

Table 10: EFA Models

Model Number	Model	Factor	Number of Items
1	Management	Management Commitment	7
		Management Training	3
		Communication	10
2	Workforce	Employee Involvement	6
		Employee Acceptance	5
3	Resources	Resource Allocation	6
		Technical Readiness	5
4	Strategy	Strategic Approach	7
		Governance	5
5	Sustainment	Performance	6
		Processes and Procedures	3
		Training and Education	5
6	Outcomes	Performance	1
		Efficiency	1
		Processes and Procedures	1
		Stakeholder Satisfaction	1
		Quality	1
		Competitive Position	1
		Success	1

The EFA approach begins with problem formulation (Fawad, 2021). For this purpose, the focus is to use the selected list of variables from the questionnaire and convert these to a new set of factors based on common constructs. Next, the requirements of EFA were then defined to ensure compliance and adequacy of the approach. The following requirements and their acceptable values were noted:

1. The sample size should use the number of cases per variable approach (N:p) and follow the recommended range of 3:1 – 6:1 (Cattell, 2012).
2. The Kaiser-Meier-Olkin (KMO) Measure of Sampling Adequacy (MSA) is an index used to investigate the appropriateness of factor analysis. Kaiser & Rice (1974) presented the following range for factoring: 0.90’s (marvelous), 0.80’s (meritorious), 0.70’s (middling), 0.60’s (mediocre), 0.50’s (miserable), and items below 0.50 are deemed unacceptable.
3. Bartlett’s test should be significant to indicate the appropriateness of analyzing the factor matrix by ensuring the sample correlation matrix is significantly different from an identity matrix.
4. If communalities, or the amount of variance a variable shares with the total variables, is less than 0.3, there is concern about the variable being a misfit for the factor solution (Fawad, 2021). It is recommended to have a commonality above 0.4 (Thompson, 2004).
5. Multicollinearity, or when multiple independent variables are correlated within the dataset, is checked through the determinant. The value of the determinant must not be zero. Further, a high correlation value is not desired as this can indicate multicollinearity (Field, 2018).

6. Between 60-70% of the variance explained is the recommended range for the Total Variance (Fawad, 2021) included in the final solution.
7. The use of the Scree Plot, or the plot of the eigenvalues and factor number, should be used to accurately identify the number of factors accounting for the correlation amongst the variables. The resulting plot determines the optimum number of factors to be included in the final solution based on the descending trend of the eigenvalues (Fawad, 2021).
8. Rotation must be performed following the selection of factors to assist in the interpretation of the factor loadings. The intent is to maximize high loadings and minimize low loadings to achieve the optimum simple structure.
9. The model fit must be evaluated (Joliffe & Morgan, 1992). The assessment of the model fit is the final stage of the EFA process.

The EFA was performed on the six independent models using IBM SPSS Statistics 28 software and followed the Principal Component Analysis (PCA) technique. PCA assumes the total variance is equal to the common variance between the items and aids in reducing the initial set of variables (Fawad, 2021). This extraction method was chosen as it simplifies complex data while also retaining the patterns or trends. Exploratory runs of the analysis using PCA were performed to confirm this is the preferred approach for the data. In addition, the factor rotation process, which optimizes the factor solution, used the oblique rotation (oblimin) rather than the orthogonal method. Following the findings in the literature, oblique rotations are more suitable as this approach assumes there are correlations between the factors (Thompson, 2004) and often provides a simpler factor structure.

Discriminate validity refers to the distinction of factors, where between groups, the correlation should be low and within groups, the variables should be highly correlated. The resulting pattern matrix from the oblimin rotation was used to confirm this validity (Thompson, 2004) and helped in determining which items to retain in the model. Specific to factor loading, it is recommended to use 0.40 as the cut-off value (Huarng et al., 1999). This value was then used within the pattern matrix, which includes the rotated solution, for the assignment of factors.

The EFA used the PCA extraction method and oblimin rotation on all six models. The minimum factor loading was set to a value of 0.40. All six models satisfied the sample size range recommendation and met the 3:1 minimum requirement. The models also had a KMO MSA greater than 0.60, which indicated the matrix is deemed acceptable for factoring. Statistically significant Bartlett's tests, which indicate the correlation matrix has significant correlations amongst some of its components, were evident in all the EFA models. The communalities of all the items within each model were above the threshold of 0.30 and multicollinearity was met by each model having a non-zero determinant. The following sections report the results from the EFA for each model; the complete output values can be found in Appendix D.

Model 1: The items in this model belonged to the following main groups: *Management Commitment, Management Training,* and *Communication* factors. The solution yielded two emergent factors, which accounted for 67% of the variation in the data. Exceeding the recommended minimum threshold of 60% indicates the strong correlation of items within each emergent factor. Examining the pattern matrix (Appendix D), most of the original managerial items were loaded on factor one, and most of the original communication items were loaded on factor two. However, two original communication items, COM1 and COM9 were loaded onto factor one. These items are associated with communication between and from management and were found to load onto factor one following the oblimin rotation. One item, MC3, was cross loaded on both factors. This item described management using tools to motivate and engage the team. Costello & Osborne (2005) recommend removing cross-loaded items if there are more strong loaders, at 0.50 or above, on other items; Thompson (2004) recommended removing if cross-loadings are above 0.30; and Matsunaga (2010) recommended removing cross-loaded items which had minimal differences (less than 0.30). Following these recommendations, MC3 was removed and an additional EFA and reliability assessment was performed to assess model fit. The table showing reproduced correlations confirmed there is an adequate model fit as there are less than 50% of nonredundant residuals with absolute values greater than 0.05.

The two emergent factors identified from the EFA were named, *Management* and *Culture*¸ respectively. Factor 1 (*Management)* includes 11 items: MC1, MC2, MC4 through MC6, MT1 through MT3, COM1, and COM9. These items relate to management and their role in implementation. Factor 2 (*Communication)* includes eight items: COM2 through COM8, and COM10. These items reference communication across organizations, with stakeholders, and within internal teams. The final EFA for Model 1 can be found in Appendix D.

Model 2: The items in this model belonged to the following main groups: *Employee Involvement* and *Employee Acceptance* factors. The solution yielded three emergent factors, which accounted for 72% of the variation in the data. Exceeding the recommended minimum threshold of 60% indicates the strong correlation of items within each emergent factor. Examining the pattern matrix (Appendix D.2), three emergent factors were identified from the EFA. The first emergent factor includes six items: EI1, EI3 through EI5, EA1, and EA3. The second emergent factor includes three items: EA2, EA4, and EA5. The third emergent factor includes two items: EI2 and EI6. However, three is the minimum number of items recommended for each construct (Watkins, 2018). The Scree Plot confirms this position of including the optimum number of factors based on the descending trend of the eigenvalues. Therefore, an additional EFA was performed to generate a two-factor solution. The communalities table was viewed to remove items with values less than 0.40, as there is a concern about this variable being a misfit for the factor solution; EI2 and EA6 were removed. Another EFA was conducted and confirmed the two-factor solution accounts for 67% of the variation in the data. The same item, EA1, from the initial Model 2 EFA was cross loaded between the two factors. This item speaks to employees understanding their new work scope once implementation is complete. Costello & Osborne (2005) recommend removing cross-loaded items if there are more strong loaders, at 0.50 or above, on other items; Thompson (2004) recommended removing if cross-loadings are above 0.30; and Matsunaga (2010) recommended removing cross-loaded items which had minimal differences (less than 0.30). Following of these recommendations, EA1 was removed and an additional EFA and reliability assessment was performed to assess model fit. The table showing reproduced correlations confirmed there is adequate model fit as there are 60% of nonredundant residuals with absolute values greater than 0.05.

The two-factor solution is similar to the initial ORM and includes Factor 3 (*Workforce Involvement)* includes five items: EI1, EI3, EI4, EI5, and EA3. These items relate to employees being aware of their roles and involved in implementation activities. Factor 2 (*Workforce Acceptance)* includes three items: EA2, E4, and EA5. These items reference employee adoption of Industry 4.0 processes and satisfaction with technologies. The final EFA for Model 2 can be found in Appendix D.2.

Model 3: The items in this model belonged to the following main groups: *Resources Allocation* and *Technical Readiness* factors. The solution yielded three emergent factors, which accounted for 72% of the variation in the data. Exceeding the recommended minimum threshold of 60% indicates the strong correlation of items within each emergent factor. Examining the pattern matrix (Appendix D.3), two items loaded in the seventh factor. However, three is the minimum number of items recommended for each construct (Watkins, 2018). The Scree Plot confirms this position of including the optimum number of factors based on the descending trend of the eigenvalues. Therefore, an additional EFA was performed to generate a two-factor solution. The communalities table was then viewed to remove items with values less than 0.40, as there is concern of this variable being a misfit for the factor solution; TECH1 and TECH2 were removed.

Another EFA was conducted and confirmed the two-factor solution accounts for 65% of the variation in the data. However, the following three items were cross loaded onto both factors: RE1, RE3, and RE4. These items pertain to having sufficient resources, adequate staffing, and appropriate time to perform tasks during implementation. Because the cross-loading for RE4 differed by more than 0.20 (Matsunaga, 2010), this item was retained. However, because of the minimal difference between the primary and secondary loadings for RE1 and RE3, these items were removed (Matsunaga, 2010). This iterative process was repeated with running an additional EFA and resulted with 72% of variation being explained by the two-factor solution. The model fit was verified as there are less than 50% of the nonredundant residuals, with absolute values greater than 0.05. The final EFA for Model 3 can be found in Appendix D.3.

The two-factor solution is similar to the initial ORM and includes Factor 5 (*Resources*) includes four items: RE2, RE4, RE5, and RE6. These items discuss having adequate funding, resources, time, and leadership support for implementation purposes. Factor 6 (*Technology*

Readiness) includes three items: TECH3, TECH4, and TECH5. These items reference technical and system compatibility prior to conducting transformation activities.

Model 4: The items in this model belonged to the following main groups: *Strategy* and *Governance* factors. Examining the rotated solution in the pattern matrix (Appendix D.4), three emergent factors were identified from the EFA. One item, STRAT5, did not populate in the matrix due to the low factor loading; this item was removed before conducting another EFA. Following this, the resulting Scree Plot confirms this position of including two-factor number based on the descending trend of the eigenvalues. Therefore, an additional EFA was performed to generate a two-factor solution. The communalities table was viewed to remove items with values less than 0.40; for this reason, STRAT1 was removed. An additional item, STRAT3, was also removed for cross-loading across two factors. Costello & Osborne (2005) recommend removing cross-loaded items if there are more strong loaders, at 0.50 or above, on other items; Thompson (2004) recommended removing if cross-loadings are above 0.30; and Matsunaga (2010) recommended removing cross-loaded items which had minimal differences (less than 0.30). Following of these recommendations, STRAT3 was removed and an additional EFA was performed. The resulting two-factor solution accounts for 61% of the variation in the data. Exceeding the recommended minimum threshold of 60% indicates the strong correlation of items within each factor.

However, observing the Scree Plot (Appendix D.4) confirms the position of including a single factor based on the descending trend of the eigenvalues. The table of eigenvalues further reiterates this visualization through showing an eigenvalue of 4.206 for component 1 and 0.952 for component to. This large difference, and because component 2 did not have an eigenvalue greater than 1, this was cause to explore an EFA with a one-factor solution. The resulting one-factor solution accounted for the same total variation, of 61%, as the two-factor solution and a higher KMO value than the initial three-factor solution. This provided additional quantitative support to use the one-factor solution.

The one-factor solution includes Factor 7 (*Documentation & Governance)* includes seven items: STRAT2, STRAT4, GOV1 through GOV5. These items relate to documentation, such as strategic plan, policies, and guidelines during and following implementation. The final EFA for Model 4 can be found in Appendix D.4.

Model 5: The items in this model belonged to the following main groups: *Performance, Processes and Procedures,* and *Training and Education* factors. The solution yielded three emergent factors, which accounted for 77.86% of the variation in the data. Exceeding the recommended minimum threshold of 60% indicates the strong correlation of items within each emergent factor. Examining the pattern matrix (Appendix D.5), four emergent factors were identified from the EFA. Two items, PER4 and PER5, were cross loaded across two factors. Costello & Osborne (2005) recommend removing cross-loaded items if there are more strong loaders, at 0.50 or above, on other items; Thompson (2004) recommended removing if cross-loadings are above 0.30; and Matsunaga (2010) recommended removing cross-loaded items which had minimal differences (less than 0.30). Following of these recommendations, PER4 and PER 5 were removed and an additional EFA was performed. The resulting Scree Plot confirms this position of including the three-factors number based on the descending trend of the eigenvalues. Therefore, an additional EFA was performed to generate a three-factor solution. The communalities table was viewed to remove items with values less than 0.40 and an additional two items, TR4 and TR6, were removed for cross-loading across two factors. Another EFA was conducted and confirmed the resulting three-factor solution accounts for 79.42% of the variation in the data. The table showing reproduced correlations confirmed there is adequate model fit as there are 50% of nonredundant residuals with absolute values greater than 0.05.

The three-factor solution is similar to the initial ORM and includes Factor 8 (*Organizational Performance)* includes five items: PER1, PER2, PER3, PER6, and PER7. These items relate to obtaining performance data and pursuing CI efforts. Factor 8 (*Education & Knowledge)* includes three items: TR1 through TR3. These items reference knowledge and education efforts associated with Industry 4.0 technologies. Factor 10 (*Processes & Procedures)* includes three items: PRO1 through PRO3. These items all had a negative factor loading as these constructs are worded in past-tense to confirm processes were identified, evaluated, and updated prior to implementing Industry 4.0 The final EFA for Model 5 can be found in Appendix D.5.

Model 6: The following items in this model belonged to the *Outcome* group: Performance, Efficiency, Processes and Procedures, Stakeholder Satisfaction, Quality, Competitive Position, and Success. By examining the pattern matrix (Appendix D.6), all of the items loaded significantly onto one factor, accounting for 75.11% of the variation in the data. and exceeding the recommended minimum threshold of 60%. This indicates the strong correlation of items within the single emergent factor and confirms the preliminary design through retaining the original structure of this factor. The loading minimum threshold of 0.40 was also satisfied, which confirms the seven items within this single factor are highly correlated.

The result of the EFA models were used to refine the initial ORM and further align with the literature review and the outcomes from the questionnaire. Although EFA is an iterative process, the remaining items correlate with the resulting factor. This indicates these items have a strong influence on the factor. Compared to the initial ORM in Figure 15, the resulting factors and their respective items have been refined. Some of the items have been removed or moved to another factor based on the EFA. The EFA results are summarized in Figure 25. Each factor has at minimum three items, which complies with Thurstone's recommendation for EFA (Andrich, 1978).

Model	Emergent Factor	Items									
1	Factor 1: Management	MC1	MC2	MC4	MC5	MC6	MT1	MT2	MT3	COM1	COM9
	Factor 2: Communication	COM2	COM3	COM4	COM5	COM6	COM7	COM8	COM10		
2	Factor 3: Workforce Involvement	EI1	EI3	EI4	EI5	EA3					
	Factor 4: Workforce Acceptance	EA2	EA4	EA5							
3	Factor 5: Resource Allocation	RE2	RE4	RE5	RE6						
	Factor 6: Technical Readiness	TECH3	TECH4	TECH5							
4	Factor 7: Documentation & Governance	STRAT2	STRAT4	GOV1	GOV2	GOV3	GOV4	GOV5			
5	Factor 8: Organizational Performance	PER1	PER2	PER3	PER6	PER7					
	Factor 9: Education & Knowledge	TR1	TR2	TR3							
	Factor 10: Processes & Procedures	PRO1	PRO2	PRO3							
6	Outcome	OUT1	OUT2	OUT3	OUT4	OUT5	OUT6	OUT7			

Figure 25: Emergent Factors and Items from EFA

Reliability Test

EFA is considered an interpretive and iterative approach, however, the reliability results are used to help with the final determination of which emergent factors should be retained. A reliability test was conducted by calculating CA using the conducted IBM SPSS Statistics 28 software package. For this study, the ideal alpha value for the respondent is at or above 0.70. The results are shown in Table 9 and used to answer Sub RQ 3.

Table 11: Reliability Analysis on Emergent Factors

Factor	**CA**
Management	0.951
Communication	0.906
Workforce Involvement	0.856
Workforce Acceptance	0.759*
Resource Allocation	0.837
Technical Readiness	0.816
Documentation & Governance	0.886
Organizational Performance	0.925
Governance	0.866
Education & Knowledge	0.791
Processes and Procedures	0.880
Outcomes	0.944

All factors, including the dependent variable (*Outcome*), resulted in an alpha value above the threshold of 0.7, indicating adequate reliability. Prior to conducting the EFA and refining the model, the Technical Readiness factor, was considered to have "poor" reliability because of having an alpha value between 0.50 and 0.60. The increased reliability confirms the valid refinement of the framework.

All factors were checked for improving the reliability scores through deletion of items. Four factors had increased alpha values when the following items were removed: EA5 within the *Workforce Acceptance* factor, TR1 from the *Education & Knowledge* factor, PRO3 from *Processes and Procedures*, and OUT4 from the *Outcome* factor. The updates can be considered substantial as, for example, the *Processes and Procedures* factor changed internal consistency from “good” to “excellent”. The results show there is high strength in the consistency measure for each concept. These updates are shown below in Figure 26 alongside the improved CA score.

Emergent Factor	Items										CA
Factor 1: Management	MC1	MC2	MC4	MC5	MC6	MT1	MT2	MT3	COM1	COM9	0.951
Factor 2: Communication	COM2	COM3	COM4	COM5	COM6	COM7	COM8	COM10			0.906
Factor 3: Workforce Involvement	EI1	EI3	EI4	EA3							0.856
Factor 4: Workforce Acceptance	EA2	EA4	EA5								0.779
Factor 5: Resource Allocation	RE2	RE4	RE5	RE6							0.837
Factor 6: Technical Readiness	TECH3	TECH4	TECH5								0.816
Factor 7: Documentation & Governance	STRAT2	STRAT4	GOV1	GOV2	GOV3	GOV4	GOV5				0.886
Factor 8: Organizational Performance	PER1	PER2	PER3	PER6	PER7						0.925
Factor 9: Education & Knowledge	TR2	TR3									0.866
Factor 10: Processes & Procedures	PRO1	PRO2									0.879
Outcome	OUT1	OUT2	OUT3	OUT5	OUT6	OUT7					0.901

Figure 26: Emergent Factors and Items Following EFA and Reliability Test

The EFA results and follow-on Reliability calculation addressed Sub RQ 3, which relates to the most significant factors for successful implementation of Industry 4.0 in A&D industries.

The assessments revealed 10 factors among the preliminary 12 variables and one outcome among the various dimensions of implementation success shown in Figure 14. The next section addresses Sub RQ 4 through exploration of the relationships between the final variables summarized in Figure 26.

Analysis of Relationships

The relationship between the factors was analyzed to find which factors are the most significant and influential to implementation outcomes. The following subsections discuss the results of the investigation, with the raw export of the analysis found in Appendix E.

Bivariate Correlation Analysis

Using Pearson's correlation metric (r), the association among the 10 variables was explored. The results are shown in Table 12.

Table 12: Correlation Analysis

Factor	1	2	3	4	5	6	7	8	9	10	Outcome
Factor 1: Mgmt	1	.673**	.543**	.551**	.498**	.413**	.601**	.585**	.410**	.434**	.529**
Factor 2: Comms	.673**	1	.699**	.504**	.502**	.383*	.594**	.523**	.362*	.577**	.580**
Factor 3: Workforce Inv	.543**	.699**	1	.327*	.592**	0.222	.420**	.541**	0.153	.393*	.528**
Factor 4: Workforce Acc	.551**	.504**	.327*	1	.366*	.593**	.700**	.529**	0.219	.645**	.442**
Factor 5: Resource	.498**	.502**	.592**	.366*	1	.377*	.489**	.347*	.482**	.422**	.315*
Factor 6: Tech	.413**	.383*	0.222	.593**	.377*	1	.599**	.491**	.332*	.601**	.385*
Factor 7: Doc&Gov	.601**	.594**	.420**	.700**	.489**	.599**	1	.667**	.431**	.822**	.764**
Factor 8: Performance	.585**	.523**	.541**	.529**	.347*	.491**	.667**	1	0.276	.541**	.652**
Factor 9: Ed&Knowledge	.410**	.362*	0.153	0.219	.482**	.332*	.431**	0.276	1	.360*	0.282
Factor 10: Process	.434**	.577**	.393*	.645**	.422**	.601**	.822**	.541**	.360*	1	.730**
Outcome	.529**	.580**	.528**	.442**	.315*	.385*	.764**	.652**	0.282	.730**	1
** Correlation is significant at the 0.01 level (2-tailed).											
* Correlation is significant at the 0.05 level (2-tailed).											

The results demonstrate almost all the correlations are statistically significant, with most being significant at the 0.01 level. Of the 10 factors, nine have statistically significant correlations with the implementation outcome. However, *Education & Knowledge* was found to not have a significant correlation with *Outcome* at the 0.01 or 0.05 level. Seven of the nine correlations were statistically significant at the $p < 0.01$ level, which also indicates strong criterion-related validity. Low positive correlations are shown between the *Outcome* and with the *Resources Allocation, Workforce Acceptance,* and *Technical Readiness* factors; moderate and positive correlations exist between the *Outcome* and with the *Management, Communication, Workforce Involvement,* and *Organizational Performance* factors; and high positive correlations are shown between the *Outcome* and with the *Documentation & Governance* and *Processes & Procedures* factors (Mosadeghrad, 2015). These results show specific factors have a stronger relationship with the outcome of implementation and suggest these can be considered critical for success.

The *Outcome* and the questionnaire item which addressed the general success of implementation were also analyzed. The result of this bivariate correlation is shown in Figure 27.

Correlations

		Success	Outcome
Success	Pearson Correlation	1	.420**
	Sig. (2-tailed)		.006
	N	42	42
Outcome	Pearson Correlation	.420**	1
	Sig. (2-tailed)	.006	
	N	42	42

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 27: General Success vs. Final Outcome

The results show the outcome of Industry 4.0 implementation, and the overall success of implementation are statistically significant at the $p < 0.01$ level. This parallels the previous Chi-

Square test which concluded there is an association between these two variables and the demographic analysis showed higher organizational performance ratings being indicative of implementation success.

In addition, the strength of this correlation is 0.42. This indicates achieving successful implementation of Industry 4.0 in A&D environments has a low correlation with achieving the outcomes. Although there is a correlation between these two constructs, the low strength may result from the respondent's viewing success differently or perceiving success as achieving more than the defined outcomes. However, this result aligns with the findings in the literature that implementation of Industry 4.0 requires motive, in the form of achievement, to support continued acceptance of the advanced systems.

Correlation and regression are considered valid methods to investigate relationships between variables. Because of this, the next section focuses on correlation amongst variables. Following this, regression testing is performed to compare results with the correlation analysis and confirm the final set of CSFs.

Interrelationships Amongst Factors

Further inspection of the correlation table (Table 12) was used to address Sub RQ 4 and reiterated the overall assertion of multiple positive inter-relationships existing amongst most of the factors, with some having stronger relationships than others. However, there are few correlations which were found to be not statistically significant at the 0.01 or the 0.05 level. For example, the *Technical Readiness* and *Workforce Involvement* factors do not have a significant correlation. The literature affirms this through stating if the new systems are unable to replace all required capabilities of the current systems, there will not be successful integration of Industry

4.0 solutions (Masood & Egger, 2019). This responsibility of ensuring proper technical and system configuration is often initiated by management rather than the workforce. In addition, Masood & Egger (2019) reiterated that leadership plays a pivotal role in innovation, through highlighting the importance of transformation and ensuring overall readiness to transform.

The lack of significant correlation is also true for the following factors and their relationship with *Education & Knowledge*: *Workforce Involvement, Performance,* and *Workforce Acceptance.* Employee involvement begins with the identification of the Industry 4.0 solution, followed by recognition of the humans within this system and their respective task scenarios. This correlation result, of the *Education and Knowledge* factor having either non-significant correlations or weak (less than 0.450) significant correlations amongst the remaining nine factors, contradicts the findings in the literature. Previous research suggested that encouraging employee involvement and increasing organizational performance through proper knowledge and training are vital Pozzi et al. (2020). Further, multiple case studies stated success was found in organizations that focused on knowledge gaps and established training activities (Sony & Naik, 2020). However, there is some alignment with the literature which concluded the *Workforce Involvement* factor is more correlated with *Workforce Acceptance,* rather than *Education & Knowledge*, as involvement from the human dimension is essential for optimization, safe implementation, and employee acceptance Neumann et al. (2021).

On the other hand, the *Documentation & Governance* and *Processes & Procedures* factors were found to have a strong, statistically significant correlation based on the correlation metric of 0.822. The literature states successful implementation begins with identification of processes or business practices that need to be improved, followed by analyzing the process to understand key metrics, such as performance indicators or associated risks. From there, the change can be acknowledged, and the Industry 4.0 technologies can be included to streamline or enhance the business process, product, or service (Butt, 2020). These updates should be documented in a clear strategic approach through unified governance. Examples of governance include designing and implementing Industry 4.0 solutions based on established standards, policies that require a common language across all components to allow for effective information exchange, and the incorporation of a globally accepted security assessment. Whether generated or modified, "standardization is the key to the connected world" (Villagran et al., 2019) and is required for implementation to ensure interoperability, uniformity, and compliance across all developers and users.

In addition, *Workforce Acceptance* and *Documentation & Governance* are also strongly correlated at the 0.01 level. This result was also found in the literature as updated documentation and guidance provides the workforce with clear instructions on performing required responsibilities. Furthermore, standardization and documentation allow for unified processes and clear expectations of personnel (Papke et al., 2019), which can promote smoother implementation of advancing tools.

The following factors all had significant correlations with the remaining nine factors: *Management, Processes & Procedures, Communications, Resource Allocation,* and *Documentation & Governance.* This finding indicates how each of these constructs can be applied to, or included in, the others. For example, *Management* can dictate the available resources through over-seeing funding and can monitor performance through tracking metrics. *Processes & Procedures* influence workforce acceptance through involvement of personnel in the updating processes. *Communications* address requirements and expectations, such as those associated with training or knowledge areas. *Resource Allocation* incorporates items such as technical readiness and confirmation of having a skilled workforce. *Documentation & Governance* can include recording updated processes or required communication efforts.

This investigation provides additional insight into which factors are correlated and central to others. These results will be used alongside the regression results to confirm which factors are essential for successful implementation of Industry 4.0 in A&D.

Assumptions of Regression Modeling

Multiple linear regression was used to assess the connection between the 10 factors and the outcome of implementation. These emergent factors, or predictor variables, from the EFA and Reliability assessment are used to conduct this predictive analysis and investigate the relationship between the independent factors and the outcome variable. To use this approach, multiple assumptions were investigated to ensure the fit and validity of the model, including linearity of the data, homoscedasticity, normality of residuals, independence of observations, influential value, and multicollinearity (Cohen et al., 2013).

The linearity assumption is verified using the P-P Plot, shown in Figure 28.

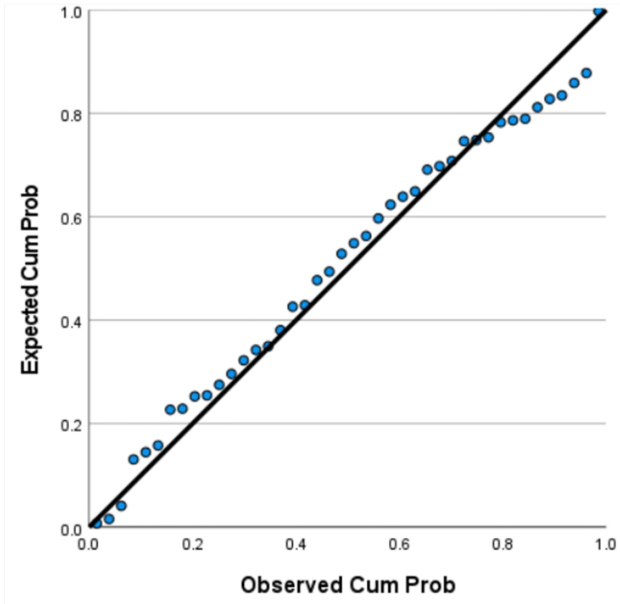

Figure 28: P-Plot for Linearity

The best-fitting straight regression line is a visual test used confirm a linear model (Gareth et al., 2013). Because most of the points on the plot near the reference line, this suggests a linear relationship between the factors and the outcome variable. This was also confirmed using the scatterplot of residuals (Appendix F).

This assumption of homoscedasticity was confirmed through generating a spread-location plot (Bruce et al., 2020). If the plot shows a horizontal line with equal spread of points, there is good indication of the variance of residuals can be considered equal. This plot, seen in Figure 29, provides somewhat equal spread across the line of best fit.

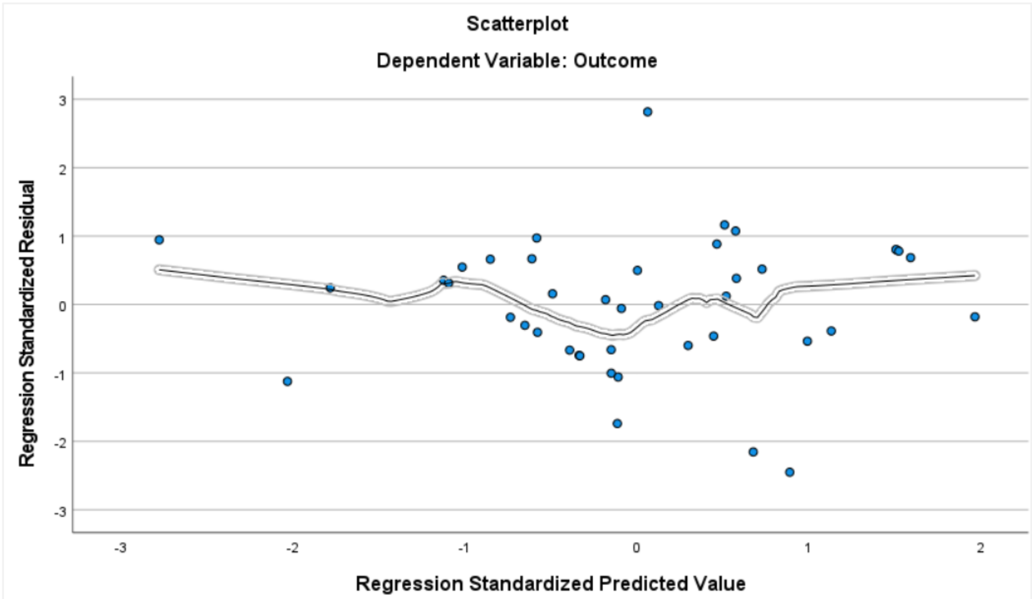

Figure 29: Plot for Homoscedasticity

Although the reference line is not strictly horizontal, the variances of the residuals can be considered stable compared with the value of the fitted outcome variable, and therefore the assumption is met. The Bartlett's test performed during the EFA also confirms this result.

The normality assumption was confirmed using the standardized and unstandardized residual plots. The Q-Q Plot of the standardized results is shown in Figure 30.

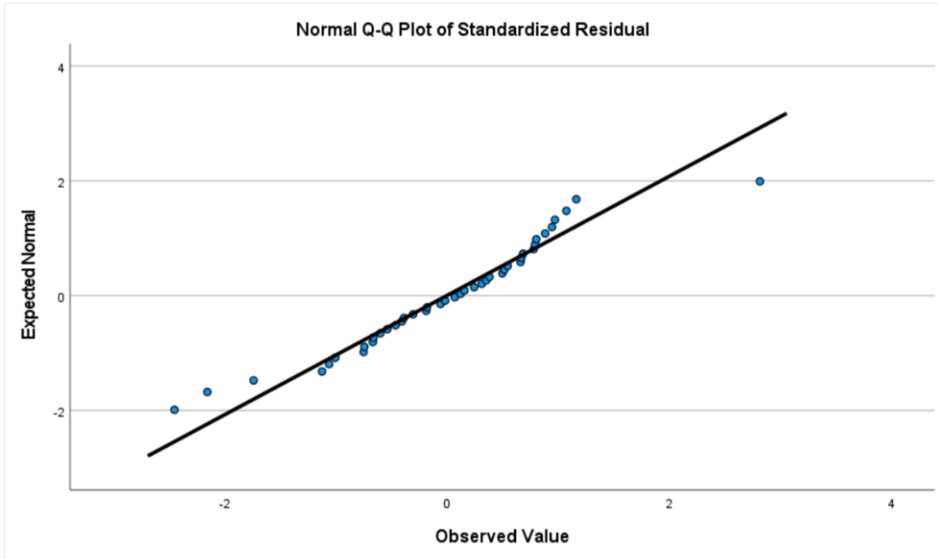

Figure 30: Q-Q Plot of Residuals

Because most of the points on the plot fall on the reference line, normality of residuals is assumed. This was reaffirmed after conducting the Shapiro-Wilk test and the histogram plot of residuals (Appendix F). The p-value for the Shapiro-Wilk Test, for both the standardized and unstandardized residuals, was 0.158. Since this value exceeds 0.05, and because of the bell-curve depicted in the histogram, the normality of residuals is confirmed.

Cook's distance was used to determine influential values. Values are considered influential if a data point is exceeding a value of 1.0 (PennState, 2018) or if the value exceeds 4/n, where "n" denotes the total number of data points (Statistics 2020). Data points exceeding 0.50 are considered worthy of further investigation prior to categorizing it as influential (PennState, 2018). IBM SPSS Statistics 28 was used to calculate Cook's distance and resulted in a maximum value of 0.167. Although this value is less than 1.0, it does exceed 0.095, which was calculated using the provided formula. A plot of Cook's distances is shown in Figure 31.

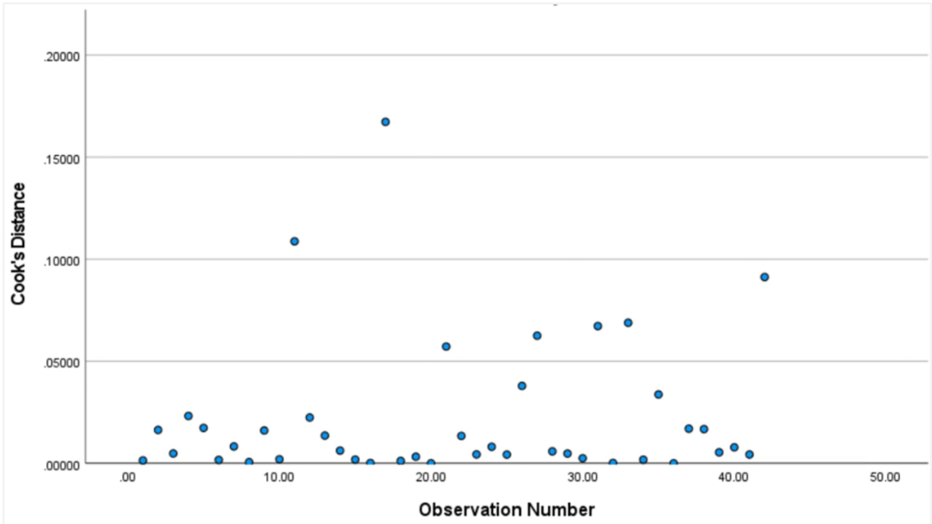

Figure 31: Cook's Distance Plot

This plot shows the model has two potential influential values if following the rule to not exceed 0.095. However, because these data points do not exceed 0.50, these data points are not classified as being influential (PennState, 2018).

The multicollinearity assumption was verified through the correlation matrix in Table 12. This table shows the factors, or predictors, are not highly linearly related to one another. Although only one pair of variables had a correlation slightly above the 0.80 threshold (Statistics, 2019), the remaining variables have no correlation of 0.80 or higher.

These above assumptions are essential to ensure the model is fit for regression. The next section uses multiple linear regression to investigate which of the final emergent factors directly impacts the final outcome variable.

Regression Modeling

The multiple linear regression model includes the ten emergent factors from the EFA and Reliability assessment, which are considered predictor variables, as well as the single outcome variable. The stepwise method was used to refine the model through selection of the best predictor variables. The complete results are found in Appendix G with summarized results provided in Table 13.

Table 13: Summarized Regression Results

Model	R^2	0.677
	ADJ R^2	0.652
	Durbin-Watson	1.774
ANOVA	F	26.659
	Sig	< 0.001

The resulting model fit indices were well met with an R^2 value of 0.677. This shows when all ten factors are taken as a set, these account for 68% of the variance in the outcome variable. However, the Adjusted R^2 value is considered a better reference when using a smaller sample size as it reflects the goodness of fit of the model to the population while considering sample size and the number of predictors. The Adjusted R^2 value of 0.652 is considered to be slightly less than substantial (Henseler et al., 2009) and indicates 65% of the variance is explained by the factors.

Using the ANOVA table (Appendix G) and referencing the significance value of less than 0.001, there is confirmation of the predictors accounting for a significant amount of variance. Further, because the F-statistic was found to be significant, there is minimal probability of having a zero-regression coefficient. This reiterates the fitness of the model and the model being significant. The independence of observations assumption was confirmed through the

Durbin-Watson metric of 1.774, which falls between the acceptable range of 1.50 and 2.50 (Statistics, 2019).

Using a p-value of < 0.05, or 95% confidence, the stepwise regression shows three final factors have a direct influence on the outcome variable. The factors are Factor 3 (*Workforce Involvement*)¸Factor 5 (*Resource Allocation*), and Factor 7 (*Documentation & Governance*). The full results for the regression model are provided in Appendix G.

The three resulting CSFs from the regression mode align with the correlation matrix in terms of having significant associations. Factor 7 (*Documentation & Governance*) had the strongest positive correlation, followed by Factor 5 (*Resource Allocation*) with a moderate positive correlation, and Factor 3 (*Workforce Involvement*) has a weak positive correlation with the outcome variable.

Summary of Results

The correlation and regression assessments revealed interaction amongst emergent factors is essential and highlighted the three CSFs for positive implementation of Industry 4.0 in A&D settings: *Documentation & Governance, Resource Allocation,* and *Workforce Involvement*. These factors reiterated embedding documented strategic guidance for implementation, ethical standards, and updated uniform policies across all organizations is crucial. Further, ensuring resources such as funding for required items and adequate time to perform associated tasks, is also vital for success. The research also showed involvement of the workforce in implementation efforts, including participation in decision-making activities and being knowledgeable about the overall implementation plan is another critical component. Following this framework and noting the resulting CSFs, the potential benefits and successful implementation of Industry 4.0

technologies is more accessible to the A&D industries. The final framework and implementation model, which addresses the main RQ, is shown in Figure 32

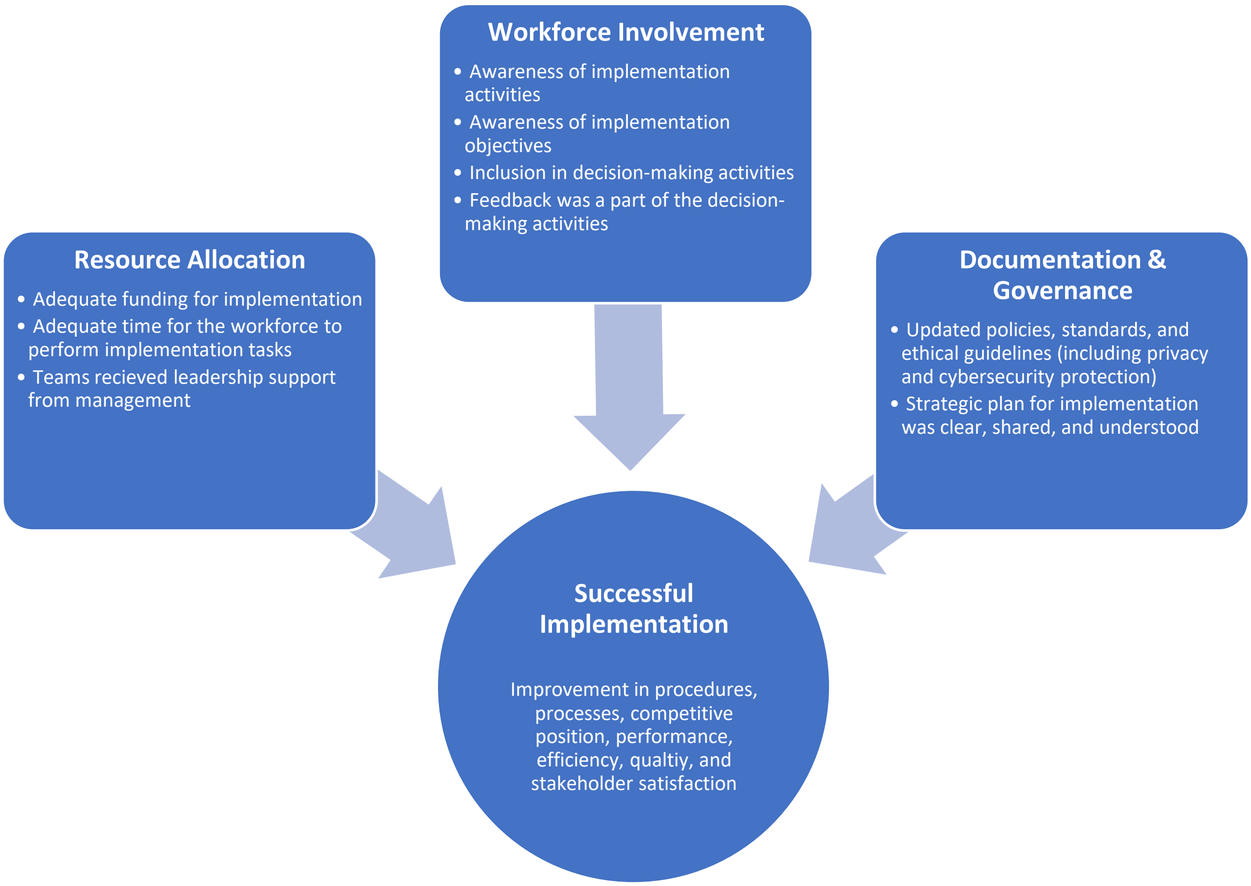

Figure 32: Framework of CSFs

CHAPTER EIGHT: DISCUSSION AND CONCLUSION

Introduction

The implementation of more complex and autonomous systems stems from the Industry 4.0 concept of integrating human-and-machine interfaces to develop intelligent processes and faster solutions. Industry 4.0 components such as cyber-physical systems (CPS), big data, cognitive computing, smart factories, connected manufacturing, and the Internet of Things (IoT) focus on revolutionizing manufacturing through embedding digital and physical systems, with the goal to maximize the desired output(s) while using minimal resources (Sony et al., 2020).

This worked aimed to support A&D industries in developing a comprehensive framework of CSFs needed for implementation of Industry 4.0 technologies. The research provides insight into the system-level view of Industry 4.0 implementation through identification of the benefits and challenges. Contributions of this doctoral research are applicable to academia and in practice due to the rigorous analyses of constructs used to develop the framework. This framework enhances chances of implementation success, where implementation of these emerging technologies within A&D industries improves model based engineering and digital transformation efforts. This can result in increased scale and speed of military actions and product development, more informed decision-making (Sigala, 2019), and reduction of the cognitive burden on the warfighter (Williams & Lawson, 2020). Other potential benefits include achieving overall military, information, and economic superiority through Industry 4.0-based transformative technologies within nuclear, aerospace, cyber, and biotechnology fields (Allen & Chan, 2017). This superiority can be accomplished through using Industry 4.0

solutions to manage complex systems, rapidly analyze and incorporate required changes, transfer applicable knowledge, and enhance collaboration across boundaries.

This chapter begins with a high-level overview of results and inferences for each phase of the research, including the contributions of the findings in research and in practice. The limitations which restrained the research are then shared and followed with detailing opportunities for future research. The chapter concludes with stating the future considerations of Industry 4.0 in A&D environments.

Results and Discussion

This section discusses the results for each phase of the dissertation and explains how each phase relates to each other. There is also an included comparison of results from the evidence within the literature and the empirical evidence from the questionnaire. Full explanations of processes, and details of outcomes, are provided within the previous respective chapters.

Phase I: SLR and Bibliometrics

Relevant publications were identified during the comprehensive SLR and bibliometric analysis detailed in Chapter 4. The purpose of this phase was to investigate and understand the current state of literature. Using Compendex, ProQuest, Web of Science, and EBSCOHost databases, 1,003 papers with relevant titles and abstracts were identified. The PRISMA technique and detailed exclusion processes were applied and narrowed the results to 23 publications. This set of papers included factors for successful implementation, descriptions of factors, explanations of success, and definitions of Industry 4.0 technologies.

To assess the maturity of the 23 papers, a bibliometric analysis was performed. The bibliometric analysis reviewed metrics that show the diversity of disciplines researching Industry

4.0. Although the authorship revealed a minimal number of industry experts empirically testing data, a multitude of countries and technologies were involved and discussed. The number of studies and research growth per year were also evaluated, as well as the approaches for data collection and analysis.

Due to the lack of empirical testing in the articles, as well as the factors and the approaches not being unified, a more detailed analysis of the existing evidence is needed to develop a preliminary framework. The TA was used to uncover common themes and identify initial factors within the publications, as the multitude of factors mentioned in the papers require categorizing and prioritizing to improve chances of success. The factors and dimensions of success identified in the papers were also used to enhance understanding of Industry 4.0 in A&D, prior to generation of the survey.

Phase II: Research Synthesis and TA

This portion of the dissertation used the publications selected from the SLR to conduct a TA on the 23 articles. The intent of the analysis was to further categorize and describe the identified factors while providing an operationalized definition of implementation success in A&D environments. Because the included papers showed inconsistencies with definitions, constructs, and lack of a comprehensive assessment of factors, this analysis helped to address these gaps and variations. Through inductively synthesizing the implementation factors noted in the papers, an initial conceptual framework was generated.

The assessment found successful implementation of Industry 4.0 was well addressed as most studies described the outcomes of implementation. However, a unified definition of implementation and success within A&D was unclear; the papers reiterated the definition of success depends on the application and the organization. Similar to the lack of a fundamental definition for implementation success, various factors of successful implementation were included in the studies. Some studies included groups of factors and others provided models for implementation. Although some studies investigated specific factors, there was lack of in-depth evaluations and lack of evaluating significant connections between the factors and outcome variable.

Because of the multifaceted implementation approach, the studies revealed three main categories of factors: organizational, technological, and strategic. The 12 factors within these groups were found within the 23 papers and coded using NVivo 12 Pro software and Microsoft Excel. This helped to list and group the constructs based on the most common factor name or applicable category. The organizational category refers to change management and the need for a deep understanding of Industry 4.0. Hence the factors within this category, such as management training, employee involvement, and communication, were included to address these needs. The technological category emphasized the importance of technical readiness, processes and procedures, and governance. These factors aligned with the A&D challenge of not having uniform standards or updated documented processes. The third group was for strategy, in terms of the approach for implementation and for tracking performance to ensure the implementation was successful. The papers emphasize the importance of the organization’s metrics and recommend using performance measures to obtain data and modify the strategy as needed.

The synthesis also identified multiple outcomes of successful implementation, such as improvements in quality, processes, procedures, performance, competitive position, enhanced stakeholder satisfaction, and overall strategic goal alignment.

This study was able to determine this comprehensive model of all factors and provided an exhaustive view through consideration of the differences, interrelationships, and categories. Following the TA, an initial ORM was generated (Figure 15). This empirical investigation was based solely on the included literature and provided a system-level view of important conclusions. The results showed the factors can be considered organizational, technological, or strategic in nature. This reflects the complex nature of implementation stated in the literature and the multidimensional of organizations within A&D environments. The TA performed in this section allowed for proper categorization and compilation to enable the survey study, which was used to gain dynamic insights from industry experts.

Phase III: Survey

This last phase of research used the constructs for each factor and tested the compilated items from the SLR and TA via a survey. The questionnaire was used to confirm the structure and investigate the interrelationship amongst the included factors. This was accomplished through empirical testing of the findings from the previous stages of research and refinement of the initial ORM. The survey results also addressed the gaps found in the literature, including identification of relationships between factors and relationships with the outcome variable. The survey included the preliminary 12 factors of success and the seven implementation outcomes. Specific details of the survey format, dissemination, and data collection is found within Chapter 6.

Once the survey concluded, data exploration and demographic analyses were performed to give context for the included population (Chapter 7). This also provided foundational perspectives and experiences of the experts included in the study. An EFA was then conducted to allow for further exploration of the initial ORM through determining the inter-relationships amongst the factors included in the survey. Six separate EFA models were developed based on the main categories of factors outlined in Figures 14 and 15. The use of separate models allowed for a more effective EFA process and ensures adequate statistical power. Table 10 shows which items were included within each model. The result of the EFA models were used to refine the initial ORM (Figure 15) and further align with the literature and outcomes from the survey. Although multiple emergent factors retained their original structure, some of the items were removed or moved to another factor based on the EFA. The EFA results, including the ten emergent factors and the outcome variable, are summarized in Figure 25. It is important to note that the factors evident through each phase of the research were designed and compiled to target A&D industries.

The ten factors emerging from the EFA and Reliability assessments were then analyzed using multiple linear regression. The quantitative assessment focused on the relationship of these factors with the outcome variable and identified three significant factors, or CSFs: *Documentation & Governance*, *Resource Allocation,* and *Workforce Involvement.* Other central factors and their interrelationships were identified for implementation although not deemed critical for the success outcome. For example, the following factors all had significant correlations with the remaining nine factors: *Management, Processes & Procedures, Communications, Resource Allocation,* and *Documentation & Governance.* This finding indicates how each of these constructs can be applied to, or included in, the others. *Management* can dictate the available resources through over-seeing funding and can monitor performance through tracking metrics. *Processes & Procedures* influence workforce acceptance through involvement of personnel in the updating processes. *Communications* address requirements and expectations, such as those associated with training or knowledge areas. *Resource Allocation* incorporates items such as technical readiness and confirmation of having a skilled workforce. *Documentation & Governance* can include recording updated processes or required communication efforts.

The investigation also identified factors with strong correlations and those with no significant corrections. For example, *Workforce Involvement* factor was found to be more correlated with *Workforce Acceptance* than *Education & Knowledge,* and *Technical Readiness* and was found to not have a significant correlation with *Workforce Involvement*.

The ten emergent factors and the three CSFs were identified through quantitative assessments while the 12 preliminary factors were based on the qualitative literature review. This combination of qualitative and quantitative research methods aids in the validity and applicability of the final framework, shown in Figure 32.

Integrated Findings

Each phase of the research provided academic and industry-based contributions that can be used for further research. Phase I provided a maturity assessment of existing literature and concluded research in this area is in the early-to-moderate stages. Phase II provided operational definitions for successful implementation of Industry 4.0 technologies and provided an initial framework of factors. Although the literature from Phase I discussed constructs of implementation, the grouping of items by categories in Phase II built on the original evidence.

Phase III focused on construct refinement and testing and provided the final framework while highlighting significant relationships amongst factors. This investigation into relationships was not common within the literature, as the studies focused on specific factors or factor groups.

Further, this dissertation used more in-depth analyses and advanced statistical methods to understand the factors.

While Phases I and II helped to generate the initial ORM, the insights provided by industry experts helped to enhance the model and provide additional evidence. For example, the initial ORM included preliminary factors, that were based on the findings in the SLR, while the final framework considered relationships amongst factors and specific items within factors based on experience in the field.

In terms of the success outcome, the literature findings in Phase I showed success of implementation was explained mostly by factors. The TA in Phase II provided an initial framework that displayed connections of themes to implementation success. Further, the TA in Phase II highlighted definitions within the literature, although applicable to the A&D scope, varied amongst studies and did not provide a uniform definition. The survey used in Phase III helped provide explicit understanding of implementation in A&D environments while showing the main factors needed to increase chances of a successful implementation of Industry 4.0 in practice. Although the number of participants was small, the insights provided by the survey were based on current A&D perspectives.

The resulting three CSFs were based on challenges identified by industry experts and within the literature. The papers noted the apprehensions regarding human integration and collaboration with Industry 4.0 solutions, particularly involvement in the decision-making (Wei et al., 2020). In terms of the workforce of A&D organizations, the papers prioritized the overall employee perspective. Butt (2020) added these human-centric factors are often overlooked in Industry 4.0 implementation where this is an overreliance on technological tools rather than organizations in transformations. To resolve these concerns, the CSF of *Employee Involvement* should be addressed. This begins with the identification of the Industry 4.0 solution, followed by recognition of the humans within this system and their respective task scenarios. This helps to assess the human impacts of task changes (Neumann et al., 2021) and allows employees to be included in the integration process. Neumann et al. (2021) stated this involvement from the human dimension is essential for optimization, safe implementation, and employee acceptance. In addition, being involved allows employees to directly observe the potential benefits and become more educated on Industry 4.0 solutions (Masood & Egger, 2019). Another challenge of implementation is the vulnerabilities of these systems, including data-poisoning attacks, hacking or gaining access for malicious purposes, and intentional attacks on the system intended to trick systems into functioning in unanticipated ways. Particularly in A&D applications which utilize the wireless capabilities for essential communication, such susceptibilities pose great risks. Mitigations can be seen with the CSF of *Documentation & Governance* through the development of a well-defined security assessment standard or ethical guidance. In addition, the strategic plan for implementation can acknowledge these risks and provide policies or standards for mitigation. Further, a clear strategic approach from executive management is needed to promote and incorporate Industry 4.0 in all business practices and across all organizational disciplines (Havle & Ulcer, 2018). The strategic plan and implementation were found to be related factors, both in the literature and in the final framework, that are essential for this smooth implementation as stakeholders, finances, and resources should be addressed. The lack of appropriate resources prior to and during implementation was another identified challenge. The CSF of *Resource Allocation* plays an essential role in resolution of concerns through ensuring availability of resources, adequate staffing, and appropriate time to perform tasks during implementation.

Evolution of the Final Framework

The framework evolved at each phase of the research, beginning with the initial ORM (Figure 15), and concluding with the final model (Figure 32). The initial model was based on the SLR while the refined final model used the ORM baseline and incorporated the results from the survey study. Comparison of the two models reiterates the refinements and re-organization of the factors and their constructs based on empirical evidence.

The 10 emergent factors from the EFA (Figure 25) are similar to the preliminary set of 12 factors (Figure 15) due to the inclusion of managerial, resource, strategy, and workforce items. Although the sustainment category group was not explicit in the model following the EFA, performance and training were included metrics from this initial category. Further, the EFA model combined the initial factors of *Management Commitment* and *Management Training* into a single *Management* category.

Following the EFA, the 10 emergent factors went through a reliability assessment to further refine the items within each construct (Figure 26). Chapter 7 gives additional information on removal of items to improve CA and enhance the internal consistency measure for each concept. The refined factors were then used in the regression model to identify the three CSFs. These three CSFs were initially included in the ORM under the main categories of *Strategy* and *Workforce*. After evolving and refining the constructs, the resulting framework with the three CSFs and their respective are detailed in Figure 32.

Empirical Literature and Survey Results

The empirical and comprehensive nature of the research in this dissertation addressed many of the limitations shared in the literature, including the need for more advanced statistical methods and rigor. This research performed a complete assessment of the success factors and outcome variable through the use of qualitative and quantitative approaches. The literature primarily used qualitative and exploratory studies and performed simple descriptive statistics on the findings. Although some studies used more advanced techniques, such as factor analyses, most of the papers did not assess the relationships between factors. This research quantitatively investigated interrelationships and provided a complete set of factors. The literature is consistent with the main findings of strategy and workforce involvement being essential factors; where strategy incorporates governance, procedures, and processes (Figure 15). Many of the studies also identified factors related to communication and resource allocation, which were found to be important for the overall implementation effort.

Similar to the authors from the SLR, the survey included many participants with a background in engineering. However, only one included paper used surveys as a means for data collection and data analysis. The results from the survey and the final framework model (Figure 32) addressed the challenges of implementing Industry 4.0 technologies mentioned in the SLR. For example, the main barriers include the lack of government regulations, the need for high financial investments, the poor technological infrastructure, organizational issues, and lack of human capital (Da Silva et al., 2019). These directly relate to the final set of CSFs: *Documentation & Governance*, *Resource Allocation,* and *Workforce Involvement.* To resolve concerns, there needs to be ethical guidance for developers and users (Rahanu et al., 2021), assurance of integrity and positive human-machine interactions (Elkaseer et al., 2018), standardization of policies, data governance, an assessment of the required resources, and knowledge of the technologies prior to incorporation. Therefore, the results from the research match the results of the literature through commonalities with the underlying concepts.

Contributions

The conclusions from this dissertation research provide critical contributions to the scholarly body of knowledge of Industry 4.0 implementation in A&D settings. Because published evidence and expert experience was used to develop the conceptual and theoretical models, the resulting comprehensive set of factors expands upon traditional studies and previous research. The previous studies focused on specific factors, rather than a set of factors, without understanding the influence of each factor or providing an in-depth analysis with the success outcome. In addition, potential contributions of the research work of this dissertation include:

1. The developed framework from this dissertation examined the CSFs for successfully and effectively implementing Industry 4.0 technologies. These findings can be used to continue to modernize and transform A&D environments and to increase operational efficiencies while using minimal resources.
2. This research provided a definition of Industry 4.0 in A&D based on relevant literature and expert experience. Further, this study operationalized the concept of implementation success to provide a clear and consistent definition for A&D environments while allowing for a better context to interpret results.
3. The expert study was conducting with various positions, titles, and roles within A&D. This quality of sampling enhances the applicability of the results through increasing the research's generalizability.
4. Contributions of this work can also shed light on remaining challenges and risks of effectively implementing Industry 4.0 solutions.
5. There are also academic contributions in the form of a framework and through identification of CSFs to implement Industry 4.0 in A&D. Because this framework

was based on the ethical principles established by the DOD in 2020, the research in this dissertation can help discover issues with current theories and assist in the development of new theories. The implementation of these theories can resolve societal concerns, including those of coexisting with autonomous and intelligent machines. The results of this study can also aid in establishing or improving ethical guidelines for development and use of Industry 4.0 technologies.

6. Additionally, there will be opportunities for further research based on the determined critical factors, which can aid in expanding the applications of Industry 4.0-based systems. There is also the ability to reexamine or further examine the determined CSFs for relevancy, while still ensuring effective transformation as organizations continue to advance.

Limitations

Although beneficial, the SLR method includes limitations and biases in the selection process. During the initial review phase, the researcher may lose some potentially relevant work when searching with the "everything but full text" feature of the database. However, this approach was used to limit capturing papers that mentioned the search term once within the article. There are also limitations in terms of the variations of terminologies used across publications. While the use of iterative searching can aid in this limitation, there is still the possibility of missing applicable research. Similar to search methods, there are limitations with the various platforms. Indexed publications are limited depending on the database. To address this, multiple platforms were used to increase the capture rate of the search. Other methods which were included involved strategic development of the inclusion and exclusion criteria to establish a specific scope and identify the range of terminology related to a single concept.

There are also limitations related to the generation and dissemination of the survey. Although the questionnaire was developed based on the rigorous SLR, the resulting independent variables (preliminary success factors) and dependent variable (outcome) were obtained from the same initial source. Therefore, this may introduce common method bias (Friedrich et al., 2009). The small sample size is considered another limitation which has potential to impact the validity and statistical strength of the analyses. To mitigate this concern, data analysis such as the EFA, was performed on a smaller subset of factors to achieve the required N:p ratio.

Although a single A&D company participated, various organizations and functional roles from this company were included to obtain data from multiple knowledge areas. For example, invites to the Design, Manufacturing, Engineering Sciences, and Systems Engineering were extended. Additionally, chosen participants span various roles and differing levels of management, such as Systems Engineer, Quality Engineer, and IT personnel, to help with applicability to the variety of roles and responsibilities within other A&D industries. Further, although the results may not be applicable to other industries, international organizations, or other contexts, the findings detail the demographics of the participants, including their title and years of experience, to allow confidence in other A&D organizations to use the results from the study, as applicable.

The results were also based on respondent's reporting only successful implementation cases. This limitation can result in incomplete conclusions and lack of a full perspective about implementation of Industry 4.0 in A&D if unsuccessful cases are not included or evaluated. The survey had other constraints, such as the ten emergent success factors and their respective items. More specifically, factors 9 and 10 included two items following the EFA and Reliability assessment. The strength of these factors could have increased if additional items or properties were added.

Future Research

Future efforts can use more search iterations and multiple knowledgeable researchers to further refine and improve the overall research approach while minimizing limitations. The research can also be extended through further investigation of the interrelationships amongst the factors, more in-depth analysis of the identified factors within A&D and operationalizing the factors to better comprehend the constructs. In addition, field studies can be performed to provide validation approaches for empirical testing.

The limitations and applicability of using one A&D business with the questionnaire were previously acknowledged. However, this provides opportunities for future research, such as increasing sample size and inclusion of other industries or fields outside of A&D. Furthermore, the questionnaire in this dissertation focused on successful implementation but did not address unsuccessful cases. This can result in incomplete conclusions. Further research can be performed to evaluate unsuccessful attempts of implementation and provide greater insight into the CSFs.

In addition, the questionnaire did not control the time between the event (completion of implementation) and data collection, however, a control method can be implemented in future research. Following the questionnaire, an EFA and Reliability assessment was performed to determine the emergent factors and their items. To increase the strength of these factors and to be able to be performed advanced statistical analyses, additional items can be added and investigated.

Future Considerations of A&D Industry 4.0

Industry 4.0 solutions are continuing to replace simple and complex human tasks in various levels of manufacturing and decision-making processes. Therefore, future efforts should include more empirical based methods to investigate theoretical frameworks or initiates. These studies can also assess contingency plans and the impact of the pandemic on Industry 4.0 implementation (Nayernia et al., 2021).

With machines becoming more evident in the field, more duties are assigned to Industry 4.0 technologies. Further, with the increased availability and usage of smart systems, more responsibilities are being assigned to such. With more tasks being allocated to the machine, there is greater freedom of the machine; with greater freedom, there is a stronger need to define moral standards. This ideology aligns with the goal of machine ethics – for machines with ethical components to share the responsibility and consequences of decisions with their human counterpart while precluding harm to personnel. A 2012 study provided an overview of existing fielded military autonomous systems and concluded humans are already assigning responsibility to devices and computers and will continue to do so as these advancements become more prevalent. In addition, when determining and assigning ethical and moral responsibilities, both autonomous power and moral quality were found to be deciding factors (Hellstrom, 2013). To transfer ethical responsibility from humans to machines, training and augmenting the level of autonomy and independence is critical. In addition, the machine should also be developed with ethics in mind to help increase trust in Industry 4.0-enabled systems.

Many studies advise the development of organizations dedicated to performing cost-benefit analyses, aiding in more applicable R&D, increasing collaboration with commercial industries, and contributing to further concept development and experimentation. There is also a need for more research to ensure systems are reliable, safe, and do not introduce new risks or hazards into existing systems (Vorm, 2020). Suggested studies include determining when it is economical to solely rely on human judgment (Dwivedi et al., 2021) and determining the benefit of analyses of unmanned verse manned systems (Brannen & Griffin, 2014). Inclusive, there should be engagement with industry and academia to ensure there is a balance between commercial and government funding and oversight of all A&D Industry 4.0 concept development and experimentation (Allen & Chan, 2017).

As A&D applications of Industry 4.0 advance across the globe, it is important to consider the growth in scale and complexities of international competition. For example, in 2017, both China and Russia announced more developmental programs in which China aims to be the optimal innovative nation in AI/ML by 2030 (Kania, 2017) and Russia hopes to fully automate their combat power using robotic platforms by 2030 (Allen & Chan, 2017). Understanding the state of adversary development and potential usage is essential as competitors could vary in ethical and legal policies of such (Allen & Chan, 2017). Additionally, with the increasing implementation of Industry 4.0 technologies, potential battlefield interactions or misconceptions between nations can occur (Kania, 2017). Because of this, future efforts should involve governments collaborating to determine a global measure including the expanded use of Industry 4.0 in A&D applications.

APPENDIX A: SLR PAPER SET

Publication Title	First Author	Year	Country	Type
Challenges and Benefits of Digital Workflow Implementation in Aerospace Manufacturing Engineering	Abollado	2017	United Kingdom	Journal Article
Aspects of Risk Management Implementation for Industry 4.0	Tupa	2017	Czech Republic	Journal Article
Defining and Assessing Industry 4.0 Maturity Levels - Case of the Defence Sector	Bibby	2018	United Kingdom	Journal Article
Approaches to a Practical Implementation of Industry 4.0	Elkaseer	2018	Egypt, Germany	Journal Article
Industry 4.0: Required Personnel Competences	Fitsilis	2018	Greece	Journal Article
Enables for Industry 4.0	Havle	2018	Turkey	Conference Proceeding
Theoretical Proposal of Steps for the Implementation of the Industry 4.0 Concept	Corderio	2018	Brazil	Journal Article
Augmented Reality in Support of Industry 4.0 - Implementation Challenges and Success Factors	Masood	2019	United Kingdom	Journal Article
The Degree of Readiness for the Implementation of Industry 4.0	Pacchini	2019	Brazil, Italy	Journal Article
Standardization: A key factor of Industry 4.0	Villagran	2019	Spain, Argentina	Conference Proceeding
Digital Engineering Transformation Across the Department of Defense	Zimmerman	2019	United States	Journal Article
Industry 4.0 Implementation Challenges and Opportunities: A Managerial Perspective	Bajic	2020	Serbia	Journal Article
A New Concept of Digital Twin Supporting Optimization and Resilience of Factories of the Future	Becue	2020	France, Germany, Portugal	Journal Article
A Conceptual Framework to Support Digital Transformation in Manufacturing Using an Integrated Business Process Management Approach	Butt	2020	United Kingdom	Journal Article
Implementation of Industry 4.0 Concept in Companies: Empirical Evidences	Da Silva	2020	Brazil	Journal Article
Implementing MBSE - An Enterprise Approach to an Enterprise Problem	Papke	2020	United States	Journal Article
A Framework of Action for Implementation of Industry 4.0: An Empirically Based Research	Pollak	2020	Poland	Journal Article
Critical Factors for the Successful Implementation of Industry 4.0: A Review and Future Research Direction	Sony	2020	Namibia, India	Journal Article
Implementing a Model-Based, Digital Enterprise for a Defense Systems Integrator - An Ongoing Journey	Wang	2020	United States	Journal Article
A Systematic Review of the Implementation of Industry 4.0 from the Organizational Perspective	Nayernia	2021	United Kingdom	Journal Article

Publication Title	First Author	Year	Country	Type
Industry 4.0 and the Human Factor - A systems Framework and Analysis Methodology for Successful Development	Neumann	2021	Canada, Germany	Journal Article
Industry 4.0 Technologies: Critical Success Factors for Implementation and Improvements in Manufacturing Companies	Pozzi	2021	Italy	Journal Article
Ethical Issues Invoked by Industry 4.0	Rahanu	2021	United Kingdom, Greece, Finland	Conference Proceeding

APPENDIX B: IRB APPROVAL

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

EXEMPTION DETERMINATION

September 6, 2022

Dear Lina Khan:

On 9/2/2022, the IRB determined the following submission to be human subjects research that is exempt from regulation:

Type of Review:	Initial Study
Title:	A Framework of Critical Success Factors for Implementation of Industry 4.0 in Aerospace and Defense Industries
Investigator:	Lina Khan
IRB ID:	STUDY00004626
Funding:	None
Grant ID:	None
Documents Reviewed:	• HRP-225-FORM - Request for Exemption_LinaKhan, Category: IRB Protocol; • Study 4626 HRP-254-FORM Explanation of Research_Khan_Rev3.pdf, Category: Consent Form; • Study 4626 Recruitment Materials_Khan_Rev3.docx, Category: Recruitment Materials; • Survey Questions (Tent.).docx, Category: Survey / Questionnaire;

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made, and there are questions about whether these changes affect the exempt status of the human research, please submit a modification request to the IRB. Guidance on submitting Modifications and Administrative Check-in are detailed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Gillian Bernal

Gillian Bernal
Designated Reviewer

APPENDIX B.2: SURVEY INVITATION E-MAIL

Invitation Email
Subject: Invitation: Survey Study on Successful Implementation of Industry 4.0 in Aerospace & Defense (A&D) Industries

Hello,
You are invited to take a survey focused on identifying factors that affect the successful implementation of Industry 4.0 technologies in A&D as part of a doctoral study being conducted at the University of Central Florida. Whether you take part is up to you, however, you must be at least 18 years of age to participate.

You were identified as a candidate due to your current or previous experience with Industry 4.0 technologies (examples include Artificial Intelligence, Digital Transformation, Model-Based Engineering, Model-Based Systems Engineering, Machine Learning, etc.) and your current role as a Lockheed Martin employee.

The purpose of this study is to investigate the factors that influence Industry 4.0 implementation in A&D organizations as part of a doctoral study focused on improving Industry 4.0 implementation success. Identifying these factors (barriers, obstacles, enablers, or any issues that can affect the implementation) and evaluating their relative impact on implementation success will support the research team in their efforts to develop strategies to improve Industry 4.0 implementation in practice.

The online survey takes approximately 15-20 minutes to complete and is administered using the UCF Qualtrics system. IP addresses will not be collected, and study results will be confidential. The survey does not collect identifiable data (your name or email). The resulting data will only be available to the principal investigator and this de-identified data will be analyzed for the study. All data will be stored for 5 years after study closure, per Florida law. De-identified data will be stored on UCF Microsoft One Drive. Only aggregate results will be used for the analysis and dissemination, which ensures that no individual participants are identifiable. The de-identified data will be included in the Dissertation appendices.

Link to further information and the research survey is provided within the email invitation.

You may also contact either of the researchers via the contact information listed below. Thank you for your time and consideration.

Lina Khan,
Principal Investigator, Ph.D. Student
Industrial Engineering & Management Systems
Email: linakhan@knights.ucf.edu

Ahmad Elshennawy, Ph.D.
Professor, Faculty Advisor
Industrial Engineering & Management Systems
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APPENDIX B.3: SURVEY QUESTIONS

How long have you been working in an Industry 4.0-related role?

- ◯ 0-2 years
- ◯ 3-5 years
- ◯ 6-10 years
- ◯ Over 10 years

What is your title in the Industry 4.0-related role? Examples include: Systems Engineer, Mechanical Engineer, IT, Manufacturing Manager, etc.

How would you rate your project team, in terms of performance (ability to meet cost, schedule, and quality targets)?

- ◯ Terrible
- ◯ Poor
- ◯ Average
- ◯ Good
- ◯ Excellent

When was the last time that you participated in or observed the implementation of Industry 4.0 in a new or redesigned process?

- ◯ It has been less than 6 months
- ◯ 6-12 months ago
- ◯ 2-5 years ago
- ◯ More than 5 years ago
- ◯ I have never participated in or observed the implementation Industry 4.0 in an aerospace or defense organization

Which type of Industry 4.0 technologies were you involved with (Select all that apply).

- [ ] Model Based Engineering
- [ ] Model Based Systems Engineering
- [ ] Digital Twin
- [ ] Machine Learning
- [ ] Artificial Intelligence
- [ ] Virtual or Augmented Reality
- [ ] Other

How many years of experience do you have with Industry 4.0 technologies?

- ◯ Less than 1 year
- ◯ 1-2 years
- ◯ 3-5 years
- ◯ More than 5 years

Which best describes the size of the immediate project team that will be using the Industry 4.0 technologies?

- ◯ Small: Fewer than 10 employees
- ◯ Medium: 10 to 20 employees
- ◯ Large: More than 20 employees

What are your role(s) during implementation? (Select all that apply).

- ☐ Team Leader
- ☐ Facilitator
- ☐ Champion
- ☐ Process Owner
- ☐ Team Member/Individual Contributor
- ☐ Management
- ☐ Observer/Studying
- ☐ Other

In general, how successful was the last implementation that you participated in or observed? Successful can be defined as being able to implement or actively working toward it without excessive issues.

- ○ Not successful
- ○ Slightly successful
- ○ Moderately successful
- ○ Very successful
- ○ Extremely successful

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree". The term, "management", in the statements below refers to your direct leadership for the Industry 4.0 related effort.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Management was involved with implementation activities.	○	○	○	○	○
Management was engaged (ongoing participation) in implementation activities.	○	○	○	○	○
Management used motivation tools to engage the team. (Examples include asking for input, support, transparency, etc).	○	○	○	○	○
Management showed commitment through effectively leading the change.	○	○	○	○	○
Management gave clear expectations as far as improvement plans.	○	○	○	○	○
Management provided a clear vision detailing the results of implementation activities.	○	○	○	○	○
Management played an important/active role in implementation activities.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree". The term, "management", in the statements below refers to your direct leadership for the Industry 4.0 related effort.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Management communicated implementation plans with the team.	○	○	○	○	○
Management flowed down applicable information to help the team with implementation activities.	○	○	○	○	○
Management showed knowledge regarding the systems being implemented or the processes being changed.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I was aware of the implementation objectives of my role.	○	○	○	○	○
I understood the benefits of using Industry 4.0 technologies.	○	○	○	○	○
I was involved in implementation activities.	○	○	○	○	○
I was included in decision-making activities.	○	○	○	○	○
I was knowledgeable about the overall implementation plan.	○	○	○	○	○
I am aware of and understand the corporate mission and vision to use Industry 4.0 technologies.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Employees understand their work scope once implementation is complete.	○	○	○	○	○
Employee satisfaction with using Industry 4.0 technologies was measured.	○	○	○	○	○
Employee feedback was a part of the decision-making activities.	○	○	○	○	○
Employees easily adopted Industry 4.0 principles and processes.	○	○	○	○	○
Employees agreed with the decision to incorporate Industry 4.0 technologies in their work processes.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
There is an understanding of the gap between employees' current skill set and skill set needed for Industry 4.0 technologies.	○	○	○	○	○
Learning and education were evaluated, and training was planned.	○	○	○	○	○
Education or training was provided.	○	○	○	○	○
Experienced Industry 4.0 employees were hired.	○	○	○	○	○
Employees performed a competency assessment of required skills.	○	○	○	○	○
My team members have the required experience.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
There was communication between different levels of management.	○	○	○	○	○
There was communication between affected organizations.	○	○	○	○	○
There was collaboration across affected organizations.	○	○	○	○	○
Team members communicated well with each other.	○	○	○	○	○
The organization considered customer needs in implementation activities.	○	○	○	○	○
Complaints were used to improve the implementation process.	○	○	○	○	○
Different disciplines collaborated to improve the results of Industry 4.0 implementation.	○	○	○	○	○
My team can easily reach out to individuals as needed.	○	○	○	○	○
I received communication updates from the project/program management office.	○	○	○	○	○
The team welcomed and encouraged customer input throughout implementation.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
There were sufficient resources to support implementation.					
There was adequate funding for Industry 4.0 implementation purposes.					
There was adequate staffing to support implementation.					
There was adequate time for staff to perform tasks associated with implementation.					
My team was able to purchase items needed to make implementation more efficient.					
My team received leadership support from management.					

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
There was technical compatibility with the new Industry 4.0 technologies and current processes.					
The process was changed to include Industry 4.0 technologies only if it was deemed value-added.					
A system configuration assessment was performed prior to implementation.					
Technical compatibility assessments were performed prior to implementation.					
Systems were ready to transform and use Industry 4.0 technologies.					

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Policies have been adopted to include the use of Industry 4.0 technologies.	◯	◯	◯	◯	◯
There are ethical guidelines in place prior to implementation.	◯	◯	◯	◯	◯
There are standards in place to be used across organizations for implementation.	◯	◯	◯	◯	◯
There are policies in place to protect the privacy of personnel when using data-vulnerable systems.	◯	◯	◯	◯	◯
There is an updated cybersecurity framework addressing Industry 4.0 technologies.	◯	◯	◯	◯	◯

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Processes or systems which are impacted by Industry 4.0 implementation were identified and defined.	◯	◯	◯	◯	◯
Processes and protocols being updated with Industry 4.0 implementation were evaluated.	◯	◯	◯	◯	◯
My team developed (or is developing) high-quality processes for implementation (documented, repeatable, mistake-proof).	◯	◯	◯	◯	◯

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The organization pursued long-term organizational goals and policies.	○	○	○	○	○
The strategic plan was known and clear prior to implementation.	○	○	○	○	○
The policies and strategies were developed according to current and future needs.	○	○	○	○	○
The implementation approach was understood and shared.	○	○	○	○	○
My team has dedicated time for project planning.	○	○	○	○	○
My team first implemented Industry 4.0 technologies in smaller-scale projects or processes.	○	○	○	○	○
My team had realistic schedule expectations for implementation.	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Performance metrics were obtained.	○	○	○	○	○
Performance data and information was analyzed.	○	○	○	○	○
Data generated from the performance measures were in decision-making or implementation activities.	○	○	○	○	○
The organization regularly updated its policies and protocols.	○	○	○	○	○
The organization continuously improves processes to implement Industry 4.0 technologies.	○	○	○	○	○
Performance indicators are compared across organizations to identify opportunities for improvement.	○	○	○	○	○
My team used principles of continuous improvement (lean manufacturing, etc.).	○	○	○	○	○

To what extent do you agree or disagree with the following statements? Reminder to give responses based on your experiences. If not applicable, please choose "neither agree nor disagree".

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
There was an improvement in organizational performance following implementation.	○	○	○	○	○
There was an improvement in organizational efficiencies following implementation.	○	○	○	○	○
There was an improvement in processes and procedures following implementation.	○	○	○	○	○
There was an increase in stakeholder satisfaction following implementation.	○	○	○	○	○
There was an improvement in quality following implementation.	○	○	○	○	○
The organization is now in a competitive position following implementation.	○	○	○	○	○
The implementation of Industry 4.0 technologies was successful.	○	○	○	○	○

APPENDIX C: CROSSTABULATION & CHI-SQUARE TEST RESULTS

Title * Success Crosstabulation

			Success					
			Extremely Successful	Moderately Successful	Not Successful	Slightly Successful	Very Successful	Total
Title	Aeronautical Engineer	Count	0	3	0	0	1	4
		% within Title	0.0%	75.0%	0.0%	0.0%	25.0%	100.0%
	Automation Engineer	Count	1	0	0	1	0	2
		% within Title	50.0%	0.0%	0.0%	50.0%	0.0%	100.0%
	Chief Engineer	Count	0	2	0	0	0	2
		% within Title	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%
	Design Engineer	Count	0	0	0	0	3	3
		% within Title	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%
	Engineering Manager	Count	1	1	1	0	2	5
		% within Title	20.0%	20.0%	20.0%	0.0%	40.0%	100.0%
	Manufacturing Engineer	Count	0	1	0	0	1	2
		% within Title	0.0%	50.0%	0.0%	0.0%	50.0%	100.0%
	Mechanical Engineer	Count	1	2	0	0	2	5
		% within Title	20.0%	40.0%	0.0%	0.0%	40.0%	100.0%
	Research Scientist	Count	0	0	0	2	0	2
		% within Title	0.0%	0.0%	0.0%	100.0%	0.0%	100.0%
	Simulation Process Engineer	Count	1	1	0	0	1	3
		% within Title	33.3%	33.3%	0.0%	0.0%	33.3%	100.0%
	Systems Engineer	Count	0	9	0	2	3	14
		% within Title	0.0%	64.3%	0.0%	14.3%	21.4%	100.0%
Total		Count	4	19	1	5	13	42
		% within Title	9.5%	45.2%	2.4%	11.9%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	49.425[a]	36	.067
Likelihood Ratio	42.716	36	.205
N of Valid Cases	42		

a. 49 cells (98.0%) have expected count less than 5. The minimum expected count is .05.

Size * Success Crosstabulation

			Success					
			Extremely Successful	Moderately Successful	Not Successful	Slightly Successful	Very Successful	Total
Size	20+	Count	1	7	1	2	11	22
		% within Size	4.5%	31.8%	4.5%	9.1%	50.0%	100.0%
	less than 10	Count	2	4	0	3	2	11
		% within Size	18.2%	36.4%	0.0%	27.3%	18.2%	100.0%
	ten to 20	Count	1	8	0	0	0	9
		% within Size	11.1%	88.9%	0.0%	0.0%	0.0%	100.0%
Total		Count	4	19	1	5	13	42
		% within Size	9.5%	45.2%	2.4%	11.9%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	16.573[a]	8	.035
Likelihood Ratio	19.160	8	.014
N of Valid Cases	42		

a. 13 cells (86.7%) have expected count less than 5. The minimum expected count is .21.

Performance * Success Crosstabulation

			Success					
			Extremely Successful	Moderately Successful	Not Successful	Slightly Successful	Very Successful	Total
Performance	Average	Count	0	6	0	4	2	12
		% within Performance	0.0%	50.0%	0.0%	33.3%	16.7%	100.0%
	Excellent	Count	4	3	0	0	3	10
		% within Performance	40.0%	30.0%	0.0%	0.0%	30.0%	100.0%
	Good	Count	0	10	1	0	8	19
		% within Performance	0.0%	52.6%	5.3%	0.0%	42.1%	100.0%
	Poor	Count	0	0	0	1	0	1
		% within Performance	0.0%	0.0%	0.0%	100.0%	0.0%	100.0%
Total		Count	4	19	1	5	13	42
		% within Performance	9.5%	45.2%	2.4%	11.9%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	31.733[a]	12	.002
Likelihood Ratio	29.585	12	.003
N of Valid Cases	42		

a. 17 cells (85.0%) have expected count less than 5. The minimum expected count is .02.

YearExp * Success Crosstabulation

			Success					
			Extremely Successful	Moderately Successful	Not Successful	Slightly Successful	Very Successful	Total
YearExp	5+	Count	3	6	0	2	8	19
		% within YearExp	15.8%	31.6%	0.0%	10.5%	42.1%	100.0%
	Less than one	Count	0	2	0	1	1	4
		% within YearExp	0.0%	50.0%	0.0%	25.0%	25.0%	100.0%
	one to two	Count	1	6	1	1	3	12
		% within YearExp	8.3%	50.0%	8.3%	8.3%	25.0%	100.0%
	three to five	Count	0	5	0	1	1	7
		% within YearExp	0.0%	71.4%	0.0%	14.3%	14.3%	100.0%
Total		Count	4	19	1	5	13	42
		% within YearExp	9.5%	45.2%	2.4%	11.9%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	8.617[a]	12	.735
Likelihood Ratio	9.439	12	.665
N of Valid Cases	42		

a. 17 cells (85.0%) have expected count less than 5. The minimum expected count is .10.

LastTime * Success Crosstabulation

			Success					
			Extremely Successful	Moderately Successful	Not Successful	Slightly Successful	Very Successful	Total
LastTime	5+	Count	0	0	0	0	1	1
		% within LastTime	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%
	Less than 6 months	Count	4	15	1	3	11	34
		% within LastTime	11.8%	44.1%	2.9%	8.8%	32.4%	100.0%
	Six to 12 months	Count	0	3	0	2	1	6
		% within LastTime	0.0%	50.0%	0.0%	33.3%	16.7%	100.0%
	two to five years ago	Count	0	1	0	0	0	1
		% within LastTime	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%
Total		Count	4	19	1	5	13	42
		% within LastTime	9.5%	45.2%	2.4%	11.9%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	7.422[a]	12	.829
Likelihood Ratio	7.950	12	.789
N of Valid Cases	42		

a. 18 cells (90.0%) have expected count less than 5. The minimum expected count is .02.

YearRole * Success Crosstabulation

			Success					
			Extremely Successful	Moderately Successful	Not Successful	Slightly Successful	Very Successful	Total
YearRole	6 to 10	Count	0	0	0	0	2	2
		% within YearRole	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%
	ten+	Count	3	5	0	1	5	14
		% within YearRole	21.4%	35.7%	0.0%	7.1%	35.7%	100.0%
	three to five	Count	1	8	0	2	2	13
		% within YearRole	7.7%	61.5%	0.0%	15.4%	15.4%	100.0%
	zero to two	Count	0	6	1	2	4	13
		% within YearRole	0.0%	46.2%	7.7%	15.4%	30.8%	100.0%
Total		Count	4	19	1	5	13	42
		% within YearRole	9.5%	45.2%	2.4%	11.9%	31.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	12.710[a]	12	.390
Likelihood Ratio	13.892	12	.308
N of Valid Cases	42		

a. 17 cells (85.0%) have expected count less than 5. The minimum expected count is .05.

APPENDIX D: FINAL EFA MODEL 1

Correlation Matrix[a]

a. Determinant = 2.354E-10

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.833
Bartlett's Test of Sphericity	Approx. Chi-Square	750.075
	df	171
	Sig.	<.001

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.741	56.529	56.529	10.741	56.529	56.529	9.743
2	2.063	10.857	67.387	2.063	10.857	67.387	7.903
3	.923	4.858	72.245				
4	.899	4.729	76.974				
5	.841	4.425	81.398				
6	.653	3.434	84.833				
7	.582	3.062	87.895				
8	.464	2.445	90.340				
9	.414	2.179	92.518				
10	.361	1.897	94.416				
11	.287	1.508	95.924				
12	.195	1.028	96.952				
13	.155	.815	97.767				
14	.118	.623	98.390				
15	.094	.497	98.887				
16	.084	.442	99.329				
17	.054	.283	99.611				
18	.043	.226	99.838				
19	.031	.162	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Communalities

	Initial	Extraction
MC1	1.000	.769
MC2	1.000	.743
MC4	1.000	.749
MC5	1.000	.560
MC6	1.000	.715
MC7	1.000	.781
MT1	1.000	.816
MT2	1.000	.837
MT3	1.000	.750
COM1	1.000	.665
COM2	1.000	.739
COM3	1.000	.733
COM4	1.000	.610
COM5	1.000	.671
COM6	1.000	.543
COM7	1.000	.549
COM8	1.000	.616
COM9	1.000	.481
COM10	1.000	.477

Extraction Method: Principal Component Analysis.

Pattern Matrix[a]

	Component	
	1	2
MC1	.988	
MC2	.923	
MC4	.807	
MC5	.741	
MC6	.841	
MC7	.857	
MT1	.793	
MT2	.724	
MT3	.733	
COM1	.768	
COM2		.671
COM3		.678
COM4		.802
COM5		.796
COM6		.714
COM7		.766
COM8		.735
COM9	.667	
COM10		.735

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

APPENDIX D.2: FINAL EFA MODEL 2

Factor Analysis

Correlation Matrix[a]

a. Determinant = .016

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.721
Bartlett's Test of Sphericity	Approx. Chi-Square	155.406
	df	28
	Sig.	<.001

Communalities

	Initial	Extraction
EI1	1.000	.720
EI3	1.000	.475
EI4	1.000	.764
EI5	1.000	.840
EA2	1.000	.739
EA3	1.000	.614
EA4	1.000	.742
EA5	1.000	.528

Extraction Method: Principal Component Analysis.

Pattern Matrix[a]

	Component 1	Component 2
EI1	.717	
EI3	.702	
EI4	.889	
EI5	.914	
EA2		.837
EA3	.644	
EA4		.867
EA5		.736

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Component Matrix[a]

	Component 1	Component 2
EI1	.847	
EI3	.510	-.464
EI4	.740	-.466
EI5	.830	
EA2	.593	.622
EA3	.783	
EA4	.504	.699
EA5	.402	.606

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.593	44.907	44.907	3.593	44.907	44.907	3.254
2	1.830	22.872	67.779	1.830	22.872	67.779	2.490
3	.807	10.086	77.865				
4	.647	8.082	85.947				
5	.401	5.013	90.961				
6	.330	4.125	95.085				
7	.257	3.219	98.304				
8	.136	1.696	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

APPENDIX D.3: FINAL EFA MODEL 3

Factor Analysis

Correlation Matrix[a]

a. Determinant = .036

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.761
Bartlett's Test of Sphericity	Approx. Chi-Square	125.792
	df	21
	Sig.	<.001

Communalities

	Initial	Extraction
RE2	1.000	.640
RE4	1.000	.819
RE5	1.000	.627
RE6	1.000	.732
TECH3	1.000	.764
TECH4	1.000	.744
TECH5	1.000	.722

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1	Component 2
RE2	.756	
RE4	.871	
RE5	.677	-.412
RE6	.594	-.616
TECH3	.581	.652
TECH4	.610	.610
TECH5	.744	.410

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Pattern Matrix[a]

	Component 1	Component 2
RE2	.737	
RE4	.806	
RE5	.794	
RE6	.889	
TECH3		.892
TECH4		.869
TECH5		.763

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.404	48.627	48.627	3.404	48.627	48.627	2.938
2	1.645	23.498	72.125	1.645	23.498	72.125	2.577
3	.626	8.942	81.066				
4	.447	6.390	87.457				
5	.386	5.510	92.967				
6	.279	3.989	96.956				
7	.213	3.044	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

APPENDIX D.4: EFA MODEL 4

Correlation Matrix[a]

a. Determinant = .017

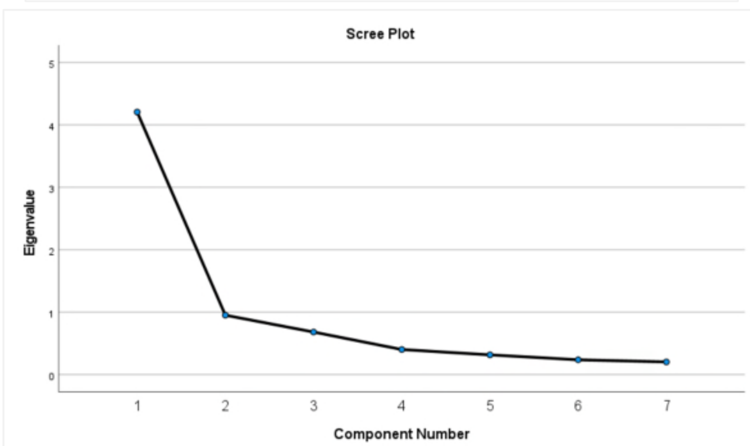
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.832
Bartlett's Test of Sphericity	Approx. Chi-Square	154.607
	df	21
	Sig.	<.001

Communalities

	Initial	Extraction
GOV1	1.000	.652
GOV2	1.000	.653
GOV3	1.000	.458
GOV4	1.000	.668
GOV5	1.000	.619
STRAT2	1.000	.569
STRAT4	1.000	.587

Extraction Method: Principal Component Analysis.



Component Matrix[a]

	Component
	1
GOV1	.808
GOV2	.808
GOV3	.677
GOV4	.817
GOV5	.787
STRAT2	.754
STRAT4	.766

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.206	60.090	60.090	4.206	60.090	60.090
2	.952	13.597	73.688			
3	.682	9.746	83.433			
4	.402	5.746	89.179			
5	.317	4.522	93.701			
6	.238	3.396	97.097			
7	.203	2.903	100.000			

Extraction Method: Principal Component Analysis.

APPENDIX D.5: EFA MODEL 5

Correlation Matrix[a]

a. Determinant = 2.452E-5

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.768
Bartlett's Test of Sphericity	Approx. Chi-Square	376.862
	df	55
	Sig.	<.001

Communalities

	Initial	Extraction
PER1	1.000	.871
PER2	1.000	.915
PER3	1.000	.868
PER6	1.000	.802
PER7	1.000	.582
PRO1	1.000	.784
PRO2	1.000	.872
PRO3	1.000	.758
TR1	1.000	.655
TR2	1.000	.858
TR3	1.000	.771

Extraction Method: Principal Component Analysis.

Pattern Matrix[a]

	Component 1	2	3
PER1	.951		
PER2	.955		
PER3	.922		
PER6	.727		
PER7	.560		
PRO1			-.787
PRO2			-.961
PRO3			-.747
TR1		.728	
TR2		.898	
TR3		.800	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 7 iterations.

Component Matrix[a]

	Component 1	2	3
PER1	.792	-.422	
PER2	.818	-.465	
PER3	.816	-.401	
PER6	.873		
PER7	.631		
PRO1	.752		
PRO2	.695		-.589
PRO3	.750		
TR1		.720	
TR2	.546	.648	
TR3	.628	.435	.433

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.548	50.432	50.432	5.548	50.432	50.432	4.575
2	2.055	18.682	69.114	2.055	18.682	69.114	2.787
3	1.134	10.306	79.420	1.134	10.306	79.420	3.836
4	.810	7.361	86.781				
5	.539	4.898	91.679				
6	.288	2.621	94.300				
7	.185	1.686	95.986				
8	.160	1.455	97.441				
9	.134	1.218	98.659				
10	.114	1.040	99.698				
11	.033	.302	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

APPENDIX D.6: EFA MODEL 6

Correlation Matrix[a]

a. Determinant = .001

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.853
Bartlett's Test of Sphericity	Approx. Chi-Square	281.619
	df	21
	Sig.	<.001

Communalities

	Initial	Extraction
OUT1	1.000	.798
OUT2	1.000	.761
OUT3	1.000	.807
OUT4	1.000	.577
OUT5	1.000	.710
OUT6	1.000	.766
OUT7	1.000	.838

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
OUT1	.894
OUT2	.873
OUT3	.898
OUT4	.760
OUT5	.843
OUT6	.875
OUT7	.915

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.258	75.108	75.108	5.258	75.108	75.108
2	.640	9.138	84.245			
3	.475	6.787	91.033			
4	.254	3.622	94.655			
5	.186	2.657	97.312			
6	.127	1.815	99.127			
7	.061	.873	100.000			

Extraction Method: Principal Component Analysis.

APPENDIX E: CORRELATION ANALYSIS

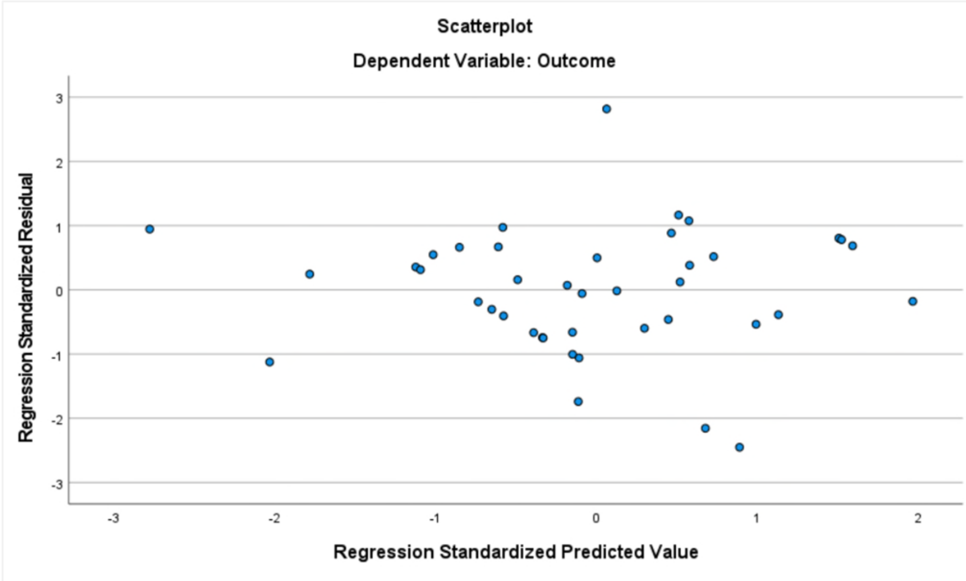
Correlations

		1	2	3	4	5	6	7	8	9	10	Outcome
Factor 1: Mgmt	Pearson Correlation	1	.673**	.543**	.551**	.498**	.413**	.601**	.585**	.410**	.434**	.529**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	.007	<.001	<.001	.007	.004	<.001
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 2: Comms	Pearson Correlation	.673**	1	.699**	.504**	.502**	.383*	.594**	.523**	.362*	.577**	.580**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	.012	<.001	<.001	.019	<.001	<.001
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 3: Workforce Inv	Pearson Correlation	.543**	.699**	1	.327*	.592**	.222	.420**	.541**	.153	.393*	.528**
	Sig. (2-tailed)	<.001	<.001		.035	<.001	.157	.006	<.001	.334	.010	<.001
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 4: Workforce Acc	Pearson Correlation	.551**	.504**	.327*	1	.366*	.593**	.700**	.529**	.219	.645**	.442**
	Sig. (2-tailed)	<.001	<.001	.035		.017	<.001	<.001	<.001	.163	<.001	.003
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 5: Resource	Pearson Correlation	.498**	.502**	.592**	.366*	1	.377*	.489**	.347*	.482**	.422**	.315*
	Sig. (2-tailed)	<.001	<.001	<.001	.017		.014	.001	.024	.001	.005	.042
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 6: Tech	Pearson Correlation	.413**	.383*	.222	.593**	.377*	1	.599**	.491**	.332*	.601**	.385*
	Sig. (2-tailed)	.007	.012	.157	<.001	.014		<.001	<.001	.032	<.001	.012
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 7: Doc&Gov	Pearson Correlation	.601**	.594**	.420**	.700**	.489**	.599**	1	.667**	.431**	.822**	.764**
	Sig. (2-tailed)	<.001	<.001	.006	<.001	.001	<.001		<.001	.004	<.001	<.001
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 8: Performance	Pearson Correlation	.585**	.523**	.541**	.529**	.347*	.491**	.667**	1	.276	.541**	.652**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	.024	<.001	<.001		.077	<.001	<.001
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 9: Ed&Knowledge	Pearson Correlation	.410**	.362*	.153	.219	.482**	.332*	.431**	.276	1	.360*	.282
	Sig. (2-tailed)	.007	.019	.334	.163	.001	.032	.004	.077		.019	.070
	N	42	42	42	42	42	42	42	42	42	42	42
Factor 10: Process	Pearson Correlation	.434**	.577**	.393*	.645**	.422**	.601**	.822**	.541**	.360*	1	.730**
	Sig. (2-tailed)	.004	<.001	.010	<.001	.005	<.001	<.001	<.001	.019		<.001
	N	42	42	42	42	42	42	42	42	42	42	42
Outcome	Pearson Correlation	.529**	.580**	.528**	.442**	.315*	.385*	.764**	.652**	.282	.730**	1
	Sig. (2-tailed)	<.001	<.001	<.001	.003	.042	.012	<.001	<.001	.070	<.001	
	N	42	42	42	42	42	42	42	42	42	42	42

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX F: ASSUMPTIONS OF REGRESSION

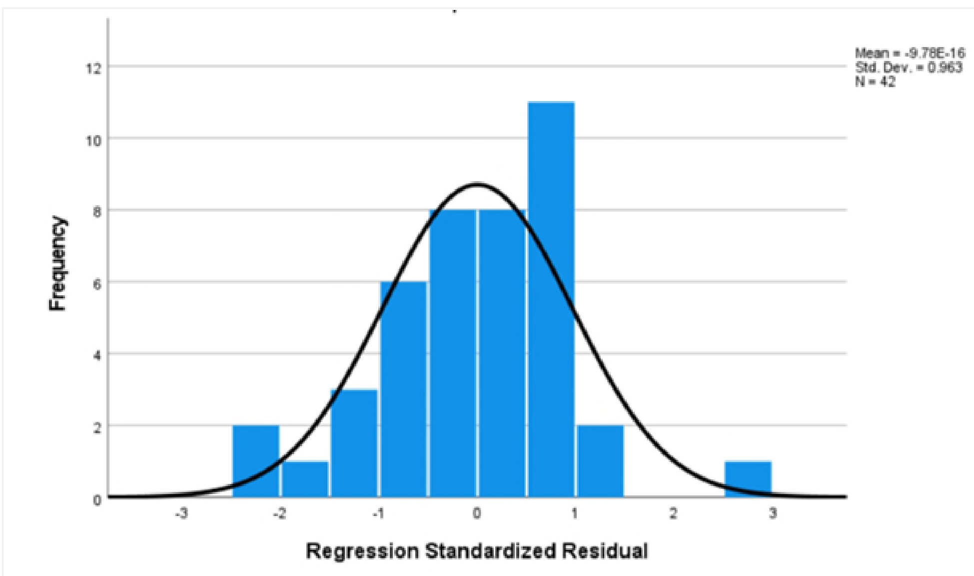


Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	.089	42	.200*	.961	42	.158
Standardized Residual	.089	42	.200*	.961	42	.158

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction



APPENDIX G: LINEAR REGRESSION ANALYSIS RESULTS

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.764[a]	.583	.573	3.22912	.583	55.948	1	40	<.001	
2	.797[b]	.636	.617	3.05781	.052	5.608	1	39	.023	
3	.823[c]	.677	.652	2.91543	.042	4.902	1	38	.033	1.774

a. Predictors: (Constant), Factor 7 Gov

b. Predictors: (Constant), Factor 7 Gov, Factor 3 WK Inv

c. Predictors: (Constant), Factor 7 Gov, Factor 3 WK Inv, Factor 5 Resource

d. Dependent Variable: Outcome

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	583.387	1	583.387	55.948	<.001[b]
	Residual	417.089	40	10.427		
	Total	1000.476	41			
2	Regression	635.819	2	317.910	34.000	<.001[c]
	Residual	364.657	39	9.350		
	Total	1000.476	41			
3	Regression	677.486	3	225.829	26.569	<.001[d]
	Residual	322.990	38	8.500		
	Total	1000.476	41			

a. Dependent Variable: Outcome

b. Predictors: (Constant), Factor 7 Gov

c. Predictors: (Constant), Factor 7 Gov, Factor 3 WK Inv

d. Predictors: (Constant), Factor 7 Gov, Factor 3 WK Inv, Factor 5 Resource

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	5.862	2.152		2.724	.010		
	Factor 7 Gov	.664	.089	.764	7.480	<.001	1.000	1.000
2	(Constant)	1.451	2.761		.525	.602		
	Factor 7 Gov	.572	.093	.658	6.175	<.001	.824	1.214
	Factor 3 WK Inv	.415	.175	.252	2.368	.023	.824	1.214
3	(Constant)	1.569	2.633		.596	.555		
	Factor 7 Gov	.640	.093	.736	6.845	<.001	.735	1.361
	Factor 3 WK Inv	.621	.191	.378	3.248	.002	.628	1.593
	Factor 5 Resource	-.361	.163	-.268	-2.214	.033	.580	1.725

a. Dependent Variable: Outcome

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	Factor 1 Mgmt	.111[b]	.866	.392	.137	.639	1.564	.639
	Factor 2 Comm	.195[b]	1.562	.126	.243	.647	1.546	.647
	Factor 3 WK Inv	.252[b]	2.368	.023	.355	.824	1.214	.824
	Factor 4 WK Acc	-.182[b]	-1.282	.207	-.201	.510	1.961	.510
	Factor 5 Resource	-.076[b]	-.646	.522	-.103	.761	1.314	.761
	Factor 6 Tech	-.113[b]	-.881	.384	-.140	.642	1.559	.642
	Factor 8 Perf	.257[b]	1.938	.060	.296	.554	1.803	.554
	Factor 9 Train	-.057[b]	-.499	.621	-.080	.815	1.228	.815
	Factor 10 Process	.314[b]	1.798	.080	.277	.324	3.086	.324
2	Factor 1 Mgmt	-.005[c]	-.036	.972	-.006	.536	1.864	.536
	Factor 2 Comm	.031[c]	.203	.840	.033	.401	2.492	.401
	Factor 4 WK Acc	-.199[c]	-1.488	.145	-.235	.509	1.966	.469
	Factor 5 Resource	-.268[c]	-2.214	.033	-.338	.580	1.725	.580
	Factor 6 Tech	-.101[c]	-.836	.409	-.134	.640	1.561	.555
	Factor 8 Perf	.163[c]	1.160	.253	.185	.472	2.119	.472
	Factor 9 Train	-.048[c]	-.447	.658	-.072	.814	1.229	.686
	Factor 10 Process	.279[c]	1.674	.102	.262	.321	3.112	.313
3	Factor 1 Mgmt	.029[d]	.229	.820	.038	.529	1.892	.529
	Factor 2 Comm	.032[d]	.216	.830	.036	.401	2.492	.401
	Factor 4 WK Acc	-.194[d]	-1.529	.135	-.244	.509	1.966	.441
	Factor 6 Tech	-.062[d]	-.526	.602	-.086	.624	1.603	.534
	Factor 8 Perf	.109[d]	.792	.434	.129	.454	2.202	.454
	Factor 9 Train	.055[d]	.483	.632	.079	.674	1.484	.480
	Factor 10 Process	.278[d]	1.753	.088	.277	.321	3.112	.299

a. Dependent Variable: Outcome

b. Predictors in the Model: (Constant), Factor 7 Gov

c. Predictors in the Model: (Constant), Factor 7 Gov, Factor 3 WK Inv

d. Predictors in the Model: (Constant), Factor 7 Gov, Factor 3 WK Inv, Factor 5 Resource

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	10.2426	29.5213	21.5238	4.06498	42
Residual	-7.14416	8.21351	.00000	2.80674	42
Std. Predicted Value	-2.775	1.967	.000	1.000	42
Std. Residual	-2.450	2.817	.000	.963	42

a. Dependent Variable: Outcome

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Factor 7 Gov	Factor 3 WK Inv	Factor 5 Resource
1	1	1.973	1.000	.01	.01		
	2	.027	8.522	.99	.99		
2	1	2.953	1.000	.00	.00	.00	
	2	.030	9.968	.20	.99	.12	
	3	.017	13.182	.80	.01	.87	
3	1	3.923	1.000	.00	.00	.00	.00
	2	.033	10.893	.28	.05	.00	.72
	3	.030	11.495	.15	.94	.10	.01
	4	.014	16.522	.57	.01	.90	.27

a. Dependent Variable: Outcome

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