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Adoption of Additive Manufacturing for Auto Parts Production: Case of Bishoftu Automotive and Manufacturing Industry

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Adoption of Additive Manufacturing for Auto Parts Production: Case of Bishoftu Automotive and Manufacturing Industry

By

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Declaration

I hereby declare that the work being presented in this thesis entitled "Adoption of Additive Manufacturing for Auto Parts Production: Case of Bishoftu Automotive and Manufacturing Industry" is original work of my own, has not been presented for a degree of any other university and all the resource of materials used for this thesis have been duly acknowledged.

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Abstract

This study investigates the adoption of additive manufacturing in the Bishoftu Automotive Industry in Ethiopia. The study applies an integrated framework of Diffusion of Innovation (DOI) and Technology-Organization-Environment (TOE). This study also used combined data from primary and secondary sources using quantitative and qualitative methodologies to allow for the exploration of the factors and constraints influencing the decision to adopt additive manufacturing. Additionally, the research undertakes a thorough literature analysis of Adoption theories such as DOI, TOE, and factors affecting additive manufacturing adoption.

Five point Likert scale was the method used to collect the useful information for this study. The questionnaire was distributed to managers, engineers, and technicians in the Bishoftu Automotive and Manufacturing Industry. Subsequently, the collected data was subjected to analysis through the application of descriptive statistics and partial least squares structural equation modeling (PLS-SEM) utilizing SPSS version 27 and SmartPLS version 4.0.9.6 software. The study outcomes revealed that several critical determinants significantly impact the adoption of additive manufacturing (AM) in the automotive sector. These determinants encompass relative advantage, compatibility, complexity, trialability, observability, technology-related factors, and organizational as well as environmental factors

The results of this study enhance our understanding of the adoption of additive manufacturing and provide valuable practical guidance for decision-makers within the Bishoftu Automotive Industry. Drawing from these findings, recommendations have been formulated to facilitate the effective integration of AM in the automotive sector. Additionally, this study identifies potential areas for future research in this field.

Keywords: Automotive manufacturing, Additive manufacturing, 3D printing, Technology Adoption

Contents

List of Figures

List of Tables

Abbreviations and Acronym

3DP: 3D printing

AI: Artificial intelligence

BAMI: Bishoftu Automotive and Manufacturing Industry

CAD: Computer-Generated Design

DOI: Diffusion of Innovations Theory

IoT: Internet of Things

MTERDC: Manufacturing Technology and Engineering Industry Research and Development Centre

TAM: Technology Acceptance Model

TOE: Technology, Organization, and Environment

UTAUT: Unified Theory of Acceptance and Use of Technology

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Words cannot express my gratitude to my family for their continuous blessings and support over the years. I have the utmost gratitude for my mother, Dise Aliyi, and father, Asefa Dina. All my friends have given me helpful advice and positive reinforcement, many thanks. Last but not least, I would like to extend my heartfelt thanks to my lovely wife, Rose Tafese Throughout the difficult process of researching and writing this article, your support, insight, and encouragement have kept me unshakable. You will always be remembered and loved in my heart.

Dedication

This thesis is dedicated to my father, Asefa Dina. His unwavering faith in education became my guiding light, and his sacrifices laid the foundation for my academic career. Though he is no longer physically present, his spirit remains alive in the pages of this paper and in every step of my journey. Thank you, Dad, for being my inspiration, my mentor, and my eternal guide. I miss you. I pray Allah to have mercy upon you and reunite us back together in Jannah.

CHAPTER ONE

1. BACKGROUND AND JUSTIFICATION

1.1 Introduction

With the speed at which technology is developing nowadays, adopting new technologies has become essential for individuals, organizations, and manufacturing industries. The pace at which technology is developing is very fast, which has widened the scope of possibilities (Ola, 2022). In the realm of manufacturing, a perpetual challenge lies in discovering innovative methods to enhance efficiency, reduce costs, and maintain competitiveness. Manufacturing enterprises face the ongoing demands of factors like globalization, intense market rivalry, and rapid technological advancements (Marak et al., 2019). To overcome these factors, manufacturing industries must improve their technological capability and adapt to modern technology. The adoption of technology is critical in today's world because it allows organizations to improve operational efficiency, reduce operational costs, and improve customer service (Kristianto et al., 2012).

The term Industry 4.0 refers to the fourth industrial revolution and it’s the incorporation of digital technologies into manufacturing processes (Javaid et al., 2022). Within this context, Additive Manufacturing (AM) emerges as a pivotal component of Industry 4.0, offering the potential for significant and immediate enhancements in production. AM is garnering escalating interest across diverse industries due to its capacity to transform manufacturing processes, enabling greater efficiency, customization, and sustainability (Mohanavel et al., 2021).

Additive manufacturing, also known as 3D printing (3DP), is a process of creating physical objects by creating material layer by layer, using digital design data (Shahrubudin et al., 2019) and is an emerging technology that is becoming increasingly popular in the industry due to its ability to manufacture parts with complicated features (Goh et al., 2021). The technology has been rapidly developing and has been adopted in various industries, including aerospace, automotive, and medical devices (Shahrubudin et al., 2019).

The automotive industry is among the sectors that have recognized the potential of Additive Manufacturing to revolutionize the manufacturing process and drive innovation. The automotive industry has seen significant advances in this technology due to revolutionizing the automotive manufacturing industry by allowing rapid prototyping, and the creation of complex geometries (Leal et al., 2017). It eliminates the need for costly and time-consuming traditional manufacturing processes such as mold-making and tooling (Steenhuis et al., 2020). As a result, it offers the potential for reduced lead times and improved agility in the production process.

The adoption of additive manufacturing in the automotive industry also has the potential to bring about improvements in customization (Dilberoglu et al., 2017; Mohanavel et al., 2021), sustainability improvements (Niaki et al., 2019; Y. Wang et al., 2022), and streamlining the supply chain (Delic & Eyers, 2020). It also allows for the production of parts using recycled materials, further reducing the environmental impact of automotive production (Böckin & Tillman, 2019). Another possibility is the use of additive manufacturing to prototype and test new vehicle designs (Ngo et al., 2018).

The automobile industry, one of Ethiopia's largest manufacturing industries, has a big impact on the economy of the nation. According to the Manufacturing Technology and Engineering Industry Research and Development Centre (MTERDC), there are currently over 50 companies producing minibuses, buses, pick-ups, trucks, and two-wheel and three-wheel vehicles with a capacity of 148,849 units per year. Currently, the Ethiopian automobile industry is limited to assembly and small-scale manufacturing, relying on imports. To achieve self-sufficiency and avoid imports, the industry must adopt current technology and upgrade its technology to gain technological advantage. Adopting additive manufacturing in the industry makes sense as it can help overcome technological challenges and serve to boost their capability.

However, adopting AM in the automotive industry comes with its share of challenges. There are a various factors, both internal and external to the industry, which can influence whether or not companies choose to adopt this technology. Hence, it is crucial to pinpoint the pivotal factors that are most likely to shape the adoption of 3D printing in the automotive sector

1.2 Problem Statement

The Ethiopian automotive industry is facing several challenges. Despite the growth and potential of the Ethiopian automotive industry, it is heavily reliant on importing parts and assembly, resulting in increased exposure to dynamic changes in the market. They are unable to produce their products and establish a competitive edge; instead, they import from other countries (Sisay et al., 2021). According to Deloitte (2019), Ethiopia imported vehicle parts, spares, and accessories worth US$1.5 billion (about 10% of imports) in 2018. The industry must also overcome obstacles to improving product value and boosting production and operational effectiveness. The industry's capacity to offer a wider range of products may be constrained by the inability to manufacture complicated spare parts using conventional techniques. Furthermore, it is challenging for them to produce a part prototype due to the time-consuming and expensive nature of conventional machinery.

Issues:

- Dependence on third-party suppliers and imports increases the cost and time of production and increases the risk of supply chain disruptions.
- Limited in-house manufacturing capabilities, which reduces the industry's flexibility and ability to respond quickly to changing market demands.
- Lack of advanced technology, which hampers the ability of the industry to innovate and produce high-quality products.
- The inability to manufacture complex spare parts with traditional methods can limit the range of products offered by the industry.
- Competition from established automotive industries in other countries and the need to continuously innovate and improve production processes to stay ahead.

To overcome these challenges, the adoption of Additive manufacturing technology is proposed as a solution.

1.3 Research Questions

1) What are the key drivers, opportunities, and inhibitors of the adoption of additive manufacturing in the Bishoftu automotive and manufacturing industry?
2) How do the technological, organizational, and environmental factors influence the adoption of additive manufacturing in the Bishoftu automotive and manufacturing industry?
3) What are the primary determining factors that will impact the adoption of additive manufacturing within the Bishoftu automotive and manufacturing industry, and what potential solutions can be considered for mitigating any challenges that arise?

1.4 Objectives of the research

General objectives

The research's general objective is to examine the adoption of additive manufacturing technology and investigate the potential solutions for successfully adopting additive manufacturing in the Bishoftu Automotive and Manufacturing Industry.

Specific objectives

- To identify the key drivers, opportunities, and inhibitors of adoption in the Bishoftu Automotive and Manufacturing Industry.
- To assess the technological, organizational, and environmental factors that influence adoption in the Bishoftu Automotive and Manufacturing Industry.
- To assess key determinant factors and recommend for the successful adoption of additive manufacturing

1.5 Scope

The scope of the study will focus on the adoption of additive manufacturing in the Bishoftu Automotive and Manufacturing Industry. Specifically, the study will explore the following:

- The impact of additive manufacturing technologies on the automotive industry in selected industry
- The challenges and barriers to additive manufacturing adoption in the Bishoftu automotive industry
- Investigate the potential solutions for successfully adopting AM in the Bishoftu automotive industry

1.6 Significance of Study

This study aims to offer valuable theoretical insights into the Bishoftu automotive and manufacturing industry concerning the adoption of additive manufacturing. It will pinpoint the pivotal factors shaping the adoption of AM and put forth recommendations for its successful implementation. The outcomes of this study hold the potential to enhance the growth and competitiveness of the Ethiopian automotive and manufacturing industry, as well as the overall development of the country. Additionally, this study will be of interest to other developing countries looking to adopt AM in their industries.

1.7 Organization of the Study

The paper contains five chapters: the first chapter of the study provides an overview of the topic and the research questions that will be addressed. The second chapter the paper provides reviews of existing literature on the topic to identify any gaps in the knowledge. The method that were used to collect data and analyzing method is described in chapter three. The fourth chapter presents the results of the study and discusses their implications. The fifth chapter summarizes and provides recommendations for future research and practice.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

Additive manufacturing, also known as 3D printing, it’s the process of three-dimensional object from a computer-generated design (CAD) by building material layer by layer(Marak et al., 2019; Shahrubudin et al., 2019). Additive manufacturing, as the name suggests, involves adding material to an object to produce it. In contrast, when creating an object traditionally, it is frequently necessary to remove material through milling, machining, carving, shaping, or other techniques (Khorram Niaki & Nonino, 2017). Additive manufacturing (AM) enables designers to produce complex parts for machinery, aircraft, and cars in a fraction of the time and expense compared to more conventional techniques like forging, molding, and sculpture (Steenhuis et al., 2020).

Since the 1980s, additive manufacturing technology has existed (Wohlers & Gornet, 2012). AM was initially employed in industrial settings to produce prototypes, but as it has advanced over time, it has become faster, more dependable, and more accurate, enabling the production of intricate products that would be difficult to produce by conventional manufacturing techniques.

(Dilberoglu et al., 2017) stated 3DP as one of the most important and cutting-edge industry 4.0 technologies. The industry has recently shifted toward intelligent production and adopt additive manufacturing technology due to its compatibility with other technologies. Systems and networks, as well as autonomous, automatic, and intelligent machines, are all able to interact in this setting and respond to production management systems. Additionally, AM is a crucial technology that allows for the production of goods based on 3D designs without the need for human intervention.

By using additive manufacturing, and particularly metal 3D printing, the problem of automotive industry is currently experiencing is simplified. In Automotive industry, it offers design flexibility and enables the development of complex yet lightweight components (Yu et al., 2022). Innovative manufacturing methods are necessary to keep up with the automotive industry's constant market and design trends. By accelerating product design and development, providing production flexibility, and producing customized car parts and optimized automotive components on demand, the ground-breaking method of additive manufacturing (AM) gives this industry a significant competitive advantage (Vasco, 2021).

Because it can create incredibly intricate geometrical structures, additive manufacturing (AM) technology has a big impact on the production of automotive parts (Y. Wang et al., 2022). Additive manufacturing (AM) has some clear advantages over traditional manufacturing. In contrast to subtractive manufacturing techniques, which are more expensive and difficult to use, additive manufacturing techniques are faster, cheaper, easier to use, and more widely available to produce everything from prototypes to finished products. In addition to reducing supply chain risk, investing in additive manufacturing can increase productivity and agility significantly (Delic et al., 2019). It also needs less specialized labor overall because of its automated processes.

This technology is quickly gaining popularity due to its use in several industries, including aerospace, automotive, and medicine. But little is understood about the use and adoption of 3D printing technology, particularly in developing nations (Marak et al., 2019). The application of various theories from various fields is seen by academics as being necessary for the adoption of technology. Several key interrelated factors, including technical viability, economic viability, organizational readiness, and regulatory compliance, must work together for this technology to be adopted.

2.2 Adoption Models

Adoption model offers a framework for understanding the variables affecting the adoption of new industrial technologies. The Technology Acceptance Model (TAM), the Diffusion of Innovations Theory (DOI), the Unified Theory of Adoption and Use of Technology (UTAUT), and Technology, Organization, and Environment (TOE) are just a few of the adoption theories that are used to explain how technology is adopted.

2.2.1 Diffusion of Innovations Theory (DOI)

The Diffusion of Innovations theory, developed by Everett Rogers in 1962, is a widely used and accepted framework for understanding how innovations spread over time among various industries and disciplines (Miller, 2015). According to Taherdoost (2018), the innovation-decision process, adopter characteristics, and innovation characteristics are combined into one cohesive whole in the DOI model. Additionally, the theory puts forth five characteristics that help to explain how innovation is adopted in an organization (Kiwanuka, 2015). They are; Relative advantage, compatibility, complexity, trialability, and observability are factors the theory pinpoints as influencing innovation adoption.

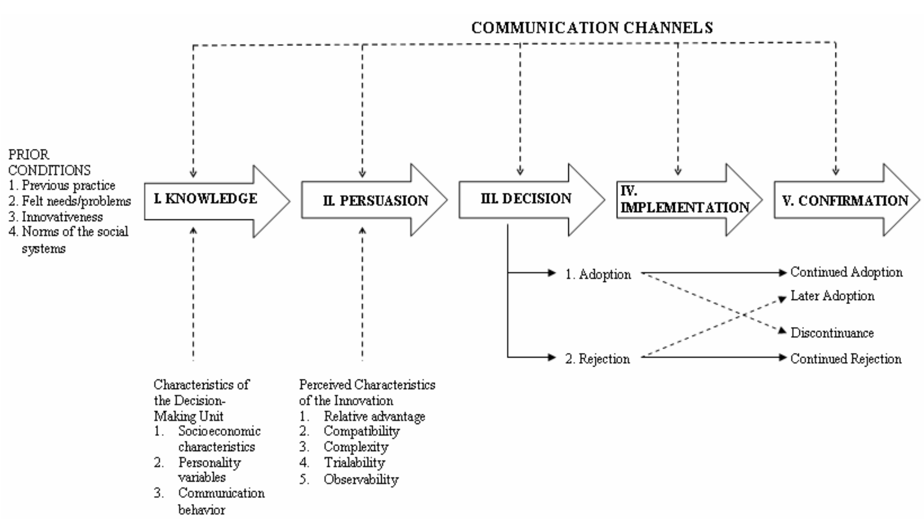

Figure 2.1 A Model of Five Stages in the Innovation-Decision Process

Source (Ismail, 2006)

Rogers theory also states, the rate at which innovations are adopted follows a bell-shaped curve, with a small group of early adopters setting the pace, then a larger group of early and late majority adopters, and finally a smaller group of laggards (Ismail, 2006). Innovators are people who are open to trying out new ideas, early adopters are somewhat constrained by social norms, and the early majority of people interact well with others but do not take on the early adopters' leadership roles (Ismail, 2006). Like the early majority, the late majority will wait to accept innovations until their peers have done so. The laggards are the most resistant to innovation and change agents of all the groups due to their increased skepticism and propensity for traditional views.

The Diffusion of Innovations theory has been used in a variety of industries, including marketing, technology, health, and education. Because it offers a framework for understanding the key factors that influence adoption and for developing strategies to assist and encourage adoption, it is seen as a useful tool for organizations looking to promote and adopt innovations.

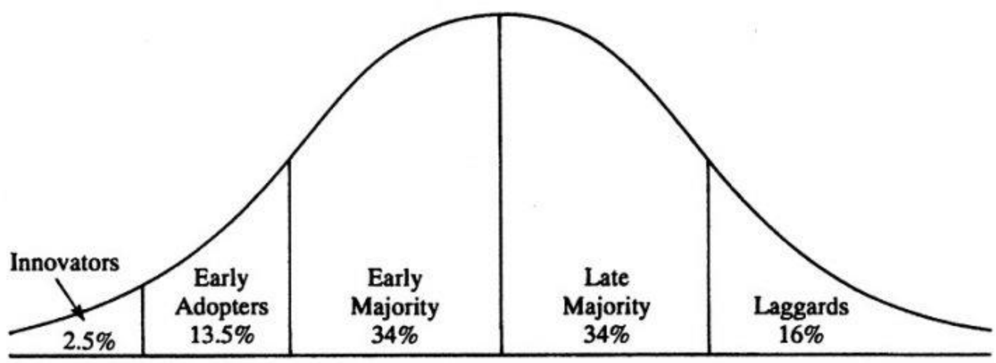

Figure 2.2: The Innovation Adoption Curve

Source (Rogers, 2003)

Despite the fact, that Rogers' idea of the diffusion of innovation has been the subject of several studies, the model has received some well-publicized criticism. Rogers himself outlined different limitations on the spread of innovation theories, including Pro-Innovation Bias, Individual-Blame Bias, recall problem, and Issue of Equality (Rogers, 2003).

2.2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a theoretical framework used for to examine and forecast how people will perceive and use technology. According to TAM, which was created by Fred Davis, Richard Bagozzi, and Paul Warshaw, the two elements that have the most impact on a user's desire to utilize technology are perceived utility and perceived ease of use (Y. L. Lai & Lee, 2020).

Perceived usefulness (PU) is the degree to which users believe that using technology will improve their performance or help them accomplish their goals, (Taherdoost, 2018). Perceived ease of use, or PEU, refers to how much consumers believe technology is easy to use and requires little effort. (Taherdoost, 2018). According to TAM, these two factors have a direct impact on user behavior, so people are more likely to adopt and use technology if they believe it to be both helpful and simple to use (Alshammari & Rosli, 2020). Additionally, TAM contends that extraneous variables, such as other people's perceptions and previous experience with related technologies, can affect how useful and simple technology is perceived to be (Bryan & Zuva, 2021). TAM has attracted a lot of interest in the field of information systems research and has been tested and shown to be effective in a variety of situations. By guiding the design and development of new technologies to enhance consumer uptake and adoption, it offers a simple framework for understanding and forecasting technology adoption (Dube et al., 2020).

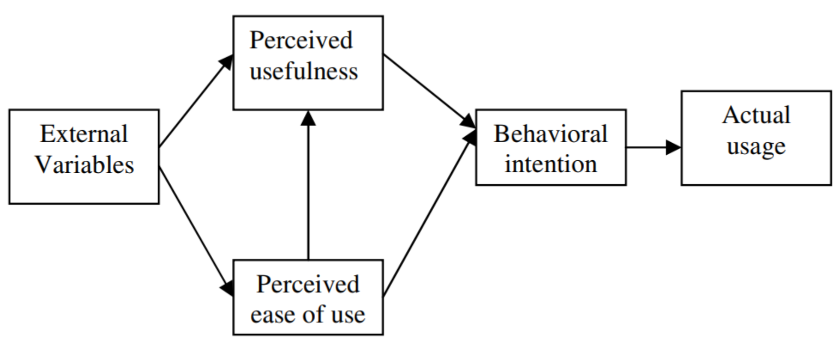

Figure 2.3: Technology Acceptance Model

Source (Venkatesh & Davis, 1996)

Despite being widely used and helpful for analyzing how people adopt new technologies, the Technological Acceptance Model (TAM) does have some drawbacks. The following are some of the main limitations:

- The TAM primarily focuses on how each user perceives technology; other factors, such as organizational or cultural issues, which may influence technology adoption, are not taken into account. The fact that it doesn't take into account social and human issues is another criticism (Bayraktaroglu et al., 2019).
- The TAM was developed in the context of specific technologies and user populations, which may have limited its applicability to other technologies or user groups.

2.2.3 Unified Theory of Acceptance and Use of Technology

Venkatesh developed the Unified Theory of Acceptance and usage of Technology (UTAUT) in 2003 to offer a full understanding of users' acceptance and usage of technology(J. Wang et al., 2022). To provide a more detailed explanation of the factors influencing user acceptance and usage behavior, UTAUT expands and incorporates earlier models like the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA) (P. Lai, 2017).

According to the unified theory of acceptance and use of technology (UTAUT), four major factors—performance expectations, effort expectations, social influence, and facilitating conditions—have a significant impact on users' willingness to accept and use technology. (Venkatesh et al., 2003). These four important variables serve as direct predictors of behavioral intention and operate as a moderator between variables and user acceptance and use by taking into account aspects such as gender, age, experience, and voluntariness of use. (J. Wang et al., 2022; Williams et al., 2015)

Performance expectancy is “the degree to which an individual believes that using the system will help him or her to attain gains in job performance”(Venkatesh et al., 2003). Effort expectancy is "the degree of ease associated with the use of the system"(Venkatesh et al., 2003) and built using perceived ease of use and complexity derived from TAM, which has identical definitions and scales (Marikyan, D. & Papagiannidis, 2023). Social Influence is "the degree to which an individual perceives that important others believe he or she should use the new system"(Venkatesh et al., 2003). Facilitating conditions is "the degree to which an individual believes that an organization's and technical infrastructure exists to support the use of the system"(Venkatesh et al., 2003).

UTAUT has undergone extensive testing and validation across a variety of technologies and environments (Marikyan, D. & Papagiannidis, 2023). It offers a thorough framework for comprehending user behavior and useful applications for designing, putting into practice, and assessing technology systems that are user-friendly, successful, and well-liked (Venkatesh et al., 2016).

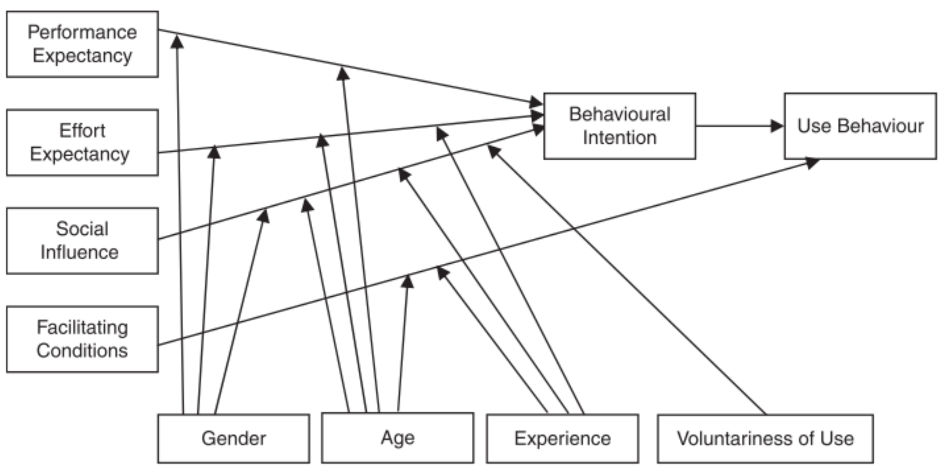

Figure 2.4: Unified Theory of Acceptance and Use of Technology

Source (Venkatesh et al., 2003)

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been applied widely and has given useful insights into how people accept and use technology, although it has certain limitations (Venkatesh et al., 2003). The following are some of UTAUT's limitations:

- UTAUT is designed to explain how technology is adopted and used in corporate settings; it could not be applicable in other circumstances because it cannot explain behavioral intention in various environments.
- Sometimes the adoption and usage of technology by users may be influenced by outside variables such as governmental policies, regulatory frameworks, and market competition, which are not taken into account by UTAUT.
- UTAUT does not address other crucial determinants of technology use, such as user satisfaction, trust, self-efficacy, innovativeness, perceived threats, and perceived risk as it is primarily concerned with understanding users' intentions to adopt and use technology.

2.2.4 Technology, Organization, and Environment (TOE)

The Technology-Organization-Environment (TOE) framework is a theoretical framework for explaining how different elements affect how new technologies are adopted and used in an organization(Baker, 2012). TOE framework provides a holistic perspective on technology adoption and implementation. It considers a variety of factors when making an adoption decision and offers a thorough understanding of the interplay between technology, organization, and environment in technology adoption and diffusion (Awa et al., 2017).

The three main parts of the TOE framework are technology, organization, and environment (Bryan & Zuva, 2021). According to Awa et al. (2016), the Technology component refers to a technology's technical features and capabilities, such as its design, functionality, and dependability. The organization component, which includes the adoption organization's goals, strategies, and decision-making procedures, refers to the adoption organization's structures, procedures, and culture (Baker, 2012). The term "environment" refers to the external factors, such as market conditions, governmental regulations, and other organizations' actions, that have an impact on how technology is adopted (Chatterjee et al., 2021; Gupta et al., 2022)

This framework has been used widely to adopt technology in organization and its best tool for understanding of adoption factor between technology, organization, and environment (Awa et al., 2017; Baker, 2012). However, there are also some limitations.

- It may be overly generic and broad, which makes it difficult to apply in certain situations.. The complexity of technology adoption and use may also not be fully captured by the framework, especially in rapidly changing situations where external factors might have a big influence on technology decisions.
- The TOE framework does not offer specific instruction on how organizations might get over the challenges of adopting new technology.

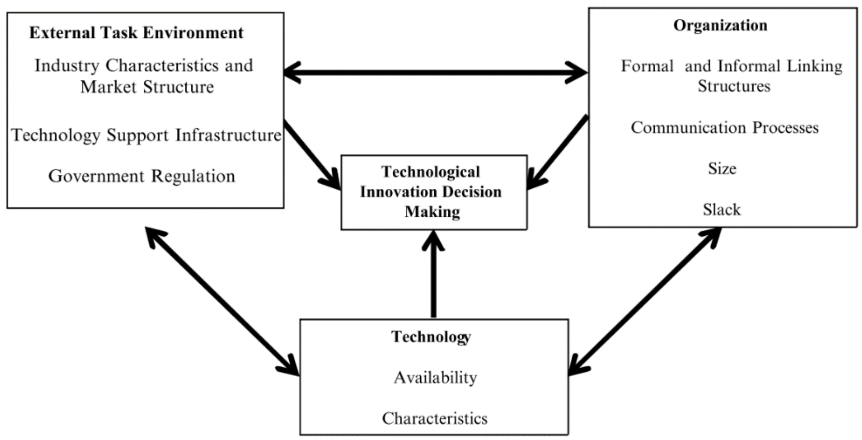

Figure 2.5: The technology–organization–environment framework

Source (Baker, 2012)

Table 2.1: Several articles utilizing various adoption theories for technology adoption

Author	Technology	Theory
(Radhakrishnan & Chattopadhyay, 2020)	Artificial Intelligence	DOI, TOE, TAM, UTAUT
(Marak et al., 2019; Ukobitz, 2020)	3D Printing	DOI
(Awa et al., 2016)	Adoption of ERP solution	TOE
(Gui et al., 2020)	Cloud computing	TOE
(Kumar Bhardwaj et al., 2021)	Blockchain Technology	DOI, TAM, TOE
(Souiden et al., 2021)	Mobile banking technology	TAM, UTAUT

2.3 Challenges of Additive Manufacturing Adoption

The adoption of additive manufacturing (AM) is influenced by a multitude of factors. These factors encompass a wide range that can influence the implementation and integration of additive manufacturing. According to (Ronchini et al., 2023) factors influencing the adoption of Additive manufacturing (AM) can be categorized into two main groups: drivers and barriers.

The drivers are factors that positively influence and promote the adoption of AM within dynamic systems. Several studies have proposed two categories to uncover the drivers behind the adoption of additive manufacturing (AM). The first category involves exogenous events, which refer to external factors that can significantly influence the adoption of AM. One example of such an event is the expiration of critical patents, which can remove barriers to accessing AM technologies and encourage their widespread adoption (Ryan et al., 2017). Another noteworthy exogenous event is the rise of Industry 4.0, also known as the Fourth Industrial Revolution. Industry 4.0 emphasizes advanced digital technologies, automation, and interconnectedness, aligning closely with the capabilities and potential of AM, thereby serving as a catalyst for its adoption (Nascimento et al., 2019). The second category focuses on the anticipated benefits of AM adoption.

These drivers may include technological advancements, cost efficiencies, design flexibility, and increased sustainability (Luomaranta & Martinsuo, 2020; Martinelli & Christopher, 2019; Thomas-Seale et al., 2018). However, some obstacles act as impediments to the adoption of additive manufacturing (AM). These obstacles, referred to as barriers, have been categorized into six primary categories (Martinsuo & Luomaranta, 2018). These categories include technological barriers, strategic barriers, supply chain barriers, operational barriers, organizational barriers, and external barriers.

The identified categories encompass various barriers to the adoption of additive manufacturing (AM). Technological barriers encompass challenges related to the AM technology itself, low production speed, high manufacturing costs for series production, technical constraints, quality issues, and post-processing requirements (Thomas-Seale et al., 2018). Strategic barriers involve uncertainties in aligning AM with an organization's strategic goals, integrating it into existing business models, and assessing its long-term value (Braziotis et al., 2019; Martinsuo & Luomaranta, 2018; Tziantopoulos et al., 2019). Supply chain barriers focus on challenges in coordinating with suppliers, managing logistics, and safeguarding intellectual property. It also involves uncertainties regarding the structure of the supply chain after AM adoption (Martinsuo & Luomaranta, 2018). Operational barriers pertain to difficulties in scaling up AM production, ensuring quality control, and adapting manufacturing processes. Operational barriers entail limitations in quality, accuracy, and reliability, restricted availability of materials, and the absence of technical standards and specifications (Chaudhuri et al., 2019; Colosimo et al., 2018). Organizational barriers revolve around internal factors like resistance to change, lack of leadership support, and limited resources. Organizational barriers also encompass a lack of skills and knowledge related to AM, as well as a scarcity of trained and skilled labor force (Martinsuo & Luomaranta, 2018; Öberg & Shams, 2019; Shukla et al., 2018). External barriers encompass external factors beyond an organization's control, such as regulatory constraints, industry standards, market uncertainties, and the availability of necessary infrastructure. It also includes the absence of certifications and regulations, as well as challenges related to intellectual property rights protection for CAD files (Boer et al., 2020; Halassi et al., 2019; Yampolskiy et al., 2018).

The process of adopting new technology is complicated, and numerous studies have been done to better understand the challenges that people and organizations encounter using a variety of approaches. Studies conducted by Dwivedi et al. (2017) concentrated on the analysis of barriers to the adoption of 3D printing in the Indian automotive industry. They did this by identifying concerns from the literature and then prioritizing them based on their importance with the help of expert judgment and the fuzzy-ISM methodology. Additionally, some studies explore the challenges SMEs face when adopting additive manufacturing technology (Martinsuo & Luomaranta, 2018), the challenges they face when adopting 3D printing (Khorram Niaki & Nonino, 2017), and other aspects of additive manufacturing technology adoption in SMEs (Kulkarni et al., 2021) by utilizing various techniques.

Some studies employ a single theory such as the Diffusion of Innovation theory (DOI) (Marak et al., 2019), and the Technology organization Environment (TOE) (Awa et al., 2016; Gui et al., 2020) to determine adoption factors in different technology adoption. However, others have blended adoption theories like the Technology Acceptance Model (TAM), the Diffusion of Innovation theory (DOI), the Technology-Organization-Environment (TOE), and the Unified Theory of Acceptance and Use of Technology (UTAUT) to adopt various technologies (Kumar Bhardwaj et al., 2021; Radhakrishnan & Chattopadhyay, 2020; Souiden et al., 2021).

Most studies on additive manufacturing (AM) adoption have either focused on adoption barriers or used a single framework. This has led to a limited understanding of the factors that influence AM adoption. This study aims to address this gap by providing a holistic approach to assessing adoption key determinants by combining the Diffusion of Innovation (DOI) and Technology-Organization-Environment (TOE) frameworks.

2.4 Gaps Identification

The literature review identified a number of major gaps in our understanding of AM Adoption. These gaps include:

- Limited focus on non-adopters and different industries: Most studies have focused on a few industries and adopters of AM, excluding non-adopters and detailed case studies in different industries using various 3D printing technologies. This limits our understanding of the factors that influence AM adoption and how they vary across different industries and contexts.
- Limited consideration of other relevant factors: Some studies have not included other relevant factors, such as those related to technology, organizational structure, the environment, and other external variables, that might have an impact on the adoption of AM. This limits our understanding of the full range of factors that influence AM adoption and how they interact.
- Limited geographic scope and use of in-depth case studies: Most studies have been conducted in a small geographic area and/or have used surveys to assess AM adoption. This limits our understanding of the factors that influence AM adoption in different contexts and our ability to gain a deep understanding of the challenges and opportunities associated with AM adoption.

2.5 Model and Hypotheses

2.5.1 Model

The model is based on two theories from the literature: Diffusion of Innovation (DOI) theory and Technology-Organization-Environment (TOE) framework. To capture the perceived advantages and disadvantages of implementing additive manufacturing, the model includes characteristics such as relative advantage, compatibility, complexity, observability, and trialability. To account for the specific features of the technology, the characteristics of the adopting organization, and the external factors influencing adoption, the model incorporates variables related to technology characteristics, organizational characteristics, and environmental characteristics from the TOE framework.

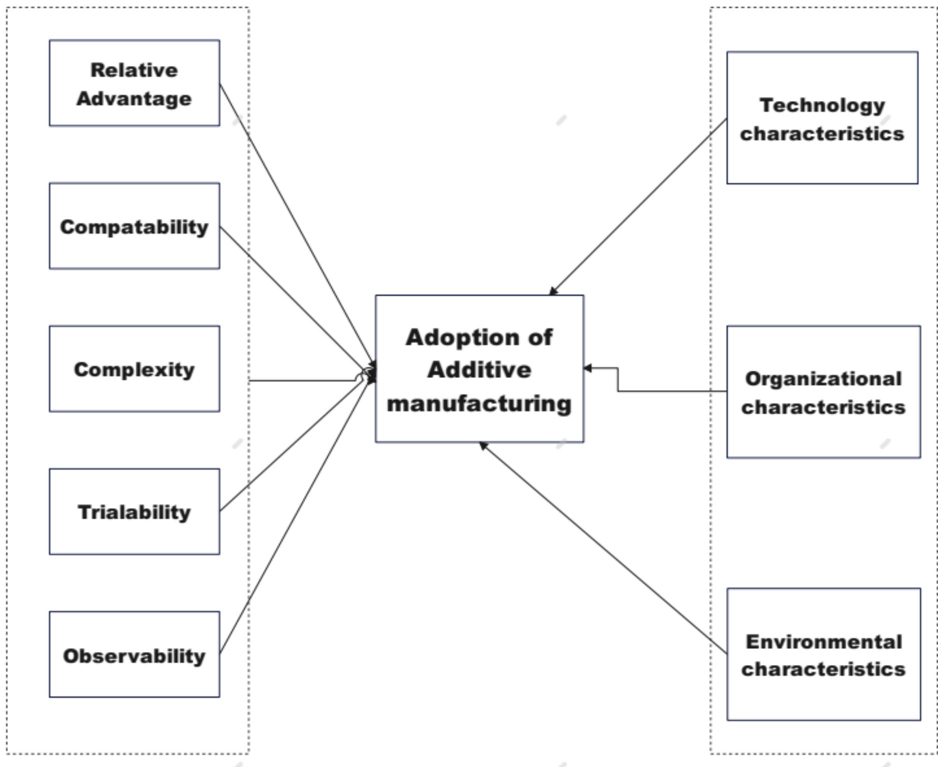

Figure 2.6: Proposed DOE and TOE model framework

Source: Adopted and modified from (Oliveira et al., 2014)

2.5.2 Hypotheses

Relative advantage is the "degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 2003). According to Rogers' theory, if innovations have advantages over the previous innovations they can be easily adopted and implemented. In this case, if the advantages of additive manufacturing outweigh traditional manufacturing processes, the results will positively influence its adoption. Based on this hypothesis is made for relative advantage.

H1: Relative Advantage have positive effect on AM Adoption.

Compatibility in the diffusion of innovation theory is the “degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers, 2003). In other words, it refers to how well the innovation integrates into the potential adopter's current way of life. Innovations that are viewed as consistent with the current values, experiences, and requirements of potential adopters are more likely to be adopted quickly. Conversely, innovations that are viewed as being incompatible are less likely to be adopted.

H2: Compatibility will positively influence AM Adoption.

Complexity is the “degree to which an innovation is perceived as difficult to understand and/or use” (Rogers, 2003). Rogers suggested that innovations can be described as either complex or simple and that people may not fully understand the importance of a new invention when it is first introduced. The level of difficulty associated with understanding and using innovation, means innovations that are simple and easy to use are generally more likely to be adopted.

H3: Complexity will negatively influence AM adoption.

Trialability is the “degree to which a new technology can be experimented with or tested before it is fully adopted” (Rogers, 2003). Trialability is significance factor in technology adoption because it allows potential adopters to learn about the technology and assess its suitability for their needs without having to make a full commitment. The opportunity to experiment with the innovation can reduce perceived risks and uncertainties.

H4: Trialability will positively influence AM adoption.

Observability is the “monitoring and understanding the performance and behavior of a new technology as it is being adopted” (Rogers, 2003). When potential adopters can observe the positive outcomes experienced by early adopters, it can positively influence their adoption decision.

According to (Rogers, 2003), the adoption of innovation in organizations is influenced by different factors. These are the personal (leadership attitude towards change), internal (centralization, complexity, interconnectivity, employee number, and organizational slack), and external (system openness) of the organization.

H5: Observability will positively influence AM Adoption.

Technology characteristics represents the technological characteristics or innovations that an organization is considering or has adopted. It includes hardware, software, infrastructure, and other related elements. In our case, factors such as technology readiness (technical infrastructure, Availability of technology, and the availability of skilled labor) are important for organizations that are considering adopting additive manufacturing (AM).

H6: Technology readiness will positively influence adoption of AM.

Organization characteristics refers to the internal aspects of an organization, including its structure, culture, processes, and resources. Organizations need to consider their readiness and ability to adopt and adapt to the new technology. Factors like top management support, industry culture, resource availability, and firm size need to consider in this context.

H7: Organizational factor will positively influence AM Adoption

Environmental characteristics are the external factors that can influence an organization's technology adoption. Understanding the external context is vital because it can have a significant impact on the success of technology adoption. Factors such as government regulations, competitive pressures, and sustainability need to consider in this context.

H8: Environmental factor will positively influence AM Adoption

CHAPTER THREE

3. RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

In this chapter, the techniques used to collect data and analysis method is presented. A focused observation of a specific issue is the first step in the research design process. To find current theories and concepts relevant to my research question, a thorough literature review is conducted. This included additive manufacturing, technology adoption theories such as DOI and TOE.

The research framework, which is depicted in the Figure 3.1, brings the innovation characteristics of Additive manufacturing within the context of the Adoption model framework. Diffusion of innovation theory (DOI) and Technology Environment Organization (TOE) were combined from Adoption theory. Direct observation, interviews, and questionnaires were used to obtain the data. Managers, engineers, and technicians served as the study's data sources.

3.2 Research Methodology

To accomplish its main goals, the study used mixed methods, which include qualitative and quantitative techniques. It also used primary and secondary sources. Below is a more detailed explanation of the methodologies used.

3.2.1 Literature Review

To gain a thorough understanding of the subject domain, a detailed review of the literature was done to achieve the research goals, focusing on several theoretical ideas that were important to this study, such as additive manufacturing and the technology adoption model. The literature review began with an examination of the global view of the adoption of various technologies utilizing various technology adoption theories. For the literature review, various sources including online databases, scholarly publications, and industry reports were reviewed.

3.2.2 Study Area

The Bishoftu Automotive and manufacturing industry is the subject of the investigation. There are more than 50 automotive companies in Ethiopia, according to data from the Metal Industry Development. Bishoftu stands out among the players in the automotive industry compared to other industries in Ethiopia. It currently produces different vehicles in the country than any other automotive company, including passenger cars, light-duty pickups, vans, and buses which allows the potential for additive manufacturing to be adopted in the automotive industry there. Its well-established industrial infrastructure, which includes manufacturing facilities, and a network of companies involved in the automotive industry, makes it the perfect place to investigate how additive manufacturing technologies might be integrated into currently used automotive manufacturing processes. Bishoftu wide range of automotive businesses, which include manufacturing body and parts, providing maintenance and repair services, and providing other automotive services, further increases the chance for a thorough investigation of additive manufacturing adoption across various subsectors within the automotive industry. Furthermore, because of its size and scope, Bishoftu is likely to see some of the most dynamic and far-reaching changes as a result of the adoption of additive manufacturing technologies.

3.2.3 Sample size

The researcher used a stratified sampling method to survey engineers and technicians. The researcher divided the population of engineers and technicians into five strata, based on the factory they work in. In each of the five factories (heavy-duty truck production, bus production, power train manufacturing, vehicle system manufacturing, and body and frame manufacturing), the researcher selected a sample of engineers and technicians.

The formula for stratified sampling is based on (Parsons, 2017)

$$ni = (Ni * nt)/N$$

Where:

- *ni* is the sample size for stratum *i*
- *Ni* is the population size for stratum *i*
- *nt* is the total sample size
- *N* is the total population size

To calculate the minimum sample size from each factory,

n_1 = (100 * 75) / 300 = 25

n_2 = (90 * 70) / 300 = 21

n_3 = (88 * 75) / 300 = 22

n_4 = (80* 75) / 300 = 20

n_5 = (75 * 68) / 300 = 17

To the minimum 105 sample, size is needed.

The researcher interviewed five managers from each department to get their perception on Am adoption.

3.2.4 Measurement Instrument

The questionnaire was designed to measure how respondents felt about the variables that affect how quickly new technologies are adopted in organizations. The questionnaire was based on two theories of technology adoption: the DOI model and the TOE framework. The questions were carefully selected from existing literature to ensure that they were relevant and reliable. The questionnaire was directly distributed to the participants. The questionnaire began with an introduction to the topic and a few demographic questions and asked about the variables that affect the adoption of new technologies in organizations. Respondents were asked to rate each set of questions on a 5-point Likert scale from strongly disagree to strongly agree.

3.2.4 Data gathering and its source

In the study, both primary and secondary data sources were used. Preliminary data was gathered through questionnaires and in-depth interviews with managers in the company, engineers, and technicians. Secondary data was acquired from academic publications, company reports.

i. **Interviews:** Five people who held managerial roles in various divisions of factories such as heavy-duty truck production, bus production, power train manufacturing, vehicle system manufacturing, and body and frame manufacturing were interviewed. The interview questions were created to cover a range of adoption-related topics, including difficulties, perceived benefits, organizational support, and influencing factors.
ii. **Observations:** By observing the company's current manufacturing techniques and how additive manufacturing is affecting the industry, the researcher was able to gain a better understanding of the factors that contribute to the adoption of additive manufacturing. This will help to understand how AM technology will be adopted, as well as the challenges and opportunities that come with integrating it into the company's operations.
iii. **Questionnaire:** The researcher used surveys to collect data from company managers, engineers, and technicians. The survey was based on existing literature on technology adoption and used Likert scales to measure each item. The survey had two sections: The first section focused on technology adoption through the DOI perspective. It had five subheadings: relative advantage, compatibility, complexity, trialability, and observability. The second section focused on technology, organizational, and environmental features. It was based on the technology-organization-environment framework.

Table 3.1: Detailed Description of gathering data

Method	Source of data	Why?
Interview	Company stakeholders: Managers, Engineers, and Technicians in selected industry	• Any difficulties or concerns related to the adoption of AM in the automotive industry as well as opportunities to overcome these difficulties. • To gain insights into the experiences, attitudes, and beliefs of automotive industry stakeholders towards additive manufacturing technologies and valuable insight into the potential solutions for successfully implementing AM
Observation	Company	• To obtain knowledge of current manufacturing practices, including their use of technology, organizational culture, and type of product, environmental effect and sustainability practices, employee productivity, and work procedures.
Questionnaires	Employees, Managers, Engineers, and Technicians in the selected industry	• To gain insight into the current state of the industry • To know the current level of knowledge and understanding of AM technologies, as well as the technological capability of the company to adopt these technologies. • To gain insight of key factors in AM technology adoption

3.3 Method of Data Analysis and Tools

This section describes the utilization of statistical methods in examining the data gathered for the model. The data was analyzed using SPSS version 27 and SmartPLS version 4.0.9.6. In SmartPLS, we utilized confirmatory factor analysis to estimate the structural equation model's parameters. This method helps combine closely related variables, which align with the hypothesized model and are supported by initial research, into a broader underlying dimension.

The aim of this analysis is to reduce an extensive dataset into a more concise set of significant dimensions and factors. This is carried out to uncover the underlying connections among the initial variables and to confirm the accuracy of the measurement instruments. After evaluating the measurement quality, bootstrapping is employed to gauge the characteristics of the sampling distribution using the collected sample data.

Bootstrapping operates by generating a bootstrap sample, which involves randomly selecting and replacing data from the original dataset. PLS offers a significant advantage in terms of assessing construct validity. However, it is important to avoid incorrectly specifying distorted factors. Another advantage of PLS is its resilience when faced with violations of regression assumptions and suboptimal measurements. In the chosen analytical method, statistical significance will be established based on a p-value of 0.05 (5%) or lower, a common significance level for data that follows a normal distribution. For more detailed information on the SmartPLS 4 conditions and result evaluation within this analytical approach, please refer to Table 3.2 and Table 3.3.

Table 3.2: Requirements and Considerations for SmartPLS 4 (PLS-SEM Algorithm)

Setting	**Value**
Initial Weights	1
Max. Number of Iterations	3000
Stop Criterion	10^{-7}
Type of Results	Standardized
Use Lohmoeller Settings	No
Weighting Scheme	Factor

Table 3.3: Structured Assessment of Results in PLS-SEM Analysis

Evaluation Criteria	**Quality Threshold**
Measurement Instrument Quality	
Cronbach's Alpha	> 0.7
Average Variance Extracted (AVE)	> 0.5
Structural Model Evaluation	
Multicollinearity Testing (VIF)	< 5
Path Coefficients, Significance and t value	$\beta > 1$, $p < 0.05$, t-value > 1.96

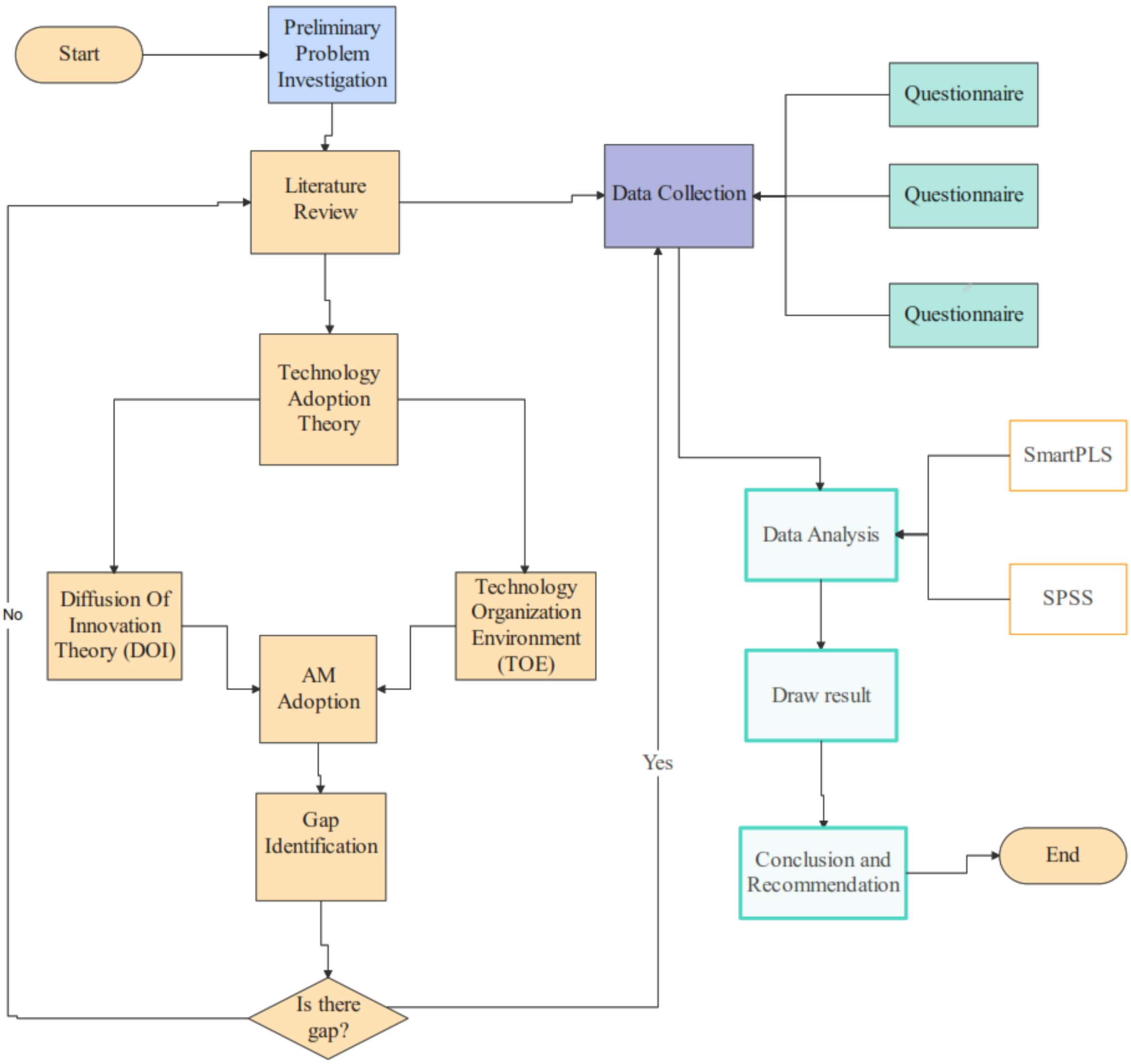

Figure 3.1: A research framework

CHAPTER FOUR

4. DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Company Background

Bishoftu Automotive and Manufacturing Industry (BAMI) is one of the industries under the Ethio Engineering group. Before the establishment of the industry, from mid-1984 to May 2008, it has been providing repair services for tanks and oral vehicles under the name of Project 40720. From May 2008 to April 2010, it provided Iron suit Military vehicles, repair and maintenance services for combat and communication equipment as well as generators by the name of Bishoftu Motorized Complex defense industry.

The Metals and Engineering Corporation was created in 2010 to reorganize the defense industry sector. Bishoftu Automotive and Locomotive Industry was the new name given to the Bishoftu Motorized Complex from that point forward. The sector underwent reorganization in 2012, creating the Bishoftu automobile industry and locomotive sub-industry. The locomotive sector is distinct from the Bishoftu automobile sector and is based in Addis Ababa. Bishoftu Automotive Industry between September 2012 and October 2017 carried out various initiatives. The Bishoftu Automotive and Engineering Industry has been set up to repair various commercial and military vehicles since October 2017.

Again, in 2020, they reorganized under Ethio Engineering Group by the name of Bishoftu Automotive and Manufacturing Industry. Currently, the industry has eight factories, namely a light vehicle manufacturing factory, a Heavy-duty truck production factory, a Bus Production Factory, a Power Train Manufacturing Factory, a Vehicle System Manufacturing Factory, a Body and Frame Manufacturing Factory, a Tank and Armored Vehicles Manufacturing Factory, and Paint Factory.

4.2 Sample and Data Characteristics

The descriptive and inferential statistics of the study found significant data on a sample of 120 respondents, who worked in the departments of factories that produced heavy-duty trucks, buses, powertrains, Vehicle system, and body and frames.

Table 4.1: Demographic and Professional Profile of Participants

Category	Number of Respondents	Percentage of Respondents
Gender	Male	93%
	Female	7%
Sub-total	120	100%
Educational Qualification	Bachelor Degree	80%
	Master's Degree	20%
Sub-total	120	100%
Year of Experience	Less than 1 year	5%
	1-3 years	7%
	3-5 years	35%
	5-10 years	35%
	More than 10 years	18%
Sub-total	120	100%
Job Title	Manager	8%
	Engineer	88%
	Technician	3%
Sub-total	120	100%

As shown in Table 4.1, 56 (93.0%) of the participants were male, while the remaining four (7.0%) were female. The majority of workers (35%) have 3-5 years of work experience, followed by those with group having 5-10 years of experience (35%). A smaller proportion of respondents had less than 1 year of experience (5%), 1-3 years of experience (7%), or more than 10 years of experience (18%). The result of employment job titles revealed that, of the 120 respondents, 5 (8.3%) are Managers, 53 (88.3%) are Engineers, and 2 (3.3%) are Technicians. As a result, with an average of good educational and experience in different position, the majority of people who are participated are in good position to give relevant information about the adoption of AM.

4.3 Determinants Characteristics

Researchers use variables based on the DOI theory and TOE framework to analyze adoption characteristics. These dimensions provide a methodological way to understand the variables that affect adoption. Through a thorough study of relevant literature, a questionnaire was developed to assess these factors.

4.3.1 Relative Advantage

Respondents were surveyed about how adopting AM compared to traditional manufacturing methods impacted efficiency, product quality, production speed, cost reduction, and rapid prototyping.

Table 4.2: Participant Responses to questions about AM Relative Advantage

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
RA1: AM Adoption will allow for increasing efficiency/productivity	4 (3.3%)	6 (5.0%)	8 (6.7%)	62 (51.7%)	40 (33.3%)	4.07 ± 0.950
RA2: AM adoption will enhance the quality of products	4 (3.3%)	2 (1.7%)	32 (26.7%)	48 (40.0%)	34 (28.3%)	3.88 ± 0.954
RA3: The Adoption of AM will allow an increase in the speed of production	8 (6.7%)	2 (1.7%)	20 (16.7%)	68 (56.7%)	22 (18.3%)	3.78 ± 0.989

RA4: Adopting AM will enable the company to reduce costs.	2 (1.7%)	14 (11.7%)	28 (23.3%)	58 (48.3%)	18 (15.0%)	3.63 ± 0.934
RA5: The use of AM will facilitate rapid prototyping and the creation of new products	2 (1.7%)	14 (11.7%)	6 (5.0%)	60 (50.0%)	38 (31.7%)	3.98 ± 0.996

As can be seen from the table, the respondents were positive about the potential benefits of the innovation, particularly in terms of improvements in efficiency, speed of production, and cost reduction. The mean scores for all five factors, as shown in the above table, are higher than the scale's midpoint (3), indicating that the respondents generally perceived the innovation to be beneficial. The standard deviations among variables are relatively low, indicating that there was a high degree of consensus among the respondents.

4.3.2 Compatibility

Table 4.3: Participant Responses to questions about AM Compatibility

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
CM1: Additive manufacturing is compatible with existing production systems.	2 (1.7%)	14 (11.7%)	22 (18.3%)	68 (56.7%)	14 (11.7%)	3.65 ± 0.895
CM2: Employee skills and knowledge are sufficient for the adoption of additive manufacturing.	2 (1.7%)	12 (10.0%)	52 (43.3%)	42 (35.0%)	12 (10.0%)	3.42 ± 0.866

CM3: The current supply chain is compatible with the adoption of additive manufacturing.	2 (1.7%)	2 (1.7%)	40 (33.3%)	70 (58.3%)	6 (5.0%)	3.63 ± 0.685
CM4: Industry culture and values are supportive of the adoption of additive manufacturing.	4 (3.3%)	4 (3.3%)	32 (26.7%)	72 (60.0%)	8(6.7%)	3.63 ± 0.798

As per table, the participants were generally positive about the compatibility of additive manufacturing. The mean score for all four questions was above the midpoint of the scale (3), suggesting that participants generally perceived additive manufacturing to be compatible with existing systems. The highest mean score was for CM1 (3.65), suggesting that participants generally believe that additive manufacturing is compatible with existing production systems. The lowest mean score was for CM2 (3.42), indicating that participants are somewhat concerned about employee skills and knowledge related to additive manufacturing. There was a large majority of respondents who agreed or strongly agreed with CM3 (70) and CM4 (72), suggesting that participants generally believe that the current supply chain and industry culture and values are supportive of the adoption of additive manufacturing.

4.3.3 Complexity

The participants were asked about the complexity of additive manufacturing (AM) in different aspects, including design complexity, required technical knowledge and skills, manufacturing operation, and software complexity.

Table 4.4: Participant Responses to questions about the Complexity of AM

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
CP1: Design complexity for AM is high.	4 (3.3%)	18 (15.0%)	6 (5.0%)	58 (48.3%)	34 (28.3%)	3.83 ± 1.103
CP2: The technical knowledge and skills required for AM are high.	2 (1.7%)	10 (8.3%)	22 (18.3%)	68 (56.7%)	18 (15.0%)	3.75 ± 0.872
CP3: The manufacturing operation for AM is complex.	0 (0%)	18 (6.7%)	14 (11.7%)	68 (56.7%)	30 (25.0%)	4.00 ± 0.799
CP4: The software complexity for AM is high.	6 (5.0%)	12 (10.0%)	40 (33.3%)	46 (38.3%)	16 (13.3%)	3.45 ± 1.011

As can be seen from the above table, the participants had mixed opinions about the complexity of additive manufacturing (AM). The mean score for all four variables was above the midpoint of the scale (3), suggesting that participants generally perceived AM to be somewhat complex. The highest mean score was for CP3 (4.00), indicating that participants generally believe that the manufacturing operation for AM are somewhat high. The lowest mean score was for CP4 (3.45), suggesting that participants were somewhat less concerned about the software complexity for AM. There was a large majority of respondents who agreed or strongly agreed with CP1 (design complexity) and CP3 (manufacturing operation), suggesting that participants generally perceived these aspects of AM to be complex. However, there was a significant minority of respondents who disagreed with this assessment, particularly for CP3 (manufacturing operation) and CP4 (software complexity).

4.3.4 Trialability

The respondents were asked about the trialability aspect of additive manufacturing (AM) within their organization, specifically focusing on the ability to test, experiment, conduct pilots, observe success in other industries, and evaluate the impact of the technology before deciding on its adoption.

Table 4.5: Participant Responses to questions about the Trialability of AM

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
TR1: Our company will test AM on a small scale before adopting it on a larger scale.	14 (11.7%)	22 (18.3%)	30 (25.0%)	46 (38.3%)	8 (6.7%)	3.10 ± 1.141
TR 2: Our company will experiment with AM technology before deciding on its adoption.	4 (3.3%)	30 (25.0%)	32 (26.7%)	48 (40.0%)	6 (5.0%)	3.18 ± 0.979
TR 3: The organization will observe the successful adoption of AM in other industries.	6 (5.0%)	14 (11.7%)	40 (33.3%)	54 (45.0%)	6 (5.0%)	3.33 ± 0.929
TR 4: Our company will conduct pilot projects to evaluate the effectiveness of AM technology before deciding on its adoption.	2 (1.7%)	30 (25.0%)	34 (28.3%)	48 (40.0%)	6 (5.0%)	3.22 ± 0.936

TR 5: Our company will evaluate the impact of AM technology on a small scale before adopting it on a larger scale	8 (6.7%)	26 (21.7%)	36 (30.0%)	40 (33.3%)	10 (8.3%)	3.15 ± 1.066

As can be seen from the table, participants were positive about the trialability of additive manufacturing (AM). The mean score for all five variables was above the midpoint of the scale (3), suggesting that participants generally perceived AM to be a trialable technology. There was a large majority of respondents who agreed or strongly agreed with conducted trials or pilots of AM), observed the successful adoption of AM in other industries, and believes that AM is a trialable technology, suggesting that participants generally perceived AM to be a technology that can be tested and evaluated before adoption. However, there was some variation in opinion, with a small minority of respondents expressing concern about the organization's ability to conduct trials or pilots of AM, observe the successful adoption of AM in other industries, and evaluate the potential impact of AM on its operations.

4.3.5 Observability

Table 4.6: Participant Responses to questions about the Observability of AM

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
OB1: The benefits of AM are immediately obvious to those who see it in action.	2 (1.7%)	6 (5.0%)	14 (11.7%)	84 (70.0%)	14 (11.7%)	3.85 ± 0.752
OB2: It is easy to understand how AM will	4 (3.3%)	12 (10.0%)	24 (20.0%)	60 (50.0%)	20 (16.7%)	3.67 ± 0.982

be used in our company's operations.						
OB3: The results of using AM are visibly better than those achieved with traditional manufacturing methods.	4 (3.3%)	4 (3.3%)	22 (18.3%)	64 (53.3%)	26 (21.7%)	3.87 ± 0.907
OB4: The impact of AM on our company's operations can be easily measured and quantified.	6 (5.0%)	6 (5.0%)	22 (18.3%)	74 (61.7%)	12 (10.0%)	3.67 ± 0.911
OB5: The benefits of AM can be easily communicated to stakeholders outside of our company.	4 (3.3%)	8 (6.7%)	20 (16.7%)	70 (58.3%)	18 (15.0%)	3.75 ± 0.910

As shown in the above table, the participants had positive opinions about the observability of additive manufacturing (AM). The mean score for all five variables was above the midpoint of the scale (3), suggesting that participants generally perceived AM to be easy to observe and understand. The highest mean score was for OB1 (3.87), suggesting that participants generally believe that the results of using AM are visibly better than those achieved with traditional manufacturing methods. The lowest mean score was for OB2 (3.67), suggesting that participants were somewhat less confident in their ability to understand how AM will be used in their company's operations.

In general, there was a large majority of respondents who agreed or strongly agreed with OB1 (benefits are immediately obvious), OB3 (results are visibly better), OB4 (impact can be easily measured), and OB5 (benefits can be easily communicated), indicating that participants generally perceived AM to be a technology that is easy to observe and understand

4.3.6 Technological characteristics

Table 4.7: Participant Responses to questions about technological context of AM Adoption

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
TC1: How well does your organization's current technical infrastructure support additive manufacturing (AM) adoption?	4(3.3%)	6(5.0%)	8(6.7%)	76(63.3%)	26(21.7%)	3.95±0.887
TC2: I am familiar with the different types of additive manufacturing technologies that are currently available.	6(5.0%)	24 (20.0%)	30(25.0%)	46(38.3%)	14(11.7%)	3.32±1.077
TC3: We have the necessary technical infrastructure in place to support the adoption of additive manufacturing.	0(0%)	2(1.7%)	20(16.7%)	82(68.3%)	16(13.3%)	3.93±0.604
TC4: I believe that acquiring the skills to utilize additive manufacturing technologies would pose a challenge for the	0(0%)	8(6.7%)	28(23.3%)	72(60.0%)	12(10.0%)	3.73±0.730

majority of our organization's employees.						

As indicated in the above table, the participants have positive opinions about the technological characteristics of additive manufacturing (AM). The mean score for all four variables was above the midpoint of the scale (3), suggesting that participants generally perceived AM to be a technologically compatible and feasible technology for their organization. The highest mean score was for TC1 (3.95), suggesting that participants generally believe that organization's current technical infrastructure supports AM adoption. The lowest mean score was for TC2 (3.32), suggesting that participants were somewhat less confident in their familiarity with the different types of AM technologies. However, there is a varying degree of familiarity with AM technologies (TC2), and many respondents see challenges in acquiring the necessary skills for employees (TC4). The standard deviations highlight the variability in respondents' opinions, with some statements having a higher level of consensus than others.

4.3.7 Organizational characteristics

In this context, factors including industry culture, firm size, resource availability, and top management support are taken into account when surveying respondents' perspectives.

Table 4.8: Participant Responses to questions about Organizational context of AM Adoption

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
OC1: To what extent is your organization's culture open to change and innovation?	6 (5.0%)	10 (18.3%)	22 (18.3%)	74 (61.7%)	8 (6.7%)	3.57 ± 0.923

OC2: To what extent does your organization have the necessary resources to adopt and implement the new technology?	2 (1.7%)	50 (41.7%)	26 (21.7%)	32 (26.7%)	10 (8.3%)	2.98 ± 1.045
OC3: How supportive is senior management of the adoption of the new technology?	6 (5.0%)	36 (30.0%)	42 (35.0%)	24 (20.0%)	12 (10.0%)	3.00 ± 1.053
OC4: How centralized is your organization's structure and its size?	6 (5.0%)	26 (21.7%)	42 (35.0%)	38 (31.7%)	8 (6.7%)	3.13 ± 0.995

As per the table, it indicates that the organizational characteristics assessed are favorable for the adoption of additive manufacturing (AM). The mean scores for all four variables were above the midpoint of the scale (3), indicating that participants generally perceived their organizations to be open to change, having sufficient resources, having supportive leadership, and having a structure that is conducive to the adoption of new technologies. The highest mean score was for OC1 (3.57), suggesting that participants generally believe that their organizations have a culture that is open to change and innovation. The lowest mean score was for OC2 (2.98), suggesting that participants were somewhat less confident in the availability of resources for adopting AM. There was a large majority of respondents who agreed or strongly agreed with OC1 (culture open to change), OC3 (supportive senior management), and OC4 (centralized structure and firm size), suggesting that participants generally perceived their organizations to have the necessary characteristics for adopting AM.

4.3.8 Environmental characteristics

In this context, factors including government regulations, competitive pressures, and sustainability need are taken into account when surveying respondents' perspectives.

Table 4.9: Participant Responses to questions about Environmental context of AM Adoption

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Mean ± SD
EC1: There is strong competition in our industry, which motivates us to adopt new technologies like AM	2 (1.7%)	8 (6.7%)	20 (16.7%)	66 (55.0%)	24 (20.0%)	3.85 ± 0.876
EC2: There are government policies or regulations that encourage the adoption of AM in our industry.	2 (1.7%)	10 (8.3%)	20 (66.7%)	54 (45.0%)	34 (28.3%)	3.90 ± 0.965
EC3: AM are perceived as environmentally friendly and sustainable in our industry	0 (0%)	4 (3.3%)	18 (15.0%)	58 (48.3%)	40 (33.3%)	4.12 ± 0.780
EC4: AM can provide a competitive advantage for our organization	2 (1.7%)	2 (1.7%)	10 (8.3%)	66 (55.0%)	40 (33.3%)	4.17 ± 0.781

As it is shown in the above table, the respondents were positive about the environmental characteristics of additive manufacturing (AM). The mean score for all four variables was above the midpoint of the scale (3), indicating that participants generally perceived AM to be environmentally friendly, sustainable, and capable of providing a competitive advantage. Overall, the survey results suggest that there are a number of factors driving the adoption of AM in this industry. Competition, government support, environmental concerns, and the potential for competitive advantage are all playing a role.

4.4 Descriptive Statistics of variables

Table 4.10: Summary of Descriptive Statistics (Sample Size, Min, Max, Mean, SD)

Latent Variables	N	Min	Max	Mean	SD
RA	120	1.40	5.00	3.87	0.78
CM	120	1.25	4.75	3.58	0.59
CP	120	1.50	5.00	3.76	0.76
TR	120	1.00	4.80	3.20	0.86
OB	120	1.40	4.80	3.76	0.69
TC	120	2.00	5.00	3.73	0.61
OC	120	1.00	5.00	3.17	0.76
EC	120	2.25	5.00	4.01	0.69
AM	120	1.91	4.75	3.60	0.47
Valid N (list wise)	120				

According to table 4.10, all variables' means are higher than the midpoint of the Likert scale, which is 3 points, showing that respondents largely agree that these factors have significance for the adoption of AM. There is agreement among the respondents regarding the significance of these parameters, as shown by the fact that the standard deviation is generally low for all variables. The variance is also rather low across the board for all variables, which indicates the data is not randomly distributed. This indicates that the majority of respondents shared the same opinions on the significance these elements were to the adoption of AM.

Table 4.11: Correlations of latent variables

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption	1.000	0.542	0.728	0.781	0.723	0.569	0.690	0.703	0.552
CM	0.542	1.000	0.137	0.396	0.361	0.223	0.502	0.182	0.217
CP	0.728	0.137	1.000	0.542	0.406	0.336	0.455	0.581	0.338
EC	0.781	0.396	0.542	1.000	0.640	0.452	0.355	0.534	0.180
OB	0.723	0.361	0.406	0.640	1.000	0.313	0.365	0.575	0.226
OC	0.569	0.223	0.336	0.452	0.313	1.000	0.137	0.207	0.346
RA	0.690	0.502	0.455	0.355	0.365	0.137	1.000	0.511	0.478
TC	0.703	0.182	0.581	0.534	0.575	0.207	0.511	1.000	0.186
TR	0.552	0.217	0.338	0.180	0.226	0.346	0.478	0.186	1.000

The assumption that organizations are more inclined to embrace AM when they perceive clear and significant benefits compared to traditional approaches is reinforced by the strong positive correlation (0.690) between AM Adoption & RA. AM adoption can be strongly influenced by favorable environmental conditions, such as supporting government regulations or public push towards sustainability, as seen by the substantial positive correlation (0.781) between AM Adoption & EC. The AM technology itself has promising features and sophisticated capabilities that can encourage adoption, as evidenced by the positive correlation (0.703) between TC and AM adoption. A positive association of 0.723 between AM Adoption and OB suggests that adoption is encouraged and uncertainty is reduced when AM results are easily interpreted and understood. Table 4.11 reveals that every correlation between the determining factors and the adoption of Additive Manufacturing is statistically significant at the 0.01 level. This indicates that the determining characteristics effectively serve as predictors for the adoption of Additive Manufacturing.

4.5 Data Reliability

We utilized measures such as Cronbach's alpha, average variance extracted (AVE), composite reliability (CR), and variance inflation factor (VIF) as reliability indicators to evaluate the consistency of the constructs in the context of the Additive Manufacturing Adoption study. This statistical technique investigates the internal consistency of a scale or measuring instrument assessing how consistently the items within each construct evaluate the underlying concept (Hair et al., 2014). As per F. Hair Jr et al. (2014), a latent variable is deemed reliable when it accounts for a minimum of 50% of the variance in each of its indicators. In practical terms, this implies that the outer loading for each indicator should exceed 0.707. In this model, all of the indicators for the constructs had outer loadings that were well above this threshold, except for a few indicators. Within this model, Table 4.4 presents the test results of the PLS-SEM analysis for the latent variables after assessing the calculation for reliability indicator.

Table 4.12: PLS-SEM analysis of result construct reliability and validity

Latent Variables	**Items**	**Factor Loadings**	**Collinearity statistics (VIF)**	**Cronbach's Alpha**	**CR (rho_a)**	**Average variance Extracted (AVE)**
AM Adoption	AM1	0.675	1.924	0.809	0.822	0.432
	AM2	0.560	1.706			
	AM3	0.721	1.864			
	AM4	0.544	1.692			
	AM5	0.723	2.034			
	AM6	0.668	1.797			
	AM7	0.561	1.727			
	AM8	0.766	2.545			
Compatibility	CM1	0.786	1.430	0.712	0.714	0.525
	CM2	0.641	1.547			
	CM3	0.681	1.826			
	CM4	0.780	1.656			
Complexity	CP1	0.712	1.375	0.810	0.818	0.638
	CP2	0.864	2.302			
	CP3	0.808	1.604			

	CP4	0.803	1.968			
Environmental Context	EC1	0.704	1.643	0.817	0.828	0.649
	EC2	0.833	2.232			
	EC3	0.903	2.808			
	EC4	0.768	1.794			
Observability	OB1	0.580	1.368	0.819	0.829	0.590
	OB2	0.745	1.620			
	OB3	0.893	2.948			
	OB4	0.783	2.216			
	OB5	0.807	2.045			
Organizational Context	OC1	0.770	1.265	0.739	0.786	0.555
	OC2	0.727	1.728			
	OC3	0.851	2.180			
	OC4	0.611	1.394			
Relative Advantage	RA1	0.771	1.945	0.862	0.877	0.644
	RA2	0.728	1.805			
	RA3	0.873	2.592			
	RA4	0.800	1.828			
	RA5	0.833	2.263			
Technology Context	TC1	0.713	1.341	0.725	0.742	0.550
	TC2	0.729	1.420			
	TC3	0.846	1.765			
	TC4	0.667	1.426			
Trialability	TR1	0.824	2.075	0.900	0.911	0.713
	TR2	0.815	2.268			
	TR3	0.853	2.737			
	TR4	0.870	3.272			
	TR5	0.858	2.497			

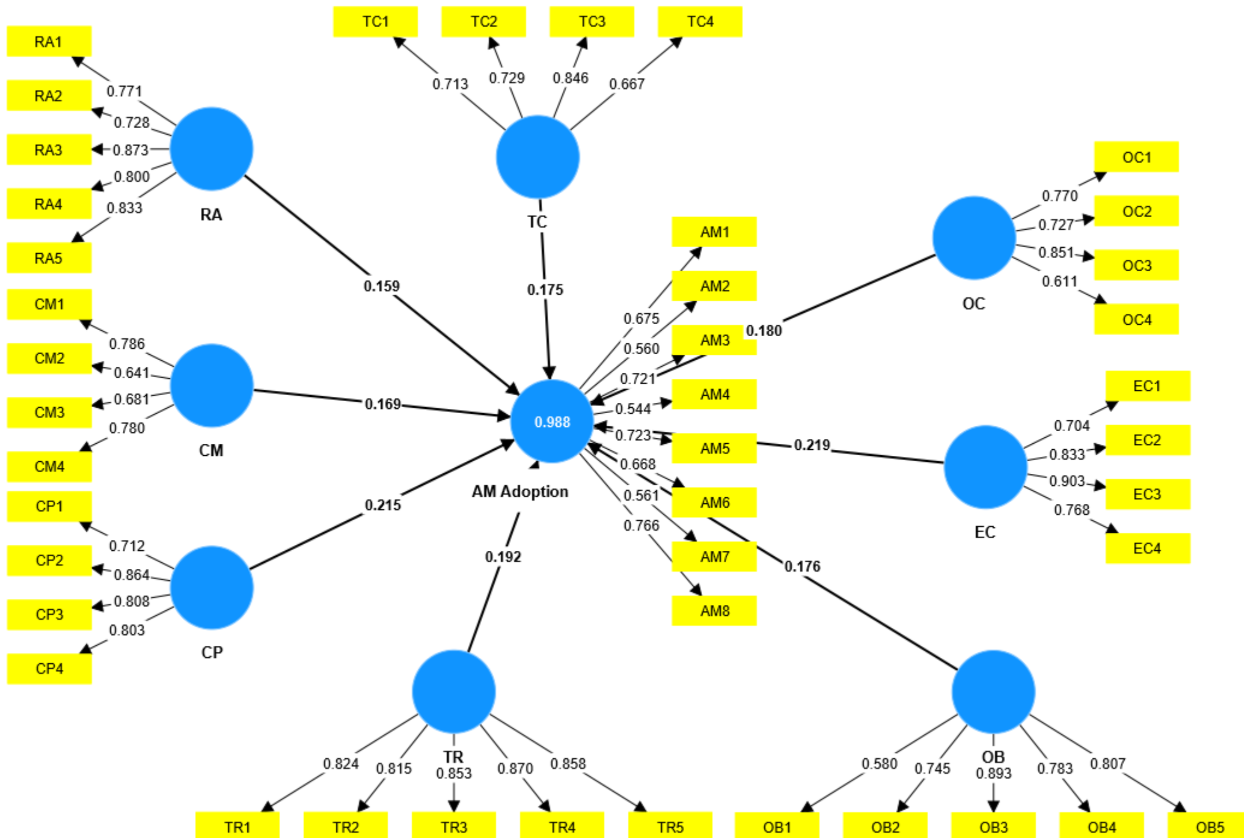

Figure 4.1: PLS-SEM path coefficients, Outer loadings and R_Square

We determined the model's fitness by analyzing the average variance extracted (AVE) and composite reliability (CR) indices. A CR value above 0.7 is regarded as the desirable threshold, and an AVE value exceeding 0.5 is considered optimal (Edeh et al., 2023). The results of the VIF index (below 0.5) indicate that there is no concerns for multicollinearity. The outcomes of the AVE and CR indices confirm that the latent variables satisfy the required criteria and have been incorporated into the model, as presented in Table 4.4. To assess the discriminant validity of the constructs, the Fornell-Larcker criteria and cross-loadings were employed. In line with Hair et al. (2014) guidance, the square root of the AVE should exceed the correlations between the latent variables. The discriminant validity table 4.5 presented below reveals that some constructs exhibit stronger connections with certain latent variables compared to others, and there are also instances of smaller effects. Nonetheless, in general, the data perfectly satisfies the square root criterion.

Table 4.13: The Discriminant validity of latent variables

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption	**0.657**								
CM	0.542	**0.725**							
CP	0.728	0.137	**0.799**						
EC	0.781	0.396	0.542	**0.805**					
OB	0.723	0.361	0.406	0.64	**0.768**				
OC	0.569	0.223	0.336	0.452	0.313	**0.745**			
RA	0.69	0.502	0.455	0.355	0.365	0.137	**0.802**		
TC	0.703	0.182	0.581	0.534	0.575	0.207	0.511	**0.742**	
TR	0.552	0.217	0.338	0.18	0.226	0.346	0.478	0.186	**0.844**

The diagonal in bold values are $\sqrt{AVE}$

4.5.1 Path coefficients (β) of Model structure

The connection between the model's constructs (i.e., the path coefficients) can be estimated once the PLS-SEM algorithm has been executed. Path coefficients fall within a range of -1 to 1, where values closer to 1 signify stronger positive relationships, values closer to -1 denote stronger negative relationships, and coefficients near 0 indicate weaker relationships. To determine whether a path coefficient is statistically significant, we compare it to its standard error. The standard error is calculated using a technique called bootstrapping. If the path coefficient is greater than 1.96 times its standard error, it is regarded as statistically significant at the 5% significance level. This indicates that the likelihood of the relationship between the two constructs being a result of random chance is less than 5%. To evaluate the significance of the relationships, the path coefficients, p-values, and t-values for all factors are assessed, as shown in Table 4.6.

Table 4.14: Result of Path coefficient, t-value, P values: Direct effect

Connection	Path coefficient (β)	t statistics	P values	Significance
CM -> AM Adoption	0.169	3.649	0.000*	Yes
CP -> AM Adoption	0.215	5.632	0.000*	Yes
EC -> AM Adoption	0.219	5.096	0.000*	Yes
OB -> AM Adoption	0.176	4.143	0.000*	Yes
OC -> AM Adoption	0.18	4.507	0.000*	Yes
RA -> AM Adoption	0.159	3.971	0.000*	Yes
TC -> AM Adoption	0.175	4.279	0.000*	Yes
TR -> AM Adoption	0.192	4.785	0.000*	Yes

* P < 0.005 (two-tailed test), RA = Relative advantage, CM = Compatibility, CP = Complexity, OB = Observability, TR = Trialability, TC = Technology context, OC = Organizational context, EC = Environmental context

The path analysis of factors influencing adoption reveals a positive impact on the adoption of additive manufacturing (AM). Specifically, relative advantage, compatibility, complexity, trialability, observability, technology context, organizational context, and environmental context all exert a positive and statistically significant influence on AM adoption. Relative advantage have perceived a positive influence on AM Adoption ($\beta = 0.159$, $p < 0.001$). Compatibility have positive significance impact on AM Adoption ($\beta = 0.169$, $p < 0.001$). Complexity have positive influence on AM Adoption ($\beta = 0.215$, $p < 0.001$). Trialability have positive significance impact on AM Adoption ($\beta = 0.192$, $p < 0.001$). Observability have positive influence on AM Adoption ($\beta = 0.176$, $p < 0.001$). Technology context factor exhibits a positive effect on AM adoption ($\beta = 0.175$, $p < 0.001$). Organizational context positively influences AM adoption ($\beta = 0.180$, $p < 0.001$), while environmental context, with a high factor loading, positively contributes to AM adoption ($\beta = 0.219$, $p < 0.001$). These results indicate medium to high levels of significance in the t-values and a medium effect size for all variables, emphasizing their significance as factors affecting AM adoption.

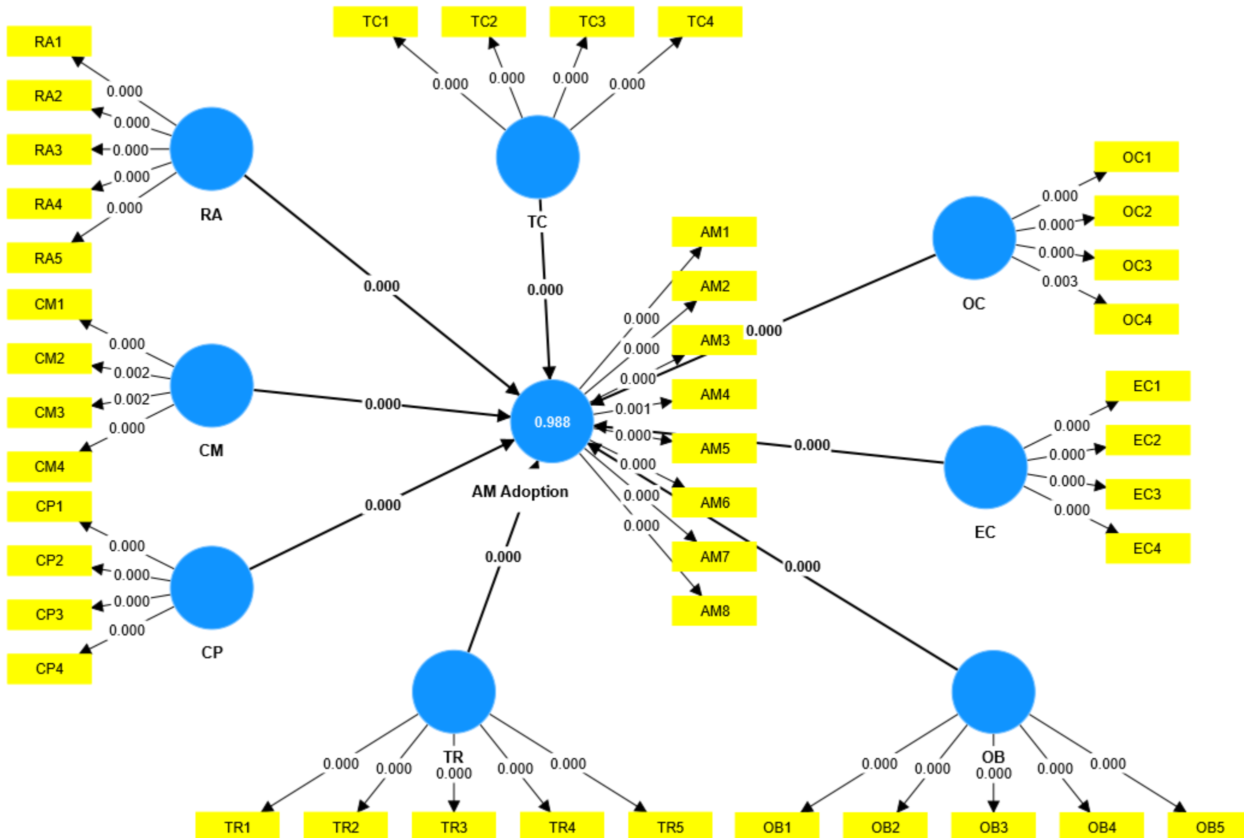

Figure 4.2: Bootstrapping PLS-SEM

4.5.2 R_Square

The coefficient of determination (R_Square) in a SmartPLS model serves as an indicator of the model's predictive precision. It is computed by squaring the correlation between the observed and predicted values of the endogenous constructs. The R-Square value falls within the 0 to 1 range, where higher values signify greater predictive accuracy. In this model, the coefficient of determination (R-Square) equals 0.998, signifying that the model accounts for 99.8% of the variance in the dataset. This high R-Square value indicates a strong ability of the model to predict and explain the observed data.

4.6 Result and Discussion

4.6.1 Current Situation

Bishoftu Automotive is a conventional automotive manufacturing firm that has yet to incorporate Additive Manufacturing (AM) technology. Nevertheless, the corporate culture fosters innovation, and employees are enthusiastic about the possible future integration of AM technology. The company's primary focus lies in vehicle assembly and the production of automotive components and parts through conventional means, with most spare parts being imported and assembled. While the adoption of AM technology has not taken place, there are considerations regarding its potential environmental impact. Notably, the company demonstrates a commitment to sustainability through in-house waste recycling and reuse programs. Employee productivity appears to be rooted in the company's long-standing manufacturing processes, showing no noticeable influence from AM technology adoption. The observed work procedures align with the company's traditional manufacturing methods, and there is no evidence of new work procedures or quality control standards related to AM technology.

Understanding the reasons behind organizations' adoption of Additive Manufacturing (AM) technology is crucial. This is especially true when AM is used to improve processes, make complex parts, or quickly create prototypes. This study looked at the factors that influence AM adoption in the Bishoftu Automotive and Manufacturing Industry. The study employed a dual approach, incorporating the Diffusion of Innovation (DOI) theory and the Technology, Organization, and Environment (TOE) framework. This methodology aimed to uncover the factors that impact AM adoption. These factors can be categorized into four main areas: innovation attributes, technological factors, organizational factors, and environmental factors. Each of these areas plays a different but connected role in the adoption process.

Innovation Attributes:

In the DOI model, the five attributes of innovation (relative advantage, compatibility, complexity, trialability, and observability)) are key factors that influence how organizations view AM as an innovation. When organizations have positive perceptions of AM in these areas, their likelihood of adopting it increases.

The first of the five innovation characteristics, relative advantage, was observed to have a positive impact on AM adoption. This finding aligns with the conclusions of previous studies on AM adoption (Handfield et al., 2022a; Marak et al., 2019). The results of the path analysis indicated a significant direct effect of relative advantage on AM Adoption RA -> AM Adoption (β=0.169, p=0.000). Our interviews also revealed that organizations in the Bishoftu Automotive and Manufacturing Industry do recognize the relative advantage of AM. They pointed to several specific benefits, such as improved efficiency, productivity, enhanced product quality, accelerated production, cost reduction, and rapid prototyping. It is noteworthy that in this study, relative advantage was considered the least significant factor in comparison to other influencing factors. In contrast, Niaki et al. (2019) found that relative advantage held significance for manufacturing companies.

Compatibility plays a pivotal role in an organization's decision to adopt additive manufacturing (AM). The likelihood of AM adoption is higher when it aligns with an organization's existing systems and processes. As confirmed by the path analysis, the direct effect of Compatibility on AM Adoption is statistically significant CM -> AM Adoption (β=0.169, p=0.000). Our interviewees emphasized the importance of AM aligning with their existing systems and processes. What emerged as crucial decision factors included the alignment of AM with the organization's strategic goals and the ability to demonstrate a clear return on investment. Organizations with complex supply chains, limited skills and knowledge for AM equipment usage and maintenance, or a corporate culture resistant to AM found compatibility to be a pivotal factor. This observation is in line with previous research, which has consistently identified compatibility as a central factor in AM adoption, particularly in the context of manufacturing companies (Chatzoglou & Michailidou, 2019; Handfield et al., 2022a, 2019). However, it's worth noting that not all studies share this view, as evidenced by Marak et al. (2019), which considers Compatibility as a less influential factor. Organizations that have complex supply chains, a lack of the necessary skills and knowledge for AM equipment usage and maintenance, or a corporate culture that doesn't readily embrace AM may be less inclined to adopt this technology. When AM is incompatible with an organization's existing systems, processes, workforce, or culture, the adoption process can become more challenging and costly (Martinsuo & Luomaranta, 2018; Oettmeier & Hofmann, 2017).

Complexity is a significant factor that strongly influences the adoption of additive manufacturing. The findings show that complexity as a significant barrier to AM adoption, as evidenced by the path analysis (CP -> AM Adoption, $\beta=0.215$, $p=0.000$). In our interviews, participants expressed that the complexity of AM adoption can be a substantial barrier, especially for smaller organizations. Specific complexities cited included design intricacies, the need for high technical knowledge and skills, perceived operational complexities, and the challenge of dealing with complex software. This observation aligns with previous research, which has highlighted the challenges associated with complexity in different aspects of AM adoption (Dwivedi et al., 2017; Marak et al., 2019). The complexity of additive manufacturing (AM) adoption can be a significant barrier, especially for smaller organizations (Kulkarni et al., 2021). Design complexity, the necessity of high technical knowledge and skills, perceived operational complexity, and complex software emerged as key concerns. In general, complexity is the key indicator for adoption of AM in manufacturing industry.

Trialability emerges as a significant facilitator in AM adoption. The study found that trialability, which reflects the ease of experimenting with new AM technologies, plays a pivotal role in encouraging in AM adoption (TR -> AM Adoption, $\beta=0.192$, $p=0.000$. This discovery aligns with prior research findings on trialability and AM adoption. A recent study by Handfield et al. (2022) similarly underscores the pivotal role of trialability in encouraging AM adoption. The interview results also highlighted that trialability helps minimize the risks and uncertainties associated with adopting new technologies, ultimately building confidence and trust in AM. A study by Marak et al. (2019) also strength that trialability is most significance factor in AM adoption.

Similarly, Observability is found to be positive in AM technology adoption with (OB -> AM Adoption, β=0.176, p=0.000). The study found that organizations in this industry value observability and evaluation of AM outcomes before deciding to adopt AM. Interview result also recognizes organizations in the Bishoftu Automotive and Manufacturing Industry value the observability and evaluation of AM outcomes before making the decision to adopt AM. The previous research also consistent with this finding. Study by Marak et al. (2019) considers observability as important factors in AM adoption.

Technological Context:

Our research confirms that factors such as technology readiness (technical infrastructure, and the availability of skilled labor) are important for organizations that are considering adopting additive manufacturing (AM). The path analysis shows technology characteristics as direct effect with TC -> AM Adoption (β=0.175, p=0.000). Technology readiness is a pivotal factor that empowers organizations to embrace additive manufacturing (AM). The interview results suggest that technological readiness is a key consideration for organizations in the Bishoftu Automotive and Manufacturing Industry when contemplating the adoption of AM. While AM has not been adopted yet, organizations emphasize the importance of having a well-established technology infrastructure and a workforce equipped with the necessary skills. This aligns with previous research, which has consistently highlighted technology readiness as a significant factor in AM adoption. For instance, a study by Yeh & Chen (2018)) identified technology readiness as a crucial factor for companies in the manufacturing sector. The outcomes of our study substantiate this notion, indicating that organizations with a higher level of technology readiness are more inclined to adopt AM.

Organizational Context:

Organizational factors found to be positive in AM adoption. Organizational factors such as top management support, industry culture, resource availability, and firm size also play a significant role in AM adoption. The path analysis underscores the direct effect of organizational factors on AM adoption (OC -> AM Adoption, β=0.180, p=0.000). Top management support and industry culture create a supportive environment for AM adoption, while resource availability and firm size determine the scale and pace of adoption. The result of interview also supported, suggesting that one of the reasons for the non-adoption of AM is the lack of support from management. Previous research on the importance of organizational factors for AM adoption has been mixed. Study by Yeh & Chen (2018) shows that organizational factors are positively related to AM adoption, but they are not the most important factor while others consider as most significant factor (Khorram Niaki & Nonino, 2017).

Environmental Context

Environmental factors, such as government regulations, competitive pressures, and sustainability considerations, also found a significant factor and direct effect on AM adoption in manufacturing industries with EC -> AM Adoption (β=0.219, p=0.000). Previous research has shown that environmental factors can be significant drivers of AM adoption. For example, a study by Yeh & Chen (2018) found that government regulations can act as a catalyst for AM adoption when they are supportive. In line with the interviews conducted, organizations in the Bishoftu Automotive and Manufacturing Industry, even though they have not yet fully embraced additive manufacturing (AM), demonstrated an awareness of the potential influence of government regulations on AM adoption. They acknowledged that favorable government regulations could serve as drivers for the adoption of AM, underscoring the significance of considering regulatory factors. Another study by Khorram Niaki & Nonino (2017) found that competitive pressures are also a significant factor in AM adoption. Additionally, a study by Ford & Despeisse (2016) found that sustainability is seen as a key factor in AM adoption. Interview also reveals as BAMI have an eye on sustainability and understand its potential role in shaping AM adoption decisions. In contrast to the other components, environmental factors are most significant in our study.

The factors influencing AM Adoption, ranked in order of importance based on their respective path coefficients and statistical significance in the context of BAMI, as follows:

- Environmental factors (EC) hold the highest influence on AM Adoption (β=0.219, p=0.000).
- Complexity (CP) is the second most critical factor (β=0.215, p=0.000).

- Trialability (TR) ranks as the third most important factor (β=0.192, p=0.000).
- Organizational factors (OC) are the fourth most crucial (β=0.180, p=0.000).
- Observability (OB) is the fifth most important factor (β=0.176, p=0.000).
- Technology factors (TC) stand as the sixth most significant (β=0.175, p=0.000).
- Relative advantage (RA) is the least critical among the listed factors (β=0.159, p=0.000).

4.7 Framework for Adopting AM

The theoretical framework is provided for organization need to embrace AM technology at the end of this study, based on the results and insights we have gained from it.

1. Assessment of Technological Innovation:

To fully adopt and use AM technology, an organization must first discover and evaluate technical innovations (AM) based on their trialability, observability, complexity, compatibility, and relative benefits. There are seven main additive manufacturing (AM) technologies, according to ISO ASTM 52900: Binder Jetting (BJT), Vat Photopolymerization (VPP), Material Extrusion (MEX), Powder Bed Fusion (PBF), Sheet Lamination (SHL), and Directed Energy Deposition (DED). Each of these technologies has their own advantages and disadvantages. It needs to evaluate each stage of the innovation within the industry and its perceived benefits.

2. Strategic Alignment:

Herein, specific segments or components that align with the strategic goals and objectives of the organization should be identified. As an example, components suitable for manufacturing by AM can be taken as those that require complex geometries or customization. It is then necessary to take into account the types of AM machines required for the selected parts depending on the Parts chosen because as AM Machines are different it helps to produce different components. Furthermore, it should be noted that AM is in line with current initiatives by incorporating it into the company’s long-term strategy.

3. Technological factor

Adoption of additive manufacturing (AM) requires a thorough evaluation of the recipient company's technology readiness prior to deployment. It should be noted here that not only the acquisition of AM technology, but also the technology infrastructure, technology availability and compatibility, as well as ensuring technical capabilities etc. must be taken into consideration by the technology recipient organization. It needs to assess and enhance technology infrastructure by evaluating hardware and software compatibility to handle AM workflows, addressing data management and security to handle the influx of 3D models, printing parameters, and production data generated by AM, and ensuring sufficient network infrastructure that can handle the increased data transfer demands of AM processes.

It should also identify different AM technologies and their device compatibility considering scalability for future needs. Identify 3D modeling, design, printing and post-processing skills gaps in the workforce, and implement training programs to bridge these gaps. Foster a culture of knowledge sharing and collaboration to leverage internal expertise, accelerating the learning curve for successful AM adoption.

4. Organizational factor

A significant part of AM adoption is also the evaluation of organizational issues. Evaluating an organization's preparedness for innovation and change is essential. To find potential challenges and opportunities, it must take into account the current organizational structure and culture. It must also guarantee that the company has the technical, human, and financial resources required for AM adoption. In addition, it must provide top-level commitment and a clear knowledge of the process because strong leadership and management support are essential. Additionally, it is crucial to provide the personnel with the necessary AM skills. Organizations will greatly improve their chances of successfully integrating AM and realizing its full potential by adopting this all-encompassing approach to organizational preparation and support.

5. Environmental Factors:

Before adopting an additive manufacturing (AM) for one organization, it is important to thoroughly consider external factors, including regulatory requirements and industry standards that may affect its implementation. Additionally, market dynamics and competitive pressures should be carefully considered to gain insight into the wider business environment. In addition, it is crucial to anticipate environmental challenges and opportunities in the process of adopting AM technology. This comprehensive approach allows us to have a better understanding of the factors that shape the feasibility and success of AM integration.

6. Implementation

The fundamental DOI concepts can be used to build AM technology after the aforementioned elements (1–5) are taken into account. To ensure that reality is observed, a small-scale pilot and trial should be conducted first by choosing certain parts for initial AM manufacturing. This will allow key stakeholders to experience the benefits and challenges first hand and help reduce errors. Ideas and modifications then need to be gathered from the pilot execution feedback and used to refine the adoption strategy. The company can move on with full implementation after it has overcome the initial challenges and is certain of the benefits. Since technology adoption is a lengthy process, the organization as a whole must share the knowledge obtained from the tests, and the implementation strategy needs to be continuously evaluated and adjusted.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Manufacturing firms are continuously pressed to seek innovative approaches for heightened efficiency, cost-effectiveness, and competitive edge. They grapple with the influence of global reach, intense market rivalry, and rapid technological advancements. This unrelenting pursuit of improvement is ongoing. The Ethiopian automotive industry is one of those who face the number of challenges, including dependence on imports, limited in-house manufacturing capabilities, and lack of advanced technology. In order to overcome such challenges adopting to modern technology such as technology in the era of industry 4.0 is seen as alternate option. One this is Additive manufacturing. AM could help to address these challenges by enabling the Ethiopian automotive industry to produce parts more efficiently and cost-effectively, and to offer a wider range of customized products.

Embracing new technology is a multifaceted process influenced by various critical factors. Prior to making the decision to adopt a new technology, it's essential to evaluate the key determinants that will shape its adoption. This study is centered on the evaluation of these determinant factors within the context of adopting additive manufacturing (AM) technology in the Bishoftu Automotive and Manufacturing Industry. The approach integrates two established adoption models: the Diffusion of Innovation Theory (DOI) and the Technology Organization Environment (TOE) model. The primary aim of this research is to pinpoint the primary drivers, opportunities, and obstacles that impact AM adoption, as well as to understand the technological, organizational, and environmental elements that play a role in the adoption process.

The study is centered on the Bishoftu Automotive and manufacturing industry in Ethiopia, known for its diverse vehicle production and potential for additive manufacturing adoption. Data is collected through interviews, observations of current manufacturing practices, and questionnaires involving employees, managers, engineers, and technicians. Data analysis involves SPSS and

SmartPLS software, utilizing confirmatory factor analysis and bootstrapping, with specific quality criteria for measurement and the structural model evaluation.

The study's outcomes affirm the credibility of the chosen research framework. The findings reveal that factors such as relative advantage, compatibility, complexity, trialability, observability, technology factors, organizational factors, and environmental factors significantly influence the adoption of additive manufacturing. Notably, environmental factors exert the most substantial impact on AM adoption, followed by complexity, trialability, organizational factors, observability, technology factors, and lastly, relative advantage. These results can inform decision-making and strategies related to AM Adoption, with an emphasis on addressing environmental and complexity-related factors.

The primary contribution of this study lies in enhancing our comprehension of the decision-making process regarding the adoption of additive manufacturing (AM) within the automotive industries of Ethiopia. The study uses an adoption model based on existing literature and theories. The information on the decision factors identified in this study will be beneficial to future researchers who study adoption factors. Furthermore, this contribution is particularly significant for developing countries seeking to integrate AM into their industries, as there is a dearth of research on non-adopters within this context.

5.2 Recommendation

Drawing from both the existing literature and the findings of this research, the researcher puts forth the following noteworthy recommendations.

- Environmental factors, including government policies, competitive pressures, and sustainability considerations, hold the most significant influence on AM adoption. Therefore, it is imperative to carefully assess these variables prior to making adoption decisions.
- Several barriers must be addressed, including concerns related to intellectual property rights, the absence of AM standards and regulations, and inadequate infrastructure. Overcoming these challenges necessitates the creation of a supportive ecosystem to facilitate AM adoption.
- Governments should formulate policies and regulations that actively support additive manufacturing (AM). This may involve offering financial incentives or tax breaks to businesses investing in AM technology, establishing AM standards and regulations to mitigate risks and uncertainties, and making investments in the necessary infrastructure to facilitate AM.

- Organizations should allocate resources to training and development initiatives to guarantee that their workforce possesses the essential skills required to bolster AM. This could also help to reduce resistance to change and build support for AM adoption.

- Companies need to develop in-house expertise or collaborate with industry partners, research institutions, and experts in the field to exchange knowledge and share best practices.

- Organizations need to flexible and foster collaboration between different departments in order to successfully adopt AM and get top management support for AM adoption.

5.3 Limitations and Future Research Study

This study carries several limitations. Firstly, the relatively small sample size, confined to the Bishoftu automotive and manufacturing industry, implies that the results may lack generalizability. Secondly, it is possible that there are other variables that need consideration, as the factors influencing AM adoption can vary depending on the specific industry or application. For instance, the significance of relative advantage may differ; it may be a more crucial factor in industries where AM can offer substantial cost or performance advantages over traditional manufacturing methods, while it might be less critical in other sectors. The study does not account for the dynamic nature of AM adoption, failing to consider how the adoption of AM technologies might be influenced by the emergence of new AM technologies or shifts in the market landscape. Future research should incorporate these dynamic elements.

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6. APPENDICES

Appendix A: Questionnaire

Addis Ababa University

Addis Ababa Institute of Technology (AAiT)

School of Mechanical and Industrial Engineering (SMIE)

Industrial Engineering Chair

Dear Participant,

My name is Sultan Asefa, and I'm currently a student in the MSc program for Industrial Engineering at Addis Ababa University. I am conducting this survey as part of my research project under the guidance of Ameha Mulugeta (Ph.D.). The aim of this research is to gather information on the topic of "**Adoption of Additive Manufacturing for Auto parts Production: Case of Bishoftu Automotive and Manufacturing Industry."** Your participation in this questionnaire is greatly valued and will contribute significantly to our data collection. Rest assured, your responses will be treated with the utmost confidentiality and used solely for research purposes. Please be truthful and give each question your best effort, as there are no right or incorrect answers. Please try your best to respond to each question; if you do not feel comfortable doing so, you are free to skip it. The survey should take approximately 10 minutes to complete. Your contributions are very helpful and will help us to expand our understanding of this subject.

Sincerely, Sultan Asefa

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Mobile: - +251917226315/+251985358987

Brief Introduction of Additive Manufacturing (3D Printing)

Additive manufacturing, also known as 3D printing, is a process where a three-dimensional object is created by adding layer upon layer of material, such as plastic, metal, or ceramic. Metal 3D printing, follows an 'additive' approach, where successive layers are added to construct a part. This is in contrast to 'subtractive' techniques, such as machining, milling, or forming, where material is removed or shaped. In 3D printing, the part's shape is always digitally defined, based on a 3D model created in a computer-aided design (CAD) program. This technology has brought about significant changes in various industries, particularly the automotive sector, by enabling the production of intricate geometries that would be challenging or even impossible to achieve through traditional manufacturing methods.

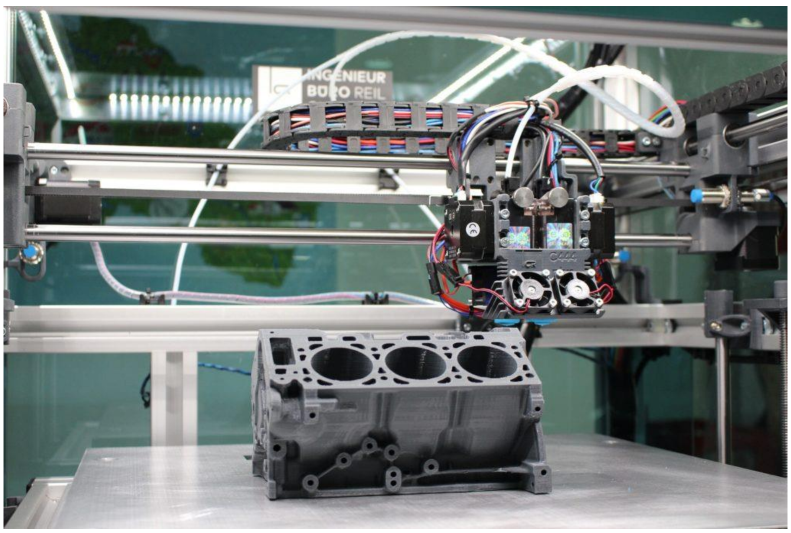

Figure displaying printing of Vehicle Engine using 3D printing

Have you read the brief Introduction to Additive Manufacturing (3D printing)? Yes☐ No☐

Did you already know about Additive manufacturing (3D printing)? Yes☐ No☐

1. Demographic Information

1. Gender ☐Male ☐Female
2. What is your job title? ☐Executive ☐Manager ☐Engineer ☐Technician☐Other
3. Educational Qualification: ☐Diploma ☐Bachelor's Degree ☐Master's Degree ☐Doctoral Degree
4. Years of Experience in the Automotive Manufacturing Industry: ☐ Less than 1 year ☐ 1-3 years ☐ 3-5 years ☐ 5-10 years ☐ More than 10 years

2. **AM Adoption**

Constructs	Items		Adopted Source
	Code	Description	
AM Adoption	AM1	What is the current phase of your organization's engagement with Additive Manufacturing (AM)? (We are not considering AM, We are presently in the process of evaluating AM, such as in a pilot study, we have assessed AM but do not intend to implement this technology, We have assessed AM and intend to implement this technology, We have already integrated AM services and infrastructure)	(Handfield et al., 2022a)
	AM2	If you expect your company to adopt AM in the future, how do you envision this happening? (Not considering AM, More than 5 years from now, Between 2 and 5 years from now, Between 1 and 2 years from now, Less than 1 year from now, We have already adopted AM services and infrastructure)	
	AM3	(1 = Not prepared at all; 2 = Somewhat prepared; 3 = Moderately prepared; 4 = Very prepared; 5 = Extremely prepared)	
	AM4	To what extent do you believe that AM will benefit your industry? (1 = Not at all beneficial; 2=somewhat beneficial; 3= moderately beneficial; 4 beneficial =5 = Very beneficial)	

	AM5	To what extent do you believe that AM will be challenging for your organization to adopt? (1 = Not at all challenging; 2=somewhat challenging; 3= moderately challenging; 4 challenging; 5 = Very challenging)	
	AM6	To what extent does your organization have the necessary resources to adopt AM? (1 = Not at all; 2=somewhat; 3= moderately; 4= great; 5 = to a great extent)	
	AM7	To what extent does your organization have the necessary support to adopt AM? (1 = Not at all; 2=somewhat; 3= moderately; 4= great; 5 = to a great extent)	
	AM8	How opportunities for AM adoption in your company relating to your manufacturing products?(1 = Not at all; 2=small; 3= moderately; 4= big; 5 = very big)	

3. Diffusion of Innovation DOI and Technology organization perspective (TOE

Constructs	Items		Adopted Source
	Code	Description	
Relative Advantage	RA1	Additive manufacturing adoption will allow for increasing efficiency/productivity	(Martinsuo & Luomaranta, 2018; Thomas, 2016)
	RA2	Additive Manufacturing adoption will enhance the quality of products	
	RA3	The Adoption of Additive manufacturing will allow an increase in the speed of production	
	RA4	Adopting additive manufacturing will enable the company to reduce costs	
	RA5	The use of additive manufacturing will facilitate rapid prototyping and the creation of new products	
Compatibility	CM1	Additive manufacturing is compatible with existing production systems.	(Mojtaba Khorram; Niaki Fabio Nonino, 2017; Oettmeier & Hofmann, 2017)
	CM2	Employee skills and knowledge are sufficient for the adoption of additive manufacturing.	
	CM3	The current supply chain is compatible with the adoption of additive manufacturing.	
	CM4	Industry culture and values are supportive of the adoption of additive manufacturing.	
Complexity	CP1	Design complexity for AM is high.	(Marak et al., 2019; Niaki et al., 2019; Steenhuis et al., 2020)
	CP2	The technical knowledge and skills required for AM are high.	

	CP3	The manufacturing operation for AM is complex.	
	CP4	The software complexity for AM is high.	
Trialability	TR1	Our company will test AM on a small scale before adopting it on a larger scale.	
	TR2	Our company will experiment with AM technology before deciding on its adoption.	
	TR3	The organization will observe the successful adoption of AM in other industries.	
	TR4	Our company will conduct pilot projects to evaluate the effectiveness of AM technology before deciding on its adoption.	
	TR5	Our company will evaluate the impact of AM technology on a small scale before adopting it on a larger scale	(Marak et al., 2019; Niaki et al., 2019; Steenhuis et al., 2020)
Observability	OB1	The benefits of Additive manufacturing are immediately obvious to those who see it in action.	
	OB2	It is easy to understand how Additive manufacturing will be used in our company's operations.	
	OB3	The results of using Additive manufacturing are visibly better than those achieved with traditional manufacturing methods.	
	OB4	The impact of Additive manufacturing on our company's operations can be easily measured and quantified.	
	OB5	The benefits of Additive manufacturing can be easily communicated to stakeholders outside of our company.	(Martinsuo & Luomaranta, 2018; Thomas, 2016)
Technology Context	TC1	How well does your organization's current technical infrastructure support AM adoption?	
	TC2	I am familiar with the different types of additive manufacturing technologies that are currently available.	
	TC3	We have the necessary technical infrastructure in place to support the adoption of additive manufacturing.	
	TC4	I believe that acquiring the skills to utilize additive manufacturing technologies would pose a challenge for the majority of our organization's employees.	(Delić, 2020; Dijk, 2016)

Organizational Context	OC1	To what extent is your organization's culture open to change and innovation?	(Lamperti & Cavedagna, 2017; Shahrubudin et al., 2019; Ukobitz, 2020)
	OC2	To what extent does your organization have the necessary resources to adopt and implement the new technology?	
	OC3	How supportive is senior management of the adoption of the new technology?	
	OC4	How centralized is your organization's structure and its size?	
Environmental context	EC1	There is strong competition in our industry, which motivates us to adopt new technologies like additive manufacturing	(Böckin & Tillman, 2019; Niaki et al., 2019)
	EC2	There are government policies or regulations that encourage the adoption of additive manufacturing in our industry.	
	EC3	Additive manufacturing technologies are perceived as environmentally friendly and sustainable in our industry	
	EC4	Additive manufacturing can provide a competitive advantage for our organization	

4. Interview Section

1. What are your thoughts on AM?
2. What are the potential benefits of AM for your organization?
3. What are the potential challenges of AM adoption for your organization?
4. What are your biggest concerns about AM adoption?
5. What steps would you need to take to adopt AM?
6. What resources would you need to adopt AM?
7. What support would you need from your organization to adopt AM?
8. What would be the key factors in your decision to adopt AM?
9. Is there anything else you would like to share about AM adoption?

Appendix B: Results of Smart PLS software

1. Path coefficients

1.1 Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption									
CM	0.169								
CP	0.215								
EC	0.219								
OB	0.176								
OC	0.180								
RA	0.159								
TC	0.175								
TR	0.192								

1.2 List

	Path coefficients
CM -> AM Adoption	0.169
CP -> AM Adoption	0.215
EC -> AM Adoption	0.219
OB -> AM Adoption	0.176
OC -> AM Adoption	0.180
RA -> AM Adoption	0.159
TC -> AM Adoption	0.175
TR -> AM Adoption	0.192

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation	T statistics	P values
CM -> AM Adoption	0.169	0.174	0.029	5.812	0.000
CP -> AM Adoption	0.215	0.215	0.023	9.225	0.000
EC -> AM Adoption	0.219	0.221	0.028	7.707	0.000
OB -> AM Adoption	0.176	0.175	0.028	6.265	0.000
OC -> AM Adoption	0.180	0.181	0.024	7.450	0.000
RA -> AM Adoption	0.159	0.153	0.025	6.421	0.000
TC -> AM Adoption	0.175	0.168	0.024	7.413	0.000
TR -> AM Adoption	0.192	0.187	0.024	7.847	0.000

Confidence intervals

	Original sample (O)	Sample mean (M)	2.5%	97.5%
CM -> AM Adoption	0.169	0.174	0.125	0.240
CP -> AM Adoption	0.215	0.215	0.174	0.267
EC -> AM Adoption	0.219	0.221	0.175	0.287
OB -> AM Adoption	0.176	0.175	0.127	0.236
OC -> AM Adoption	0.180	0.181	0.136	0.234
RA -> AM Adoption	0.159	0.153	0.105	0.202
TC -> AM Adoption	0.175	0.168	0.120	0.213
TR -> AM Adoption	0.192	0.187	0.136	0.233

Confidence intervals bias corrected

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
CM -> AM Adoption	0.169	0.174	0.005	0.120	0.232
CP -> AM Adoption	0.215	0.215	-0.001	0.179	0.274
EC -> AM Adoption	0.219	0.221	0.002	0.177	0.291
OB -> AM Adoption	0.176	0.175	-0.001	0.133	0.247
OC -> AM Adoption	0.180	0.181	0.001	0.137	0.235
RA -> AM Adoption	0.159	0.153	-0.006	0.118	0.218
TC -> AM Adoption	0.175	0.168	-0.007	0.138	0.229
TR -> AM Adoption	0.192	0.187	-0.005	0.147	0.243

2. INDIRECT EFFECTS

2.1 Total effects

2.1.1 Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption									
CM	0.169								
CP	0.215								
EC	0.219								
OB	0.176								
OC	0.180								
RA	0.159								
TC	0.175								
TR	0.192								

2.2.2 List

	Total effects
CM -> AM Adoption	0.169
CP -> AM Adoption	0.215
EC -> AM Adoption	0.219
OB -> AM Adoption	0.176
OC -> AM Adoption	0.180
RA -> AM Adoption	0.159
TC -> AM Adoption	0.175

TR -> AM Adoption	0.192

Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation	T statistics	P values
CM -> AM Adoption	0.169	0.174	0.029	5.812	0.000
CP -> AM Adoption	0.215	0.215	0.023	9.225	0.000
EC -> AM Adoption	0.219	0.221	0.028	7.707	0.000
OB -> AM Adoption	0.176	0.175	0.028	6.265	0.000
OC -> AM Adoption	0.180	0.181	0.024	7.450	0.000
RA -> AM Adoption	0.159	0.153	0.025	6.421	0.000
TC -> AM Adoption	0.175	0.168	0.024	7.413	0.000
TR -> AM Adoption	0.192	0.187	0.024	7.847	0.000

Confidence intervals

	Original sample (O)	Sample mean (M)	2.5%	97.5%
CM -> AM Adoption	0.169	0.174	0.125	0.240
CP -> AM Adoption	0.215	0.215	0.174	0.267
EC -> AM Adoption	0.219	0.221	0.175	0.287
OB -> AM Adoption	0.176	0.175	0.127	0.236
OC -> AM Adoption	0.180	0.181	0.136	0.234
RA -> AM Adoption	0.159	0.153	0.105	0.202
TC -> AM Adoption	0.175	0.168	0.120	0.213
TR -> AM Adoption	0.192	0.187	0.136	0.233

Confidence intervals bias corrected

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
CM -> AM Adoption	0.169	0.174	0.005	0.120	0.232
CP -> AM Adoption	0.215	0.215	-0.001	0.179	0.274
EC -> AM Adoption	0.219	0.221	0.002	0.177	0.291
OB -> AM Adoption	0.176	0.175	-0.001	0.133	0.247
OC -> AM Adoption	0.180	0.181	0.001	0.137	0.235
RA -> AM Adoption	0.159	0.153	-0.006	0.118	0.218
TC -> AM Adoption	0.175	0.168	-0.007	0.138	0.229
TR -> AM Adoption	0.192	0.187	-0.005	0.147	0.243

3. Outer Loadings

3.1 Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM1	0.675								
AM2	0.560								
AM3	0.721								
AM4	0.544								
AM5	0.723								
AM6	0.668								
AM7	0.561								
AM8	0.766								
CM1		0.786							
CM2		0.641							
CM3		0.681							
CM4		0.780							
CP1			0.712						
CP2			0.864						
CP3			0.808						
CP4			0.803						
EC1				0.704					
EC2				0.833					
EC3				0.903					
EC4				0.768					
OB1					0.580				

OB2					0.745				
OB3					0.893				
OB4					0.783				
OB5					0.807				
OC1						0.770			
OC2						0.727			
OC3						0.851			
OC4						0.611			
RA1							0.771		
RA2							0.728		
RA3							0.873		
RA4							0.800		
RA5							0.833		
TC1								0.713	
TC2								0.729	
TC3								0.846	
TC4								0.667	
TR1									0.824
TR2									0.815
TR3									0.853
TR4									0.870
TR5									0.858

3.2 List

	Outer loadings
AM1 <- AM Adoption	0.675
AM2 <- AM Adoption	0.560
AM3 <- AM Adoption	0.721
AM4 <- AM Adoption	0.544
AM5 <- AM Adoption	0.723
AM6 <- AM Adoption	0.668
AM7 <- AM Adoption	0.561
AM8 <- AM Adoption	0.766
CM1 <- CM	0.786
CM2 <- CM	0.641
CM3 <- CM	0.681
CM4 <- CM	0.780
CP1 <- CP	0.712
CP2 <- CP	0.864
CP3 <- CP	0.808
CP4 <- CP	0.803
EC1 <- EC	0.704
EC2 <- EC	0.833
EC3 <- EC	0.903
EC4 <- EC	0.768
OB1 <- OB	0.580
OB2 <- OB	0.745
OB3 <- OB	0.893
OB4 <- OB	0.783
OB5 <- OB	0.807
OC1 <- OC	0.770
OC2 <- OC	0.727
OC3 <- OC	0.851
OC4 <- OC	0.611
RA1 <- RA	0.771
RA2 <- RA	0.728
RA3 <- RA	0.873
RA4 <- RA	0.800
RA5 <- RA	0.833
TC1 <- TC	0.713

TC2 <- TC	0.729
TC3 <- TC	0.846
TC4 <- TC	0.667
TR1 <- TR	0.824
TR2 <- TR	0.815
TR3 <- TR	0.853
TR4 <- TR	0.870
TR5 <- TR	0.858

4. Outer weights

4.1 Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM1	0.202								
AM2	0.159								
AM3	0.207								
AM4	0.151								
AM5	0.218								
AM6	0.194								
AM7	0.149								
AM8	0.226								
CM1		0.438							
CM2		0.350							
CM3		0.174							
CM4		0.401							
CP1			0.293						
CP2			0.322						
CP3			0.362						
CP4			0.274						
EC1				0.267					
EC2				0.284					
EC3				0.342					
EC4				0.348					
OB1					0.221				
OB2					0.259				
OB3					0.273				

OB4					0.270				
OB5					0.279				
OC1						0.466			
OC2						0.219			
OC3						0.393			
OC4						0.241			
RA1							0.215		
RA2							0.187		
RA3							0.274		
RA4							0.297		
RA5							0.265		
TC1								0.365	
TC2								0.288	
TC3								0.399	
TC4								0.288	
TR1									0.288
TR2									0.177
TR3									0.231
TR4									0.245
TR5									0.242

4.2 List

	Outer weights
AM1 <- AM Adoption	0.202
AM2 <- AM Adoption	0.159
AM3 <- AM Adoption	0.207
AM4 <- AM Adoption	0.151
AM5 <- AM Adoption	0.218
AM6 <- AM Adoption	0.194
AM7 <- AM Adoption	0.149
AM8 <- AM Adoption	0.226
CM1 <- CM	0.438
CM2 <- CM	0.350
CM3 <- CM	0.174
CM4 <- CM	0.401

CP1 <- CP	0.293
CP2 <- CP	0.322
CP3 <- CP	0.362
CP4 <- CP	0.274
EC1 <- EC	0.267
EC2 <- EC	0.284
EC3 <- EC	0.342
EC4 <- EC	0.348
OB1 <- OB	0.221
OB2 <- OB	0.259
OB3 <- OB	0.273
OB4 <- OB	0.270
OB5 <- OB	0.279
OC1 <- OC	0.466
OC2 <- OC	0.219
OC3 <- OC	0.393
OC4 <- OC	0.241
RA1 <- RA	0.215
RA2 <- RA	0.187
RA3 <- RA	0.274
RA4 <- RA	0.297
RA5 <- RA	0.265
TC1 <- TC	0.365
TC2 <- TC	0.288
TC3 <- TC	0.399
TC4 <- TC	0.288
TR1 <- TR	0.288
TR2 <- TR	0.177
TR3 <- TR	0.231
TR4 <- TR	0.245
TR5 <- TR	0.242

Mean, STDEV, T values, p values of outer loading

	Original sample	Sample mean	Standard deviation	T statistics	P values
AM1 <- AM Adoption	0.675	0.671	0.072	9.339	0.000
AM2 <- AM Adoption	0.560	0.565	0.079	7.094	0.000
AM3 <- AM Adoption	0.721	0.719	0.065	11.022	0.000
AM4 <- AM Adoption	0.544	0.538	0.102	5.347	0.000
AM5 <- AM Adoption	0.723	0.714	0.070	10.293	0.000
AM6 <- AM Adoption	0.668	0.665	0.083	8.030	0.000
AM7 <- AM Adoption	0.561	0.554	0.069	8.135	0.000
AM8 <- AM Adoption	0.766	0.765	0.035	21.726	0.000
CM1 <- CM	0.786	0.785	0.056	13.958	0.000
CM2 <- CM	0.641	0.624	0.109	5.883	0.000
CM3 <- CM	0.681	0.660	0.109	6.257	0.000
CM4 <- CM	0.780	0.779	0.054	14.369	0.000
CP1 <- CP	0.712	0.705	0.081	8.772	0.000
CP2 <- CP	0.864	0.863	0.042	20.405	0.000
CP3 <- CP	0.808	0.809	0.049	16.533	0.000
CP4 <- CP	0.803	0.799	0.057	14.180	0.000
EC1 <- EC	0.704	0.703	0.049	14.483	0.000
EC2 <- EC	0.833	0.828	0.046	17.949	0.000
EC3 <- EC	0.903	0.905	0.017	52.557	0.000
EC4 <- EC	0.768	0.769	0.045	17.017	0.000
OB1 <- OB	0.580	0.575	0.087	6.664	0.000
OB2 <- OB	0.745	0.750	0.039	19.184	0.000
OB3 <- OB	0.893	0.887	0.031	28.817	0.000
OB4 <- OB	0.783	0.777	0.061	12.926	0.000
OB5 <- OB	0.807	0.803	0.050	16.284	0.000
OC1 <- OC	0.770	0.771	0.049	15.618	0.000

OC2 <- OC	0.727	0.718	0.079	9.259	0.000
OC3 <- OC	0.851	0.844	0.045	19.026	0.000
OC4 <- OC	0.611	0.594	0.116	5.286	0.000
RA1 <- RA	0.771	0.761	0.082	9.404	0.000
RA2 <- RA	0.728	0.711	0.095	7.669	0.000
RA3 <- RA	0.873	0.871	0.048	18.292	0.000
RA4 <- RA	0.800	0.802	0.056	14.239	0.000
RA5 <- RA	0.833	0.831	0.049	17.004	0.000
TC1 <- TC	0.713	0.700	0.084	8.532	0.000
TC2 <- TC	0.729	0.721	0.079	9.283	0.000
TC3 <- TC	0.846	0.849	0.043	19.754	0.000
TC4 <- TC	0.667	0.665	0.083	8.077	0.000
TR1 <- TR	0.824	0.823	0.050	16.507	0.000
TR2 <- TR	0.815	0.812	0.061	13.453	0.000
TR3 <- TR	0.853	0.848	0.054	15.869	0.000
TR4 <- TR	0.870	0.869	0.048	18.245	0.000
TR5 <- TR	0.858	0.856	0.054	15.895	0.000

5. Latent variables

5.1 Scores

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
0	0.334	1.192	0.737	0.825	-0.816	-1.276	1.479	0.480	0.430
1	1.248	1.429	-0.439	-0.050	0.349	1.737	1.479	1.286	0.750
2	0.063	0.281	-0.545	-0.346	0.036	0.402	-0.408	-0.042	1.865
3	-1.351	-2.961	0.183	-0.357	-0.445	0.776	-2.996	0.623	-1.379
4	-0.314	0.942	0.287	-1.092	-0.513	-0.691	0.387	-1.387	0.271
5	-0.926	-1.139	-0.624	-1.237	-1.118	1.019	-0.449	-1.387	-0.237
6	-0.317	-3.791	1.652	-1.409	-1.366	-2.987	1.479	2.095	1.611
7	-0.747	-0.126	-0.519	-1.694	-0.181	-1.145	-0.449	0.482	-0.590
8	-1.446	-0.800	-1.913	-0.814	-0.488	-0.501	-1.832	-1.639	-0.174
9	-0.659	0.294	0.287	-1.679	-1.126	-0.151	0.067	-0.846	-0.423
10	1.295	1.178	1.652	1.132	-0.256	1.019	1.479	0.102	0.943
11	0.326	0.026	0.382	-0.959	0.349	-0.417	1.479	0.767	0.943
12	-3.730	-0.969	-2.982	-2.727	-3.491	-1.948	-3.093	-2.751	-1.913
13	0.242	-0.465	0.741	-0.206	0.084	1.019	0.893	0.225	0.258
14	-0.423	0.026	-0.811	-0.786	-0.820	0.191	-0.130	-1.243	1.197
15	2.437	1.585	1.652	1.438	1.243	1.362	1.479	2.095	1.425
16	2.072	1.585	1.013	0.992	0.911	1.869	1.201	1.682	1.171
17	1.005	-0.156	1.380	1.143	0.044	2.355	-0.253	-0.328	0.762
18	1.229	0.687	1.652	1.438	-0.810	1.637	0.190	0.354	0.943
19	0.125	0.196	-0.993	-0.050	0.041	0.138	-0.078	-0.059	0.680
20	-1.344	-0.643	-0.172	-1.528	-1.120	0.159	-1.945	-2.859	0.202
21	-0.772	0.687	-0.248	-2.134	-1.995	-0.638	0.893	-0.183	0.943
22	-0.414	-1.460	-1.345	-0.050	0.349	1.019	-1.636	0.354	0.181
23	-1.961	-1.867	-1.345	-1.539	-1.420	-0.559	-2.152	-0.705	-1.460
24	-0.146	1.839	-2.444	0.101	-0.823	-0.151	1.479	-0.042	0.280
25	0.285	-0.478	0.287	1.438	0.915	-0.395	0.457	0.371	-1.409
26	0.012	0.281	0.287	-0.050	0.349	-1.409	0.457	0.354	-0.897
27	0.071	0.281	0.287	-0.050	0.618	-0.527	0.260	0.354	-1.160
28	-0.128	0.687	-0.248	0.552	0.349	-0.395	-0.287	0.085	-1.409
29	-0.789	-0.478	-0.248	-0.050	-0.240	-0.638	-0.327	-0.561	-1.409
30	-0.091	0.281	0.287	-0.050	0.349	-0.284	-0.408	0.354	-1.409
31	-0.048	1.178	-0.791	-0.050	0.349	-0.263	0.179	1.017	-1.409
32	-0.428	0.281	-0.524	-0.050	-0.256	-1.034	-0.221	-0.294	-0.233

33	-0.371	-0.885	-0.356	-0.050	-0.256	0.434	0.260	0.085	-0.728
34	0.861	-0.956	1.013	0.530	0.084	1.019	0.893	0.371	1.447
35	0.362	-0.197	0.737	0.390	-0.274	0.434	-0.478	-0.578	0.123
36	0.139	-0.126	0.287	-0.050	1.220	-0.020	-0.018	0.230	-0.428
37	0.272	0.026	0.287	1.438	0.349	-0.638	0.417	-0.183	-0.233
38	0.214	-0.478	0.287	1.132	0.349	-0.263	-0.605	0.354	-0.026
39	0.043	0.281	0.015	-0.050	0.958	-1.409	0.190	0.354	-0.156
40	0.751	0.687	0.741	0.256	1.521	0.223	0.190	0.085	0.943
41	0.222	-0.126	-0.439	0.692	0.651	0.598	-0.204	0.085	0.715
42	0.682	0.687	0.287	0.992	0.958	-0.020	0.654	0.354	-0.233
43	0.615	0.281	1.652	1.132	0.643	-0.116	-0.007	2.095	-2.585
44	1.240	0.603	1.380	0.847	0.961	0.290	-0.316	0.750	1.197
45	0.294	0.026	0.287	0.836	0.921	-0.395	-0.007	-0.183	0.943
46	0.147	0.281	0.015	-0.050	0.921	-0.020	0.685	-0.183	-0.233
47	0.375	0.687	0.554	-0.050	0.908	-0.073	0.457	-0.435	0.465
48	0.344	-0.210	-0.628	1.438	0.349	0.191	0.098	0.354	-0.233
49	0.116	0.687	-0.999	0.836	0.915	-0.395	-0.130	0.085	-0.233
50	0.326	0.183	0.287	1.132	0.349	0.434	-0.377	-0.311	-0.720
51	0.285	1.178	-0.811	-0.050	0.915	-0.316	0.685	-0.183	0.689
52	0.959	-0.478	0.282	0.685	0.954	1.394	0.417	0.767	0.689
53	-0.181	-0.308	-0.252	-0.050	0.349	-0.427	-0.007	-1.010	0.943
54	0.286	0.687	0.015	-0.050	1.256	-0.559	-0.833	0.767	0.508
55	-0.126	-0.072	0.015	-0.050	0.349	-1.145	-0.007	0.354	-0.233
56	-0.241	-0.969	-0.891	-1.232	0.349	1.019	0.893	-1.010	0.384
57	-0.619	-0.813	0.183	-0.357	-0.445	0.776	-0.594	0.623	-1.379
58	1.229	0.687	1.652	1.438	-0.810	1.637	0.190	0.354	0.943
59	-2.930	-0.969	-2.171	-1.834	-3.491	-1.948	-1.116	-2.751	-1.913
60	0.334	1.192	0.737	0.825	-0.816	-1.276	1.479	0.480	0.430
61	1.248	1.429	-0.439	-0.050	0.349	1.737	1.479	1.286	0.750
62	0.063	0.281	-0.545	-0.346	0.036	0.402	-0.408	-0.042	1.865
63	-1.351	-2.961	0.183	-0.357	-0.445	0.776	-2.996	0.623	-1.379
64	-0.314	0.942	0.287	-1.092	-0.513	-0.691	0.387	-1.387	0.271
65	-0.926	-1.139	-0.624	-1.237	-1.118	1.019	-0.449	-1.387	-0.237
66	-0.317	-3.791	1.652	-1.409	-1.366	-2.987	1.479	2.095	1.611
67	-0.747	-0.126	-0.519	-1.694	-0.181	-1.145	-0.449	0.482	-0.590
68	-1.446	-0.800	-1.913	-0.814	-0.488	-0.501	-1.832	-1.639	-0.174
69	-0.659	0.294	0.287	-1.679	-1.126	-0.151	0.067	-0.846	-0.423
70	1.295	1.178	1.652	1.132	-0.256	1.019	1.479	0.102	0.943

71	0.326	0.026	0.382	-0.959	0.349	-0.417	1.479	0.767	0.943
72	-3.730	-0.969	-2.982	-2.727	-3.491	-1.948	-3.093	-2.751	-1.913
73	0.242	-0.465	0.741	-0.206	0.084	1.019	0.893	0.225	0.258
74	-0.423	0.026	-0.811	-0.786	-0.820	0.191	-0.130	-1.243	1.197
75	2.437	1.585	1.652	1.438	1.243	1.362	1.479	2.095	1.425
76	2.072	1.585	1.013	0.992	0.911	1.869	1.201	1.682	1.171
77	1.005	-0.156	1.380	1.143	0.044	2.355	-0.253	-0.328	0.762
78	1.229	0.687	1.652	1.438	-0.810	1.637	0.190	0.354	0.943
79	0.125	0.196	-0.993	-0.050	0.041	0.138	-0.078	-0.059	0.680
80	-1.344	-0.643	-0.172	-1.528	-1.120	0.159	-1.945	-2.859	0.202
81	-0.772	0.687	-0.248	-2.134	-1.995	-0.638	0.893	-0.183	0.943
82	-0.414	-1.460	-1.345	-0.050	0.349	1.019	-1.636	0.354	0.181
83	-1.961	-1.867	-1.345	-1.539	-1.420	-0.559	-2.152	-0.705	-1.460
84	-0.146	1.839	-2.444	0.101	-0.823	-0.151	1.479	-0.042	0.280
85	0.285	-0.478	0.287	1.438	0.915	-0.395	0.457	0.371	-1.409
86	0.012	0.281	0.287	-0.050	0.349	-1.409	0.457	0.354	-0.897
87	0.071	0.281	0.287	-0.050	0.618	-0.527	0.260	0.354	-1.160
88	-0.128	0.687	-0.248	0.552	0.349	-0.395	-0.287	0.085	-1.409
89	-0.789	-0.478	-0.248	-0.050	-0.240	-0.638	-0.327	-0.561	-1.409
90	-0.091	0.281	0.287	-0.050	0.349	-0.284	-0.408	0.354	-1.409
91	-0.048	1.178	-0.791	-0.050	0.349	-0.263	0.179	1.017	-1.409
92	-0.428	0.281	-0.524	-0.050	-0.256	-1.034	-0.221	-0.294	-0.233
93	-0.371	-0.885	-0.356	-0.050	-0.256	0.434	0.260	0.085	-0.728
94	0.861	-0.956	1.013	0.530	0.084	1.019	0.893	0.371	1.447
95	0.362	-0.197	0.737	0.390	-0.274	0.434	-0.478	-0.578	0.123
96	0.139	-0.126	0.287	-0.050	1.220	-0.020	-0.018	0.230	-0.428
97	0.272	0.026	0.287	1.438	0.349	-0.638	0.417	-0.183	-0.233
98	0.214	-0.478	0.287	1.132	0.349	-0.263	-0.605	0.354	-0.026
99	0.043	0.281	0.015	-0.050	0.958	-1.409	0.190	0.354	-0.156
100	0.751	0.687	0.741	0.256	1.521	0.223	0.190	0.085	0.943
101	0.222	-0.126	-0.439	0.692	0.651	0.598	-0.204	0.085	0.715
102	0.682	0.687	0.287	0.992	0.958	-0.020	0.654	0.354	-0.233
103	0.615	0.281	1.652	1.132	0.643	-0.116	-0.007	2.095	-2.585
104	1.240	0.603	1.380	0.847	0.961	0.290	-0.316	0.750	1.197
105	0.294	0.026	0.287	0.836	0.921	-0.395	-0.007	-0.183	0.943
106	0.147	0.281	0.015	-0.050	0.921	-0.020	0.685	-0.183	-0.233
107	0.375	0.687	0.554	-0.050	0.908	-0.073	0.457	-0.435	0.465
108	0.344	-0.210	-0.628	1.438	0.349	0.191	0.098	0.354	-0.233

109	0.116	0.687	-0.999	0.836	0.915	-0.395	-0.130	0.085	-0.233
110	0.326	0.183	0.287	1.132	0.349	0.434	-0.377	-0.311	-0.720
111	0.285	1.178	-0.811	-0.050	0.915	-0.316	0.685	-0.183	0.689
112	0.959	-0.478	0.282	0.685	0.954	1.394	0.417	0.767	0.689
113	-0.181	-0.308	-0.252	-0.050	0.349	-0.427	-0.007	-1.010	0.943
114	0.286	0.687	0.015	-0.050	1.256	-0.559	-0.833	0.767	0.508
115	-0.126	-0.072	0.015	-0.050	0.349	-1.145	-0.007	0.354	-0.233
116	-0.241	-0.969	-0.891	-1.232	0.349	1.019	0.893	-1.010	0.384
117	-0.619	-0.813	0.183	-0.357	-0.445	0.776	-0.594	0.623	-1.379
118	1.229	0.687	1.652	1.438	-0.810	1.637	0.190	0.354	0.943
119	-2.930	-0.969	-2.171	-1.834	-3.491	-1.948	-1.116	-2.751	-1.913

Correlations

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption	1.000	0.542	0.728	0.781	0.723	0.569	0.690	0.703	0.552
CM	0.542	1.000	0.137	0.396	0.361	0.223	0.502	0.182	0.217
CP	0.728	0.137	1.000	0.542	0.406	0.336	0.455	0.581	0.338
EC	0.781	0.396	0.542	1.000	0.640	0.452	0.355	0.534	0.180
OB	0.723	0.361	0.406	0.640	1.000	0.313	0.365	0.575	0.226
OC	0.569	0.223	0.336	0.452	0.313	1.000	0.137	0.207	0.346
RA	0.690	0.502	0.455	0.355	0.365	0.137	1.000	0.511	0.478
TC	0.703	0.182	0.581	0.534	0.575	0.207	0.511	1.000	0.186
TR	0.552	0.217	0.338	0.180	0.226	0.346	0.478	0.186	1.000

Covariance

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption	1.000	0.542	0.728	0.781	0.723	0.569	0.690	0.703	0.552
CM	0.542	1.000	0.137	0.396	0.361	0.223	0.502	0.182	0.217
CP	0.728	0.137	1.000	0.542	0.406	0.336	0.455	0.581	0.338
EC	0.781	0.396	0.542	1.000	0.640	0.452	0.355	0.534	0.180
OB	0.723	0.361	0.406	0.640	1.000	0.313	0.365	0.575	0.226
OC	0.569	0.223	0.336	0.452	0.313	1.000	0.137	0.207	0.346
RA	0.690	0.502	0.455	0.355	0.365	0.137	1.000	0.511	0.478
TC	0.703	0.182	0.581	0.534	0.575	0.207	0.511	1.000	0.186
TR	0.552	0.217	0.338	0.180	0.226	0.346	0.478	0.186	1.000

QUALITY CRITERIA

R-square

	R-square	R-square adjusted
AM Adoption	0.988	0.987

Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption									
CM	1.371								
CP	1.895								
EC	1.579								
OB	1.221								
OC	1.790								
RA	0.865								
TC	1.087								
TR	1.914								

List

	f-square
CM -> AM Adoption	1.371
CP -> AM Adoption	1.895
EC -> AM Adoption	1.579
OB -> AM Adoption	1.221
OC -> AM Adoption	1.790
RA -> AM Adoption	0.865
TC -> AM Adoption	1.087
TR -> AM Adoption	1.914

Construct reliability and validity

Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AM Adoption	0.809	0.822	0.857	0.432
CM	0.712	0.714	0.815	0.525
CP	0.810	0.818	0.875	0.638
EC	0.817	0.828	0.880	0.649
OB	0.819	0.829	0.876	0.590
OC	0.739	0.786	0.831	0.555
RA	0.862	0.877	0.900	0.644
TC	0.725	0.742	0.829	0.550
TR	0.900	0.911	0.925	0.713

Discriminant validity

Heterotrait-monotrait ratio (HTMT) – Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption									
CM	0.713								
CP	0.869	0.208							
EC	0.927	0.515	0.642						
OB	0.855	0.473	0.489	0.791					
OC	0.753	0.369	0.408	0.538	0.406				
RA	0.817	0.572	0.520	0.413	0.424	0.262			
TC	0.873	0.337	0.747	0.652	0.733	0.374	0.592		
TR	0.684	0.283	0.375	0.249	0.265	0.424	0.534	0.259	

Heterotrait-monotrait ratio (HTMT) – List

	Heterotrait-monotrait ratio (HTMT)
CM <-> AM Adoption	0.713
CP <-> AM Adoption	0.869
CP <-> CM	0.208
EC <-> AM Adoption	0.927
EC <-> CM	0.515
EC <-> CP	0.642
OB <-> AM Adoption	0.855
OB <-> CM	0.473
OB <-> CP	0.489
OB <-> EC	0.791
OC <-> AM Adoption	0.753
OC <-> CM	0.369
OC <-> CP	0.408
OC <-> EC	0.538
OC <-> OB	0.406
RA <-> AM Adoption	0.817
RA <-> CM	0.572
RA <-> CP	0.520
RA <-> EC	0.413
RA <-> OB	0.424
RA <-> OC	0.262
TC <-> AM Adoption	0.873
TC <-> CM	0.337
TC <-> CP	0.747
TC <-> EC	0.652
TC <-> OB	0.733
TC <-> OC	0.374
TC <-> RA	0.592
TR <-> AM Adoption	0.684
TR <-> CM	0.283
TR <-> CP	0.375
TR <-> EC	0.249
TR <-> OB	0.265
TR <-> OC	0.424
TR <-> RA	0.534
TR <-> TC	0.259

Fornell-Larcker criterion

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption	0.657								
CM	0.542	0.725							
CP	0.728	0.137	0.799						
EC	0.781	0.396	0.542	0.805					
OB	0.723	0.361	0.406	0.640	0.768				
OC	0.569	0.223	0.336	0.452	0.313	0.745			
RA	0.690	0.502	0.455	0.355	0.365	0.137	0.802		
TC	0.703	0.182	0.581	0.534	0.575	0.207	0.511	0.742	
TR	0.552	0.217	0.338	0.180	0.226	0.346	0.478	0.186	0.844

Cross loadings

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM1	0.675	0.496	0.446	0.336	0.342	0.133	0.998	0.494	0.475
AM2	0.560	0.975	0.123	0.415	0.414	0.263	0.446	0.159	0.258
AM3	0.721	0.163	0.975	0.517	0.392	0.335	0.447	0.520	0.345
AM4	0.544	0.210	0.331	0.172	0.220	0.341	0.476	0.184	0.999
AM5	0.723	0.369	0.402	0.642	1.000	0.312	0.368	0.567	0.226
AM6	0.668	0.068	0.612	0.451	0.413	0.340	0.398	0.916	0.242
AM7	0.561	0.225	0.304	0.420	0.204	0.934	0.153	0.195	0.425
AM8	0.766	0.420	0.511	0.995	0.646	0.472	0.324	0.498	0.148
CM1	0.470	0.786	0.112	0.339	0.353	0.083	0.595	0.314	0.108
CM2	0.376	0.641	0.129	0.319	0.169	0.354	0.144	0.007	0.256
CM3	0.186	0.681	-0.014	0.168	0.210	0.088	0.037	-0.089	-0.011
CM4	0.431	0.780	0.113	0.265	0.277	0.119	0.461	0.143	0.205
CP1	0.540	0.035	0.712	0.460	0.366	0.308	0.209	0.347	0.348
CP2	0.593	0.154	0.864	0.383	0.346	0.179	0.394	0.483	0.237
CP3	0.665	0.204	0.808	0.498	0.359	0.305	0.506	0.574	0.332
CP4	0.503	0.012	0.803	0.380	0.210	0.283	0.307	0.423	0.143
EC1	0.536	0.500	0.250	0.704	0.502	0.464	0.117	0.143	0.051
EC2	0.569	0.363	0.324	0.833	0.562	0.444	0.165	0.360	-0.045
EC3	0.685	0.250	0.536	0.903	0.537	0.310	0.288	0.541	0.176
EC4	0.697	0.212	0.577	0.768	0.468	0.277	0.512	0.600	0.343
OB1	0.468	0.435	0.237	0.427	0.580	0.382	0.213	0.282	0.066
OB2	0.549	0.468	0.204	0.532	0.745	0.167	0.373	0.243	0.158

OB3	0.579	0.276	0.309	0.510	0.893	0.203	0.281	0.519	0.179
OB4	0.572	0.100	0.312	0.437	0.783	0.286	0.212	0.556	0.277
OB5	0.592	0.150	0.475	0.542	0.807	0.191	0.313	0.566	0.170
OC1	0.555	0.305	0.346	0.522	0.429	0.770	0.202	0.287	0.174
OC2	0.261	0.035	0.179	0.158	-0.008	0.727	-0.107	0.053	0.213
OC3	0.468	0.083	0.306	0.301	0.222	0.851	0.069	0.203	0.388
OC4	0.287	0.170	0.063	0.231	0.115	0.611	0.163	-0.077	0.275
RA1	0.472	0.262	0.312	0.296	0.221	0.095	0.771	0.434	0.271
RA2	0.410	0.373	0.279	0.035	0.005	0.112	0.728	0.140	0.456
RA3	0.600	0.368	0.416	0.281	0.309	0.203	0.873	0.430	0.476
RA4	0.650	0.443	0.438	0.392	0.358	0.175	0.800	0.472	0.474
RA5	0.580	0.542	0.347	0.344	0.472	-0.045	0.833	0.505	0.238
TC1	0.560	0.155	0.504	0.458	0.543	0.112	0.413	0.713	0.168
TC2	0.442	-0.044	0.385	0.346	0.310	0.300	0.153	0.729	0.050
TC3	0.612	0.261	0.425	0.473	0.460	0.161	0.587	0.846	0.199
TC4	0.442	0.117	0.405	0.271	0.359	0.053	0.286	0.667	0.108
TR1	0.555	0.403	0.368	0.262	0.244	0.339	0.467	0.040	0.824
TR2	0.341	0.052	0.157	0.033	0.102	0.238	0.361	0.127	0.815
TR3	0.445	0.036	0.256	0.120	0.241	0.342	0.357	0.229	0.853
TR4	0.472	0.132	0.280	0.163	0.178	0.324	0.397	0.250	0.870
TR5	0.466	0.212	0.316	0.128	0.158	0.198	0.412	0.157	0.858

Collinearity statistics (VIF)

Outer model – List

	VIF
AM1	1.924
AM2	1.706
AM3	1.864
AM4	1.692
AM5	2.034
AM6	1.797
AM7	1.727
AM8	2.545
CM1	1.430
CM2	1.547
CM3	1.826

CM4	1.656
CP1	1.375
CP2	2.302
CP3	1.604
CP4	1.968
EC1	1.643
EC2	2.232
EC3	2.808
EC4	1.794
OB1	1.368
OB2	1.620
OB3	2.948
OB4	2.216
OB5	2.045
OC1	1.265
OC2	1.728
OC3	2.180
OC4	1.394
RA1	1.945
RA2	1.805
RA3	2.592
RA4	1.828
RA5	2.263
TC1	1.341
TC2	1.420
TC3	1.765
TC4	1.426
TR1	2.075
TR2	2.268
TR3	2.737
TR4	3.272
TR5	2.497

Inner model – Matrix

	AM Adoption	CM	CP	EC	OB	OC	RA	TC	TR
AM Adoption									
CM	1.687								
CP	1.979								
EC	2.447								
OB	2.047								
OC	1.469								
RA	2.364								
TC	2.269								
TR	1.557								

Inner model – List

	VIF
CM -> AM Adoption	1.687
CP -> AM Adoption	1.979
EC -> AM Adoption	2.447
OB -> AM Adoption	2.047
OC -> AM Adoption	1.469
RA -> AM Adoption	2.364
TC -> AM Adoption	2.269
TR -> AM Adoption	1.557

Model fit

Fit summary

	Saturated model	Estimated model
SRMR	0.157	0.157
d_ULS	23.184	23.184
d_G	n/a	n/a
Chi-square	infinite	infinite
NFI	n/a	n/a

Model selection criteria

Matrix

	BIC (Bayesian information criterion)
AM Adoption	-484.989

Posthoc minimum sample size

	Path coefficients	Alpha 1%, power 80%	Alpha 5%, power 80%	Alpha 1%, power 90%	Alpha 5%, power 90%
CM -> AM Adoption	0.169	351.000	217.000	455.000	300.000
CP -> AM Adoption	0.215	217.000	134.000	281.000	185.000
EC -> AM Adoption	0.219	210.000	130.000	273.000	180.000
OB -> AM Adoption	0.176	325.000	200.000	421.000	277.000
OC -> AM Adoption	0.180	309.000	190.000	400.000	264.000
RA -> AM Adoption	0.159	397.000	245.000	515.000	339.000
TC -> AM Adoption	0.175	330.000	203.000	427.000	281.000
TR -> AM Adoption	0.192	273.000	168.000	353.000	233.000

Appendix C: Summary of research gap

No	Author	Title	Methodology	Result	Gap
1	(Niaki et al., 2019)	“Why manufacturers adopt additive manufacturing technologies: The role of sustainability”	Multi-stage survey	The primary driving force behind the adoption of additive manufacturing across various sectors is its capability to produce nearly any complex design.	The study focused on a few industries, excluding non-adopters, and did not take into account detailed case studies in different industries while employing various 3D printing technologies to investigate unknown variables. The study also used a survey to assess, but surveys may not provide a deep understanding.
2	(Marak et al., 2019)	“Adoption of 3D printing technology: an Innovation Diffusion Theory perspective”	Survey method	A higher likelihood of adoption is linked to factors such as relative advantage, ease of use, and trialability.	Other relevant factors, such as those related to technology, organizational structure, the environment, and other external variables, that might

				Additionally, the research highlights several challenges related to adoption.	have an impact on the adoption of additive manufacturing were not included in the study.
4	(Mojtaba Khorram; Niaki Fabio Nonino, 2017)	“Impact of additive manufacturing on business competitiveness: a multiple case study”	Exploratory study with 16 firms	The implementation AM has led to increased productivity in the production of metal AM products.	Companies that have not adopted AM are not taken into consideration
5	(Oettmeier & Hofmann, 2017)	“Additive manufacturing technology adoption: an empirical analysis of general and supply chain-related determinants”	Questionnaire survey	Supply chain-related factors exert a significant influence on the adoption of Additive Manufacturing (AM).	Researchers should study the factors that influence companies to adopt additive manufacturing (AM)

6	(Oettmeier & Hofmann, 2016)	"Impact of additive manufacturing technology adoption on supply chain management processes and components"	Case Study	AM has an impact on internal processes, management activities, and supply chain operations	There are two cases to consider, one of which involves a medium-sized entity. Further investigation is required in the areas of engineer-to-order environments, the procurement of pre-made AM parts, the interaction between the purchasing firm and the contract manufacturer, as well as various industry scenarios.