ANALYSIS INTO ARTIFICIAL INTELLIGENCE AND ITS DEVELOPING

DYNAMIC AND RELATIONSHIP IN AGRICULTURAL

SUPPLY CHAINS

A Thesis

presented to

the Faculty of California Polytechnic State University,

San Luis Obispo

In Partial Fulfillment

of the Requirements for the Degree

Master of Science in Packaging Value Chain

by

Samantha Ault

August 2021

COMMITTEE MEMBERSHIP

TITLE: Analysis Into Artificial Intelligence and Its
           Developing Dynamic and Relationship in
           Agricultural Supply Chains

AUTHOR: Samantha Ault

DATE SUBMITTED: August 2021

COMMITTEE CHAIR: Ahmed Deif, Ph.D.

           Associate Professor of Industrial Technology

           at California Polytechnic State University

ABSTRACT

Analysis Into Artificial Intelligence and Its Developing Dynamic and Relationship in
Agricultural Supply Chains

Samantha Ault

The thesis explores artificial intelligence (AI) in agricultural (Ag) supply chains
(SCs) and presents a new typology to understand artificial intelligence-based solutions in
agricultural SCs. The thesis was performed utilizing a research-based review to investigate
the current uses of artificial intelligence-based solutions in agricultural SCs. The AI-based
solutions were found in case studies that reviewed AI operations in different areas
internationally.

The typology was formed on the foundation of two dynamics, the location of AI
applications in Ag SCs and the driving values to integrate the AI applications. In order to
develop the typology, the AI applications were studied in a series of different analyses. The
analyses helped to critique and scrutinize the AI applications to gain new perspectives. The
series of analyses consists of exploring the AI applications' location within the supply
chain, the value additions to the supply chain from integrating the AI applications, and the
resulting depth of the effect of AI application has on the supply chain. Each additional
evaluation of the AI applications examining another parameter further exposed more
insight and started to build a structured ideology of AI.

The proposed typology aims to create a tool of measurement to infer AI
technology's relation in the SCs and create a new viewpoint that will lead investigation
and provide insight for predictions of AI's future in agricultural SCs. In addition, the new
typology should aid agriculture firms in understanding and capturing the potential
synergies stemming from the driving values of innovation.

The study found that AI applications with a strong relationship in the supply chain
provide the greatest beneficiary relationship between technology value creation and supply
chain logistics. Furthermore, AI applications will have the strongest relationship and
implementation when operating in collaboration with other supply chain locations and AI
integrated firms. Concluding the thesis, relevant policy and business practice
recommendations are proposed.

ACKNOWLEDGMENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

1.0 Introduction and Background into Agricultural Supply Chains:

The agricultural industry is a crucial division in sustaining everyday human activities. Agriculture (Ag) is defined as "the art and science of cultivating the soil, growing crops and raising livestock" (National Geographic Society, 2012). The development of Ag spans over thousands of years, with its beginning origins starting with humans planting grains and legumes. Throughout history, agricultural practices have changed due to various factors, including human cultures, accessible resources, climate variations, and evolving technologies. Ag methods have additionally evolved and expanded to keep up with the increasing world population and threats that have come forward. As the human race has progressed, Ag has transformed into a well-established industry.

The Ag industry has more than tripled in production between 1960 and 2015 due to advancing technologies and vast enlargement of the use of available natural resources. That time period also witnessed massive advancements from the industrialization and globalization of food and agriculture. The globalization of the food and agriculture industry significantly increased the physical length of SCs. Now agriculture SCs must travel further lengths from farm to table to meet demand and reach consumers globally. Consequently, the requirements necessary to keep products protected during distribution have also increased (FAO).

Even though the agricultural industry has significantly advanced, food scarcity is still a growing industry concern. As the world continues to grow, the possibility of overpopulation is looming around the corner. Overpopulation can lead to food scarcity and depleted resources, posing an enormous threat and challenge to the agricultural SCs. It is

estimated that the current food production systems and technologies will find it challenging to sustain the food demands for the next billion people (Elferink and Schierhorn, 2016). The need to adapt and grow the agricultural industry has become imperative. The Food and Agriculture Organization of the United Nations shared that the world's population is expected to grow to almost ten billion by 2050. The rise in population will significantly contribute to other external factors that influence food scarcity (FAO).

Ag SCs are composed of cross-functional networks with various operating functions interacting. The SCs are dependent on continuous material and information flows within its system to facilitate the production and supply of products from the farming level to the consumers. The typical Ag SC involves three steps: farmers to intermediate silos, intermediate silos to transformation plants, and transformation plants to consumers (Denis et al., 2020). At each stage, multiple decisions are required to be made and for a supply chain to operate successfully requires multiple functions engaging and interacting together. Additionally, decisions made in one sector of the supply chain can affect the entire supply chain and weigh heavily on the flow of the supply chain. Crucial practices such as forecasting, purchase scheduling, production, and processing programming significantly impact supply chain operations. The retailers' segment of the supply chain activities, such as sales promotion, new market, and product launches, etc., has a substantial influence on various operations in the earlier stages of the supply chain. Operating with multiple interacting functions creates opportunities for conflicts to arise due to varying objectives and numerous needs between material and information flows. As a result, the SCs mandate extensive pre-planning and coordination to ensure all processes work in cohesion.

Additionally, Ag SCs are complex productions due to the high uncertainty associated with farming operations. Some common problems in agricultural SCs are caused by difficulties associated with unpredictable yields, such as environmental conditions, farmer capabilities, and pricing volatility (Denis et al., 2020).

Another component that adds to the complexity of Ag SCs is that these SC are responsible for supplying safe food for consumers on a global scale. Products produced from the supply chain given to consumers are made to meet the consumers' requirements, including safety, quality, quantity, and price. Furthermore, the SCs manage the transport of perishable products that require timely production and delivery guarantees. Because the Ag industry provides products that consumers consume, there are numerous hazards that supply chain members are accountable to mitigate and prevent. Some hazards the industry face include disease, excessive exposure to pesticides and fertilizers, allergens, and toxic other chemicals, as these hazards can cause harm if consumed. On top of the industry-related dangers, there are external threats that the industry must prepare to combat. Moreover, solutions need to be identified to understand the different layers and intricate features of agriculture.

Today agricultural SCs face looming challenges of food scarcity, depletion of recourses, and climate change. Current agricultural SCs encounter increasingly demanding environments, but artificial intelligence technology offers potential tools that most of the industry has not yet witnessed. Artificial intelligence technology provides opportunities for agriculture businesses to enhance their SCs and meet market demands. The agriculture industry is on the cusp of harnessing the power to tackle and outmaneuver imposing threats.

Artificial intelligence had a slow introduction to the agricultural industry, but it has demonstrated momentous progression over the last twenty years. Integration of AI can help improve agricultural productivity and work as an indirect mechanism to empower farmers to make informed decisions (Lakshmi, V. 2020). While AI applications are not a new notion, it is still an emerging solution and foreign to many working in agriculture.

The unfamiliarity of AI can be connected to the lack of study of Artificial Intelligence related to agricultural SCs. Artificial intelligence alone has received extensive attention from researchers, but AI and its impacts on agricultural SCs have not received the same attention. The study of the adoption and diffusion of AI technology is just in the beginning stages (Lakshmi, 2020). The agriculture industry is unalike other traditional industries and, so the Ag industry faces different challenges and limitations with using and adopting AI applications. The full capabilities of AI in Ag SC have yet to be discovered. A greater understanding of AI applications and Ag interactions will result in the supply chain acquiring more value from AI technology.

1.1 Problem Statement:

This thesis conducted a research-based literature review investigating the current uses of artificial intelligence-based solutions in agricultural SCs. While examining the current industry state, the research review looked for areas that have yet to be explored. The focus of the study was directed towards reviewing the AI's location in the supply chain and the value received from the integration of the AI applications. To further understand the relationship between AI technology and agriculture SCs, the research attempted to find a connection between the location of the supply chain the impact of the AI technology.

The thesis set out to answer the following three questions:

1. Is there a relationship between agricultural supply chain location and the success of artificial intelligence applications implementation?

2. How can we understand driving values within the agricultural supply chain as it relates to artificial intelligence implementation?

3. How can a relationship between agricultural supply chain location and success of artificial intelligence applications and driving values of the supply chain to integrate artificial intelligence in agricultural SCs be illustrated to see AI dynamics and the evolution of AI in agricultural SCs?

1.2 Methodology:

This thesis employed a literature review, explicitly focusing on analyzing published papers with an unbiased examination of artificial intelligence in Agriculture SCs. The objective of the research review changed throughout the study's duration. The research review's beginning stages widely look at artificial intelligence (AI) and its current stages. The early stages of research focused on examining AI to help to understand better the technology's capabilities and its current uses in other industries. After gaining a comprehensive understanding of AI, the motivation shifted to studying AI in Agriculture SCs.

Three primary databases were used to obtain research papers on the subject, including ResearchGate, Google Scholar, and ScienceDirect. With the databases, the beginning research stage search centered on finding articles containing the keywords "Artificial Intelligence (AI) in Agricultural Supply Chains." Publications found in the

beginning explorations introduced broad ideas of AI and its capabilities related to Agriculture (Ag).

Early in the research review, finding case studies of current AI applications in AG SCs proved challenging. The challenge of finding case studies of current AI applications in Ag SCs uncovered a theme that many journal authors articulate in their findings: AI in AG is in the early stages of research.

While reviewing publications and making ongoing records of AI applications, it became evident that there are gaps in available research. Researchers have yet to construct a connection to where AI applications are being integrated into Agriculture SCs and why the AI applications are being integrated.

After establishing this gap in the current research, the literature review redirected attention to collecting secondary data from papers that reviewed existing AI applications operating in various locations in Ag SCs. The review's objection was now finding AI applications and open discovery to new insights surrounding the applications' value creation for Ag SCs and stakeholders. However, it proved challenging to continue collecting data directed towards AI in the Ag SCs. Therefore, after the research search using the key terms "Artificial Intelligence (AI) in Agricultural Supply Chains" was exhausted, the thesis proceeded using different search terms to widen the exploration and collect more data to find AI applications in the agriculture industry. Various key terms in the literature search included:

> *"AI Ag consumer trends," "AI applications agricultural," "AI technology food*
>
> *retail," "AI future agriculture industry," "AI opportunities agriculture industry,"*
>
> *"AI down-stream Ag," "AI Ag management," "AI robots Ag," "Ag supply chain*

value creation," "innovation Ag supply chains," "digital twins Ag management,"

"computer vision Ag management"

Throughout the entirety of the literature review, eighty-three papers were examined. The eighty-three papers were scrutinized to determine if viable to use for data collection of AI applications in Ag SCs. A criterion was devised to conclude if a research journal provided essential information needed for the data collection. The following questions guide the criterion for examining the research journals:

- Does the paper discuss at least one current AI application in an agricultural supply chain?

- Does the paper disclose where the AI application is in the agricultural supply chain?

- Does the paper discuss the functions of the AI application?

- Does the literature provide sufficient details to contextualize value creation from the AI application to the supply chain?

- Does the paper present data that is recent enough to be applicable to the current study and state of the Agriculture Industry?

Based on the criterion questions from the original eight-three reviewed research papers, twenty-five research papers were determined to contain the necessary information. The publication dates of the research journals range from 2015 to 2021. Journals published before 2015 were determined not to be a relevant reflection of the state AI and the Agriculture Industry.

Continuing to gather more AI applications, it was discovered that previous researchers did not concentrate their studies on analyzing AI's connection and support to Ag SCs. Moreover, as the research stages progressed, a new gap was discovered: existing research

primarily concentrates on AI in the early stages of Ag SCs. The early stages mainly highlighted AI technology and its role in aiding farming activities.

When adjusting the search to examine other supply chain locations, the number of available publications that explore AI applications significantly decreased. Specifically, the most prominent area lacking exploration is the down-stream location of the supply chain.

The data was evaluated and critiqued using different quantitative analysis techniques following the secondary data collection phase and literature review. With the information captured from the data, a new framework was created in the form of a typology to present a comprehensive understanding of the depth of AI technology in Ag SCs from comparing where AI application is operating and what is driving AI innovation into the SCs. The typology works to give a new lens and parameter to use while studying AI integration in Ag SCs.

1.3 Overview of Thesis:

The thesis provides an introduction and foundation into AI and its current state in Ag SC. The introduction includes a discussion on limitations, challenges, and opportunities for AI in the Ag SC. Next, the thesis presents a literature review that captures various AI applications in current Ag SCs, examining the applications based on their location in the SC and the value the AI applications added to the SC. The thesis next presents a typology evolved from the literature review to aid in understanding AI technology's progressing dynamic and relationship to Ag SCs. The AI applications from the literature review are then examined through the lens of the typology, followed by a summary of the thesis

discussing the work and discoveries made throughout the research journey. Lastly, the thesis closes with final conclusions and recommendations.

Chapter 2:

2.0 Artificial Intelligence Overview:

Artificial Intelligence (AI) is a subdivision of computer science concentrating on manufacturing smart machines that can think at the same intelligence level as humans or better. It is typically defined "as the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem-solving" (McKinsey Analytics). AI aims to create applications that can perform operations that otherwise require human intelligence (Artificial Intelligence (AI) - Overview, Types, Machine Learning). Uses and applications of AI components are commonly seen in everyday modern life and are often used to solve many problems that arise for everyday businesses. Standard AI applications used to help solve business problems include robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning (McKinsey Analytics).
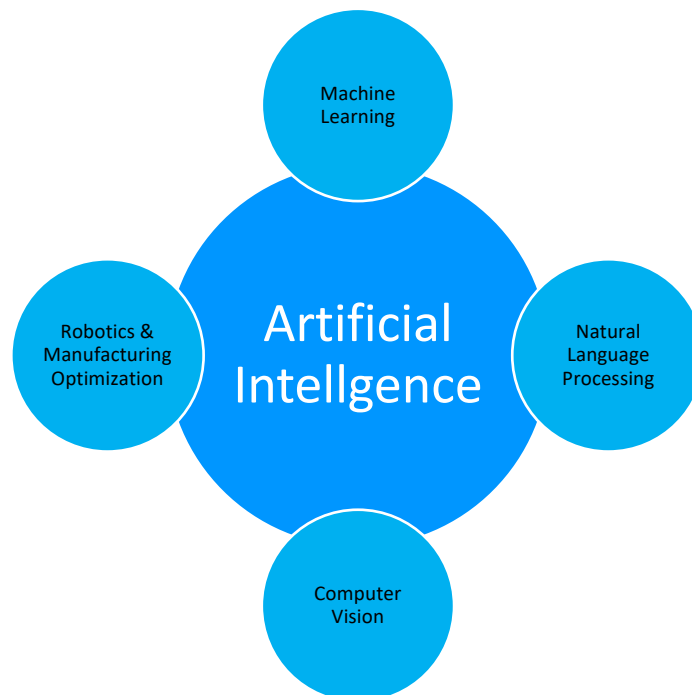
Figure 1: Artificial Intelligence Divisions

Artificial intelligence (AI) can be broken down into four main components: 1) Machine Learning, 2) Natural Language Processing, 3) Computer Vision, and 4) Robotics & manufacturing optimization, etc. (Goutham, R. 2020). Figure 1 above shows the four different components that make up artificial intelligence.

The most intricate of the four components is Machine learning. While the most intricate, it is a significant factor in Artificial intelligence's growing popularity in the 21st century and has led to the most recent new Artificial Intelligence advances. Machine learning develops systems that improve upon themselves, which is accomplished through the identification of algorithms. Machine learning is a scientific study of algorithms and statistical models that computer systems use to perform a specific task without explicit instructions, relying on patterns and inference derived from data instead. The machine learning programs apply different algorithms to very large data sets. With the data, the programs can find patterns and make predictions and recommendations from those patterns. As the application learns and expands its erudition as it receives new data, the algorithms adapt and improve its forecasts and recommendations. Thus, machine learning provides predictive allowing users to see and anticipate what will happen, and prescriptive analytics, enabling the program to provide recommendations on achieving the user's goals.

One company that has found considerable success implementing machine learning is Delta Airlines. The airline company recently shared that using machine learning can leverage their flight pricing and strengthen the customer experience. The machine learning application analyzes Big Data to create hypothetical outcomes and probabilities, allowing Delta Airlines to optimize its flight scheduling with data-driven decisions (Delta News Hub, 2020).

There are three major types of machine learning supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses a provided algorithm with training data and human feedback to learn the relationship of given inputs to a given output. Unsupervised learning operates by giving allowing an algorithm to explore input data without being given an explicit output variable. Reinforcement learning works by allowing an algorithm to learn how to perform a task. The machine receives a reward if the action brings the device closer to maximizing the highest rewards available. The machine with reinforcement learning often works well when the goal is to increase optimization (McKinsey Analytics).

Lastly, there is another commonly discussed application associated with Machine Learning, deep learning. Deep learning is a subtype of machine learning. It differs from machine learning as deep learning can process a broader range of data resources, requires less data preprocessing from humans, and can sometimes produce more accurate results (*AI technical - Machine Learning vs. Deep Learning*, 2019). Deep learning is the closest algorithm that can mimic how the human brain thinks. It uses software-based calculators known as "neurons" to form a neural network. Each artificial neuron is a mathematical function that takes a weighted combination of inputs and produces an output. Deep learning is similar to the way humans think because it uses multiple artificial neurons, similar to how humans use various experiences, knowledge, past and present facts to produce an output.

Figure 2 below shares a graphic illustrating the differences and relations between artificial intelligence, machine learning, and deep learning.
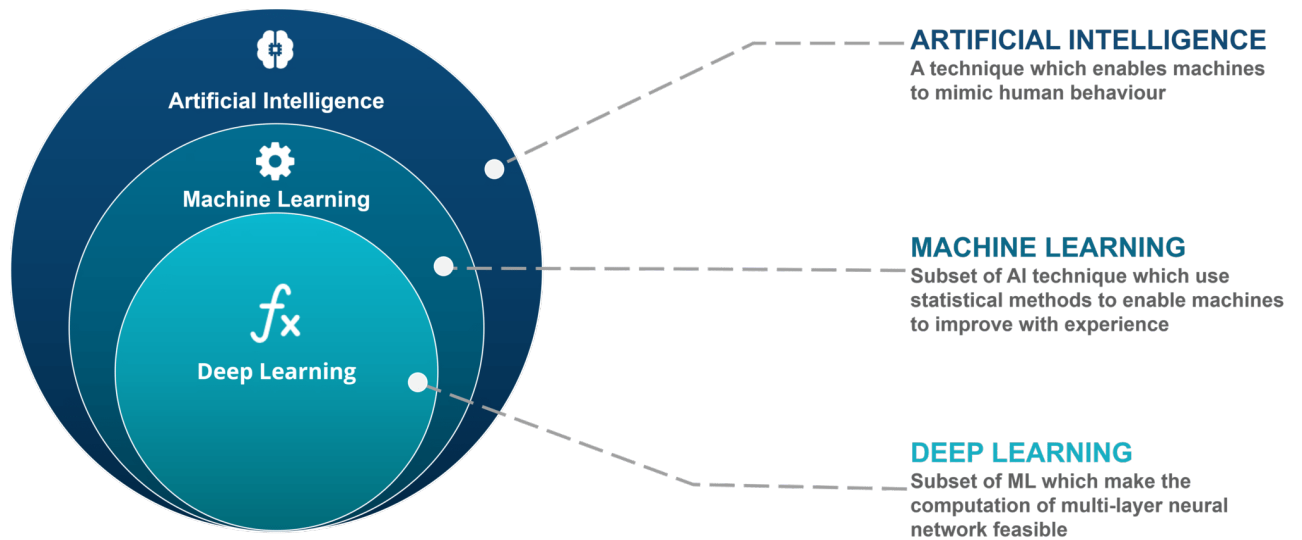
Figure 2:AI vs Machine Learning vs Deeping Learning (Atul, 2020)

2.1 Artificial Intelligence in Agricultural Supply Chains:

The agricultural supply chain relies upon a foundation of farmers. The farmers have established the industry's farming practices, and some practices date back to times before the industrial revolutions. Agriculture has created a way of survival for humanity. It was invented between 7,000 to 10,000 years ago during the New Stone Age by humans (Marcin). In early times the were no opportunities for farmers to advance their practices. The farm management relied upon unindustrialized mechanics and generations of passed-down agriculture knowledge. Now in modern times, farming has seen new possibilities for advancement through new technologies.

According to a research study AI in the Agriculture Market is estimated at USD 750 million in 2019 and is predicted to reach USD 2,400 million by 2026 (*Global AI in Agriculture Market Size & Share Estimated to Reach USD 2,400 million by 2026: Facts & Factors 2021*). The increase in market use is agreeable to a prediction given by researcher Dr. Asaf Tzachor of the University of Cambridge, who shared that AI applications are

anticipated to generously benefit the global agricultural system's resilience (Tzachor, 2020).

AI technology in the agriculture industry offers new contributions to support different agriculture operations and supply chain stages. Through correct integration and proper practices, artificial intelligence will assist in increasing the sustainability and efficiency of the agricultural industry. Furthermore, as Ag SCs increase in their use of AI applications, they will begin to observe that issues associated with social and environmental challenges are mitigating.

With AI, the concept of precision farming has become possible. Precision farming is defined as the practice of using "a series of strategies and tools that allow farmers to optimize and increase soil quality and productivity putting in place a series of targeted key interventions" (*Precision farming: what is it and what benefits does it offer?* 2021). Precision farming poses a solution for farm management that will optimize farming efforts and resources, reduce consumption and waste, and boost land productivity. AI technology has made it possible for producers to practice precision farming as AI applications can provide more significant insights into weather, soil, and water conditions than previous methods. The AI applications are trained to analyze the data looking for patterns, problems, and predictions. Information gathered from AI applications delivers data in real-time. Utilizing AI has enabled farmers to see previously unobtainable data and ultimately has empowered farmers to implement better management decisions.

Precision farming poses a solution for farm management that will optimize farming efforts and resources, reduce consumption and waste, and boost land productivity. Without AI and precision farming practices, farmers have no choice but to speculate the dosages of

inputs the crops need. When farmers over-apply necessary inputs, it poorly impacts the environment. Excessive use of fertilizers and herbicides contributes to soil degradation, loss of soil nutrients, and nitrogen leaching, among other harmful activities. Overusing water can increase weed pressure and affect neighboring communities as it strips away the natural resource. AI technology helps deliver insights that enhance farm productivity and help farmers have a heightened understanding of how to manage their farmlands. The increased comprehension will result in practices that optimize resources and increase the efficiency of operations, which will prove to be more profitable for the farmers and other stakeholders involved in the processes (Lakshmi, 2020; *Precision farming: what is it and what benefits does it offer?* 2021).

Apart from the operational benefits of AI, AI can help mitigate risks associated with agricultural SCs. Risks that occur in agricultural SCs contain a wide degree of uncertainty. Stakeholders can use AI applications to detect problems in SCs before any human would have been able to discern the same dilemmas. For example, machine learning applications have been applied to detect nutritional and soil defects, plant pests, and other diseases by using data of foliage patterns (Lakshmi, 2020).

Examining agriculture SCs in various global regions reveals significant regional differences that impact the integration of AI technology. Developing countries remain significantly more vulnerable to risks as opposed to developed countries due to an overall lack of resources. With increased vulnerability risk, it is concluded that developing countries need AI integration the most. Agriculture businesses in developing countries greatly struggle to compete with other advanced countries. Consequently, these producers are in jeopardy of buyers outsourcing to other areas. However, as AI applications usage

continues to advance in approval and become standard practice, developing countries will have the power to compete with developed countries.

Although developing countries need AI technology innovation the most, integrating AI applications is estimated to be the most restricted in those regions. This theory is corroborated in a study from Dr. Asaf Tzachor that states SCs in developed countries are significantly more receptive to AI technologies. In addition, developed countries are further suitable for AI due to several factors, including possession of necessary infrastructure, financial resources, and skilled workers (Tzachor, 2020).

Artificial intelligence in agricultural SCs will help to increase supply chain visibility, transparency, and product traceability. Increasing overall transparency of SCs will also improve the product's safety being moved throughout the SCs and safeguard the product's authenticity. However, achieving these various benefits will require immense understanding from all different supply chain entities and utilizing outsource help. Therefore, on account of agricultural SCs in the early stages of AI technology integration and adoption, benefits achieved from AI applications in later years will be more substantial than benefits the supply chain is receiving now. As AI continues to grow in popularity and use in agricultural SCs, so will future advancements.

2.2 Artificial Intelligence Challenges:

The integration of AI technology and applications has encountered various barriers to entry into the agriculture industry. The process of AI implementation is different for each application, sector of the supply chain, geographical location, etc. As a result, AI applications have varying levels of difficulty associated with entry into the supply chain.

The differing ease of entry can be related to multiple components and obstacles originating from problems not associated with the AI technology itself. Often, challenges stem from data supply, data use, and a lack of enabling infrastructure (Cook, 2020). In addition, there is no one-size-fits-all model for farming operations, and agricultural methods vary from region to region, as terrain differs in terms of elevation, slope, and orientation.

A large majority of the world's farming takes place in rural and developing farmland. Unfortunately, farmers in those areas face considerably more obstacles when integrating AI applications in the supply chain. In rural and developing farmlands, economic differences often prevent farms from growing and advancing their technology as the initial costs prevent them from access. Other barrier entry factors include lower education, lack of training, hard to manage terrain, minimal to no access to the internet, language differences, and distrust of new methods.

From reviewed case studies, the two of the most discussed barriers of entry are economic disadvantages and rough terrain. These external factors create the most demanding challenges to breakthrough to entry. These challenges are especially troubling for small and medium-sized farms, as they lack resources that large farms can access.

Smaller farms are economically disadvantaged and often lack the monetary funds needed to access AI technology. As typically, AI technology machinery is expensive to purchase and maintain (Anitei, 2021). Figure 3 below, titled *AI Barriers*, highlights the different areas that create barriers to entry for AI in AGSCs.

Economic
- Cost
- Support Infrastructure

Technical
- Data
- Model creation
- Internet reach
- Problem Selection

Social
- Lack of knowledge
- Safety
- Trust
- Stakeholders' Perspectives
- Safety
- Trust
- Jobs
- Language barriers

Environmental
- Terrian
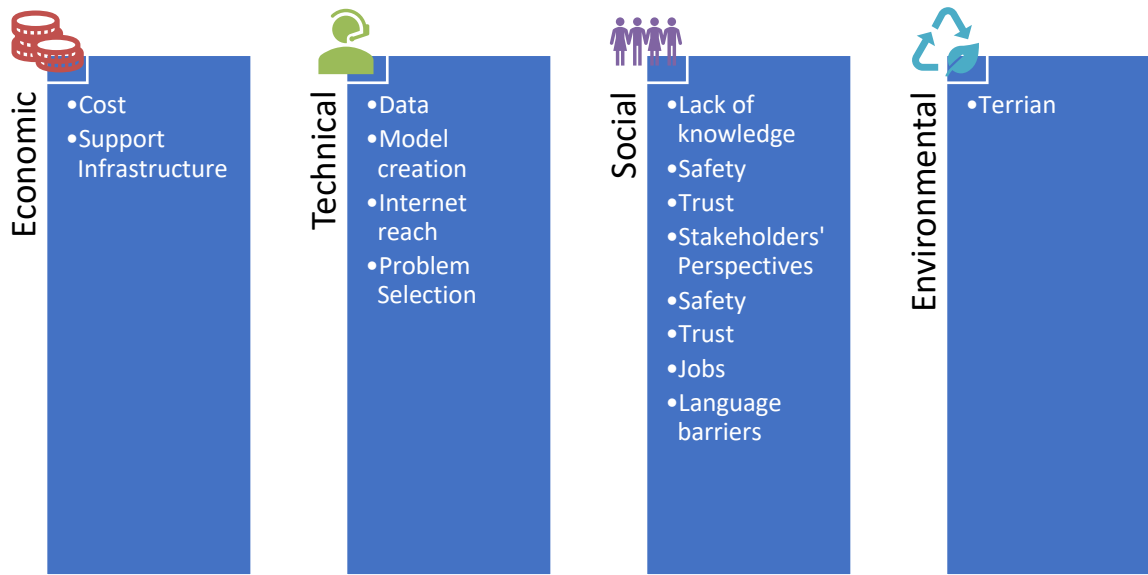
Figure 3: AI Barriers

The magnitude of the barriers is an essential component to be conscious of when looking at how AI integration adapts to Ag SCs. Furthermore, looking into the depth of the problem imposed by the barriers can help us understand the current market state of AI in the Ag SCs.

Apart from the initial barrier of entry, numerous challenges for AI applications remain in Ag SCs. Some of those challenges include the need to create new regulatory rules and sharing of previously private data. Those challenges stem from "limited regulatory frameworks, both in relation to autonomous vehicles as well as the ownership, security and third-party use of agricultural data and control of the product life cycle of agriculture equipment" (Klerkx, 2019). As AI is relatively new to the agriculture industry, creating and enforcing new policies is now necessary. There are currently limited reports of policy and law-making processes related to data ownership regulations (Klerkx, 2019). In addition, many of the AI technologies using machine learning and deep learning will

require extensive data sharing across stakeholders. The level of data sharing that the AI applications demand is at a magnitude that the agriculture industry has not previously attempted. In order to guarantee adequate security measures, current data-sharing policies will need to be reviewed.

Some industry members have expressed hesitation towards digitally advancing the agriculture industry and SCs. The skepticism comes from the idea that AI applications will remove and replace the necessity of human workers. As a result, industry members fear AI will negatively impact agriculture jobs and leave workers without employment. There is some evidence that supports this fear. For instance, some agriculture companies have integrated AI robotics to complete and assume responsibility for tasks previously performed by farmworkers.

Industry members on the opposition of this argument express that AI technology is vital due to the agriculture industry experiencing labor shortages and increased demand for agricultural goods. There is a risk that AI could diminish the market for some current jobs, but the necessity for human labor will not entirely dimmish. On the contrary, artificial intelligence brings an opportunity to create new roles for labor workers. Furthermore, AI applications will require skilled operators to run and oversee the AI machinery.

2.3 Artificial Intelligence Opportunities:

Artificial intelligence has the power to decipher and interpret data that is beyond the comprehensible understanding of any human being. As a result, AI technology has contributed new skillsets that far surpass human capabilities. AI is in the early stages of work in the agriculture industry, and the beginning adaptation processes have been slow to start. Nevertheless, agriculture sectors that have risen to integrate AI applications have

already started witnessing improvements in various operations. With the help of AI and its applications, the agriculture industry has the opportunity to advance and reach new lengths.

Currently, AI technology's most significant motivations and driving demands for implementation in Ag SCs is to avoid current and future risks. Nevertheless, as the use of AI technology grows, so will the agricultural industry's resilience. AI technology applications will empower agricultural SCs to be adaptable to rapid change.

Agriculture is greatly impacted by global warming, and the effects of climate change can lead to the depletion of once violable farmlands. As much as agriculture is affected by climate change, it is also a significant contributor to the problem. Current farming operations in the industry have negative repercussions on the environment. One extensive agricultural activity that poorly harms the environment is clearing land for farming. Clearing land directly results in widespread deforestation and contributes to 40% of global methane production (Young, 2020). AI applications possess the capabilities to help lessen the agricultural industry's contribution to environmental harm.

It is predicted that with the implementation of AI, the industry can reach a point where farming can be performed in urban areas. Farming in urban areas would lead to decreased land clearing and deforestation from the AG industry. In addition, farming capability in urban areas would also positively improve farming activities in rural areas that typically are known for having difficulty managing terrain by creating different opportunities to farm elsewhere and increase food production.

In order to further achieve new heights through AI innovation in agricultural SCs, the industry will also have to adjust to meet the requisites for integration and advancement. The initial cost to integrate and operate AI applications can be prohibitive, and many

companies lack the necessary financial infrastructure to integrate AI. However, as AI continues to grow in AG SCs, there is potential for costs to decrease. The decreases in costs would be made possible through the standardization of practices. One significant cause for the high cost of implementing AI technology is that the industry has yet to establish standard procedural practices. As a result, companies are currently required to devise personal operational induction and training processes. In consequence of individual Ag SCs and AI applications' specifications varying, creating standard operating procedures poses a great difficulty for the industry.

Another possibility for the industry to witness a reduction in AI-integration costs would be if AI application manufacturing expenses decrease. Currently, more organizations are rising to the challenge of creating AI applications specifically for agricultural practices. Therefore, as more organizations produce AI technology, the costs of the applications will decrease as the market for manufacturing becomes more competitive.

Once AI has gained substantial advancement in Ag SCs, more and more areas of opportunity will arise for AI to improve the industry. However, these early stages of integration are just scratching the surface of value potential and creation for SCs. Currently, the agriculture supply chain's most significant motivation and driving demand for AI technology implementation is to avoid current and future risks. As the use of AI technology grows, so will the agricultural industry's resilience. AI technology applications will empower agricultural SCs to be adaptable to rapid changes.

Chapter 3

3.0 Literature Review:

This thesis reviewed eighty-three papers, and the research focused on collecting information on current AI applications operating in various agricultural SCs. From the original reviewed eighty-three papers, twenty-five papers were identified discussing current artificial intelligence in agricultural SCs. From the twenty-five research papers, eight-nine artificial intelligence applications were distinguished. The applications uncovered in the research review are in current use in various agricultural SCs. The SCs that were reviewed varied in locations globally. Please reference Appendix A, B, and C provided in the Appendices section of the thesis to find complete lists of AI applications cited in this thesis and a short description of their functions.

The literature review concentrated on studying and analyzing two primary perimeters of AI applications in Ag SCs. The first perimeter included a location perspective of where the AI application was operating in the supply chain. The second perimeter focused on researching the motivations influencing Ag businesses to integrate the AI applications into the supply chain.

3.1 Agriculture Supply Chain Location Review:

This thesis will be analyzing current use AI applications found from reviewed research papers along with different areas of the supply chain. The thesis will break the agricultural supply chain into three divisions: 1) Up-stream, 2) Mid-stream, and 3) Down-stream. The up-stream stage of the production process involves searching for and extracting raw materials, and its essential operational functions focus on planning, planting, farming, and harvesting materials. Mid-stream activities include processing of raw materials,

packaging, logistics/forecasting, and transport. The final stage of the supply chain is down-stream. At this stage, operations include distribution/trade, retail/e-commerce, food safety, and consumer consumption. Figure 4 below outlines some of the key processes in each division of a standard agricultural supply chain.
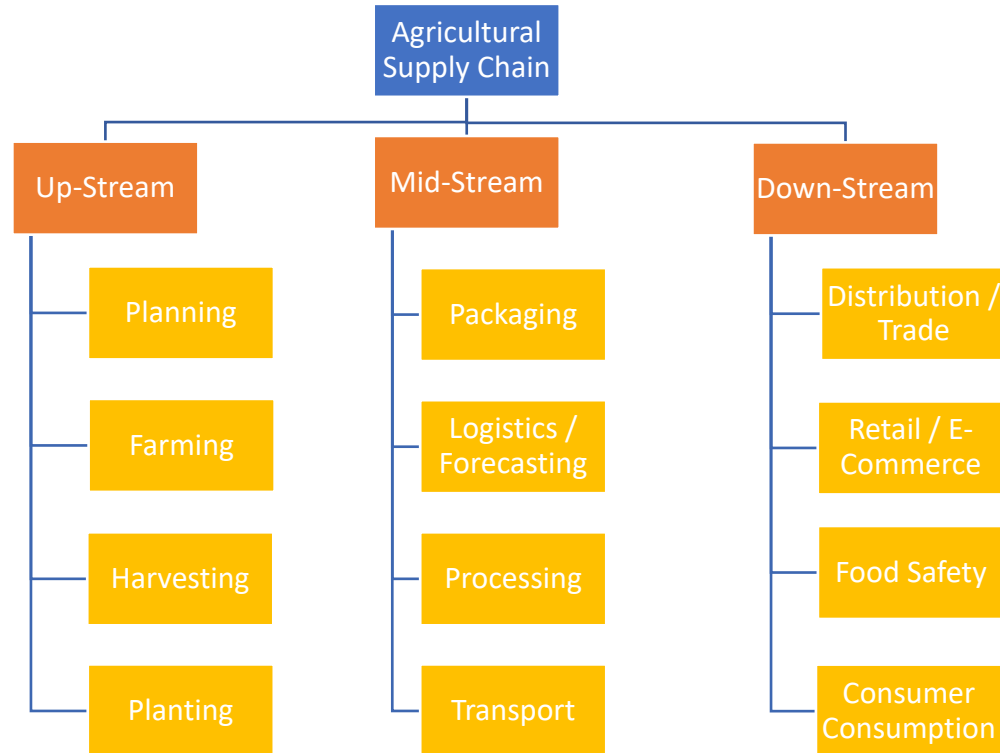
Figure 4: Agriculture Supply Chain Divisions

Additionally, it is essential to identify the stakeholders in a typical agricultural supply chain. Generally, a stakeholder is any person, group, or organization that is impacted in some way by the action or inaction of another (Fernando, 2021). The stakeholders in the SCs hold a crucial role in the strategic decision-making processes and ensuring that all required activities are met.

As previously stated, agricultural SCs pose a complex system compared to other typical SCs. The complexity comes from many different factors, including the perishability of the product, high demand fluctuations as different products are in higher demand at different seasons, and increasing consumer awareness towards producing safety quality and environmental concerns. When discussing artificial intelligence integration, awareness of the different stakeholders in the supply chain is vital. The stakeholders are the ones ensuring that the applications are used successfully and will be the ones interacting with the applications. Making sure that stakeholders understand how artificial intelligence works will be crucial as they are the ones who ensure that the supply chain runs smoothly. Figure 4 below highlights some of the typical stakeholders commonly seen in agricultural SCs.
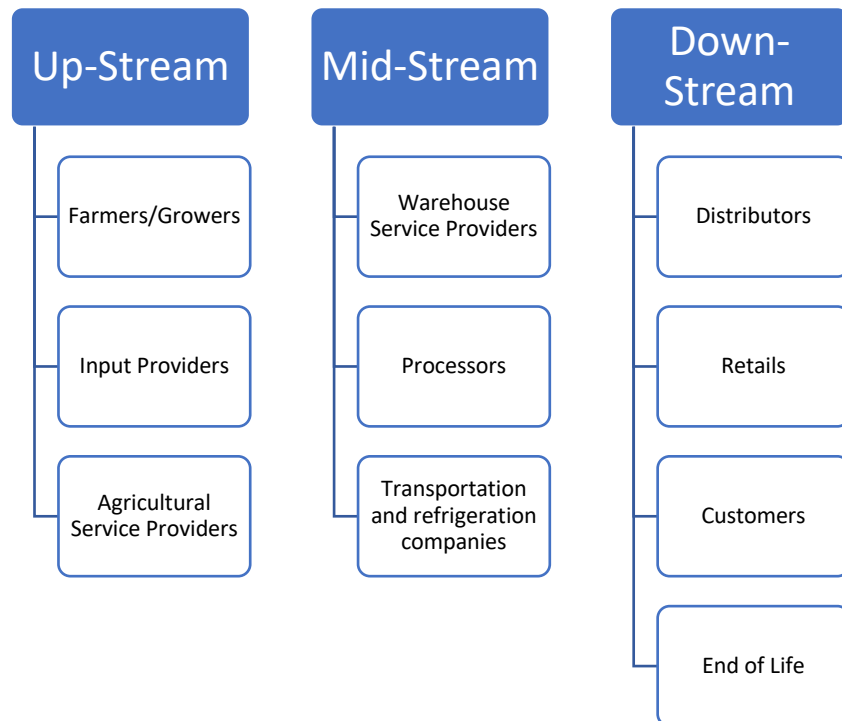
Figure 5: Stakeholders in Agriculture Supply Chains

After defining the three SC locations, the eighty-six AI applications identified in the research review were sorted into their respective locations. The location of the AI application was determined by the position at which the AI application operates in the SC. Sixty-nine applications were observed operating in the Up-Stream processes, twenty-four in the Mid-Stream, and fifteen in the Down-Stream. Twelve of the artificial intelligence applications were found conducting operations in multiple areas of the SC. These results actively prove that the artificial intelligence application has operating control in multiple sectors. Ten applications were found operating in all three locations up-stream, mid-stream, and down-stream, and two applications were found operating in both the mid-stream and down-stream. Figure 6 below depicts the locations at which the AI applications were supporting and performing operational functions. In figure 6, applications that were found in various locations were counted in each location that the technology was conducting operations.
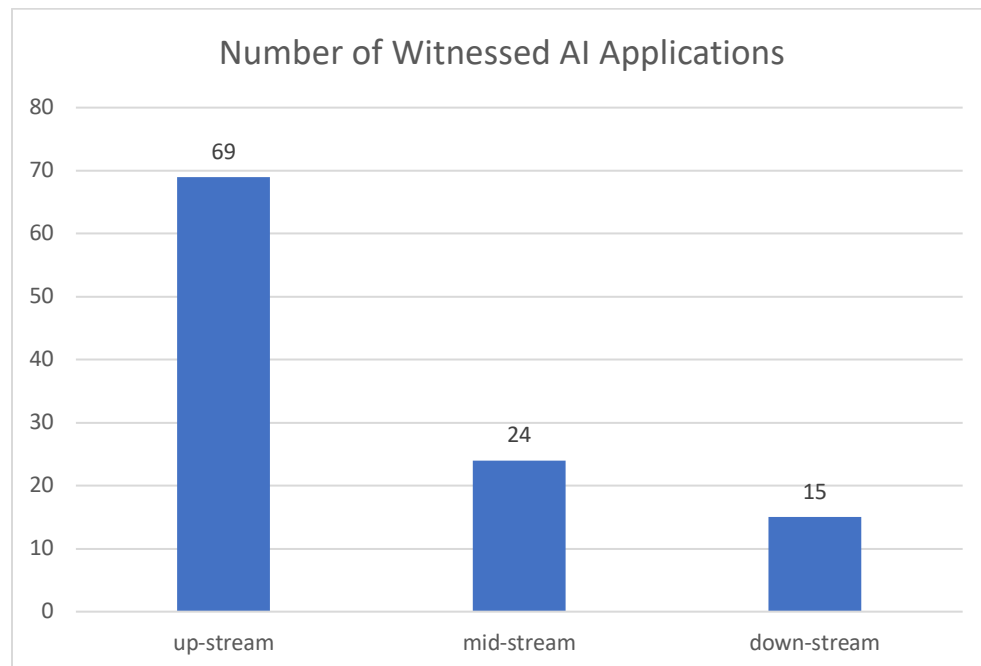
Figure 6: Locations that Witness AI Application Support

The literature review was performed to capture and collect information from numerous AI applications in all areas of the SC. The findings of AI applications predominantly came from applications operating in the up-stream location of agricultural SCs. The literature review found that the least explored area of AI application in agricultural SCs is the down-stream sector. The down-stream location of the SC includes distribution and trade, retail and E-Commerce, food safety, and consumer consumption. One reason that perhaps contributed to the down-stream sector being least explored is that researchers do not characterize this area specifically as an agricultural activity. The down-stream of the agriculture SC can overlap with other various industries. Another potential factor that could lead to the research gap is that generally when discussing agriculture, examination efforts are directed towards the up-stream sector and operations in that location. The up-stream sector primarily focuses on crop and livestock management, planting, harvest, and other various operations relating to farming and growing. Unlike the operations that occur in the down-stream, these up-stream operations are typically attributed to agriculture processes.

3.2 Values of Artificial Intelligence Applications:

Concluding the SC location analysis, the thesis proceeded to categorize the AI technology applications further. The next objective was to reveal and establish the fundamental drivers of innovation for the Ag SCs. From the literature analysis, it became apparent that the push to innovate agricultural SCs can be separated into two main categories.

The first innovation driving category is operation-oriented values. Operation-oriented values focus on improving operation activities in the SC to meet supply and demand, ensure optimal production capacity use, and foster employee growth. An example of innovation driven by operation-oriented values is autonomous robots that automatically sort, unload, and pack bins at warehouses. The robots help to improve operational activities and alleviate labor demand and costs.

The second category of innovation drivers is customer-oriented values. In this category, the drive to innovate SC technology is connected back to the customers. Customer values focus on product safety, SC transparency, consumer wants, and market prediction. These values improve consumers' overall experience with the final products and companies producing the products. An example of AI innovation driven by customer-oriented values is a machine learning program that analyses data and uses algorithms to predict consumer demand, perception, and buying behavior. The machine learning program helps stakeholders to prepare and adequately meet the wants of consumers.

With the two categories established, the AI applications were inspected to determine what driving innovation value stems from integrating the AI technology into agriculture SCs. Figure 7 below illustrates the findings from categorizing the AI applications by their primary innovation driving value. From the eighty-six reviewed applications, eighty-one observe operation-oriented values, and eight observe customer-oriented values. In addition, three applications were cited having both operation-oriented and customer-oriented innovation value drivers.
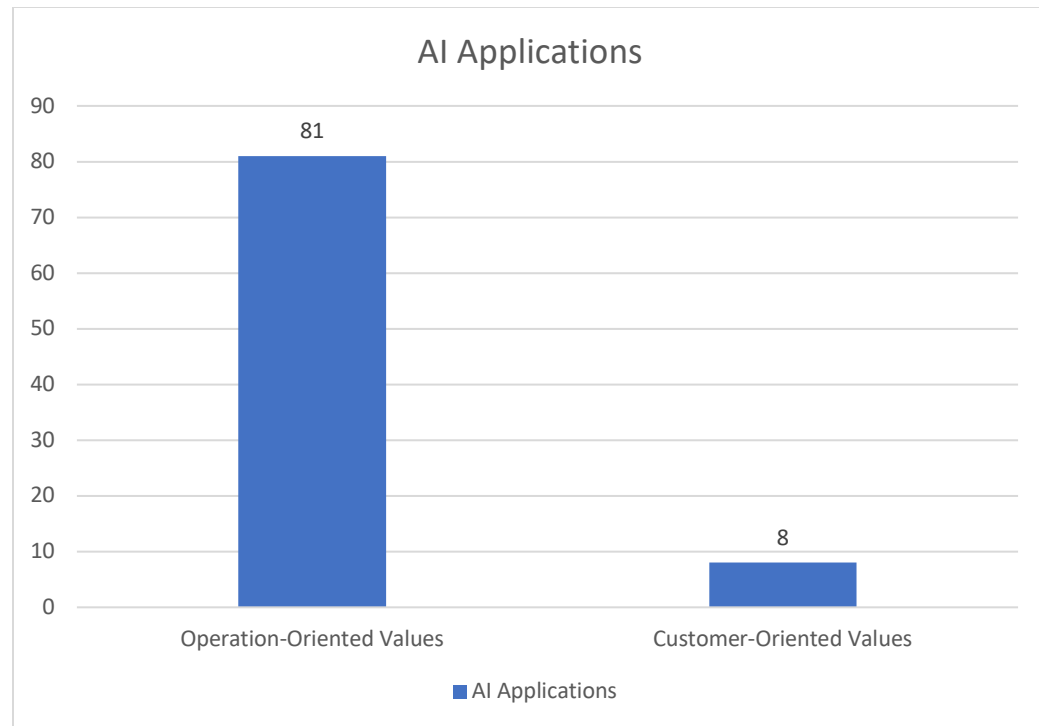
Figure 7: AI Applications from Literature Research's Driving Innovation Values

As illustrated in figure 7 above, most AI applications examined in the literature review are driven by operation-oriented values. Therefore, it can be theorized that the AI applications in the SCs predominantly focus on improving operations within the SC.

To further observe and extract information from the AI applications, the applications were then sorted into their respective locations in the SC. Which consequentially allowed insight to see the value drivers of innovation of each SC location. Determining the main innovation drivers of each location provides additional insight into the SC's desires and needs. Moreover, a comprehensive understanding of an individual location's desired innovation value category can be vital, as this knowledge can help spearhead further discoveries outside of this dimension.

Figure 8 below shares the data of the AI applications' driving innovation values by location. The chart's data is expressed in percentages to standardize the data, as there are

varying quantities of applications in each location. In the up-stream location, the primary innovation driving value comes from operation-oriented values. The up-stream found that 93.06% of its AI applications innovation driving value came from operation-oriented, and 6.94% of applications had customer-oriented values. In the mid-stream, it was noted that 81.48% of the innovation came from operation-oriented values, and 18.52% of applications had customer-oriented values. Finally, the downstream location observed the AI applications having a precise separation of 50% operation-oriented and 50% customer-oriented values.
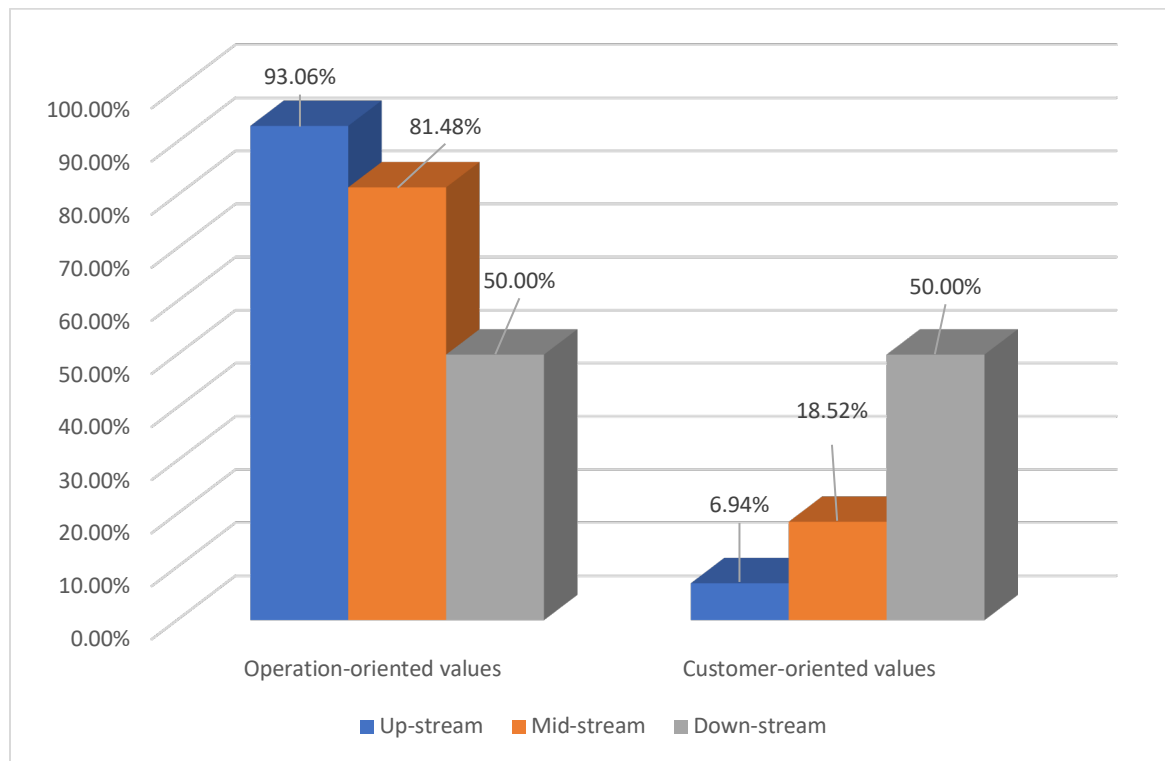
Figure 8: Innovation Drivers vs Location

This analysis revealed that the vast majority of upstream AI applications are introduced into the SC to help improve operational activities. In the midstream and upstream locations, the primary reason for integrating AI technology is to improve SC

operational activities. The downstream sector of the SC is the only sector that witnesses that AI technology is integrated to serve both operation and customer-oriented values.

Concluding the investigation of primary innovation drivers, each AI application was reviewed to define the specific values the AI advancements added to the SC. In order to uncover the value-added benefits received from each application, the AI applications were reviewed in their original literature context. Analyzing the applications in their literature context gave more extensive insight into how the AI application helps promote and serve the SC.

Upon first completing the research review of value-added attributes, twenty-seven attributes were found. The twenty-seven value-added attributes were then reviewed and contrasted. The reviewing process was set forth to find any values that were deemed duplicates and could be conjoined. During this time, it also served to solidify the found values further and discover any values from the AI applications that might have been overlooked. After completing this evaluation, the final count of individual values was determined to be nineteen. These value-added attributes directly result from the integration of an AI application into an agricultural SC. Definitions of value-added activities and attributes are provided in table 1 below. The values were defined formulated on how agricultural SCs profit from the value addition. Additionally, table 1 shares and expresses the value-added activities' associated innovation driving value category.

Table 1: Value Definitions

Operation-Oriented Values	Efficiency	Increases effective operations in supply chain and decreases time spent on operations.
	Costs	Lowered operational costs spent towards producing product, excluding labor costs
	Yield	Optimizing and improving yields for various product productions
	Labor Costs	AI performs roles the previously required labor workers and decreases the need for labor, resulting in fewer labor costs
	Crop Health	AI Applications improve crop conditions, mitigate disease, early detection of disease, and find solutions to better the crops.
	Prediction	AI provides predictive information regarding crops, livestock, transportation, and customer wants. To help reduce waste and improve the effectiveness of supply chain operations.
	Farming Practices	Improves current farming practices by reducing needed work and improving operations
	Livestock Health	AI provides more invasive methods to individually monitor livestock, track health, early disease detection, and giving real-time data
	Production Planning	Planning accuracy of supply chain activities is improved
	Transportation	Improves vehicle routing and transportation methods
	Accuracy	AI has been used to set different requirements for the food (Di Vaio et al., 2020), detect and inform users if a product container is inconsistent in a warehouse with radiography images (Hellingrath & Lechtenberg, 2019), and automatically sort and grade food (Farhadi et al., 2020).
	Reduce Waste	Reduce waste of unnecessary inputs and waste from unconsumed product
	Operations Maintenance	Notifies when machine parts are broken and need to be replaced
	Protection	Protects product from damage in the supply chain
Customer-Oriented Values	Quality Assurance	AI works to control and improve product quality and reach product requirements.
	Market Prediction	Focuses on improving predictions associated with consumer demand, perception, and buying behavior. Market prediction helps processors, retailers and wholesalers better forecast their consumption and what is likely to sell. Achieving precise demand prediction of food requirements helps to avoid overstocking, overproduction, and overutilization of resources (Sharma et al., 2020).
	Consumer Wants	AI helps to forecast consumer trends and behaviors to match demand and meet consumer wants
	Safety	Increasing traceability and monitoring of conditions of product throughout the whole life cycle
	Transparency	Consumers and stakeholders can see where the products come from and the path the products travel

After the final determination of the added values, a graph of the total values was created. The chart found in figure 8 below illustrates the different added values and their frequencies. The chart helps to reveal common occurrences and highlight the most

significant value-added activities into the SCs from the integration of AI applications. Figure 8 shares the data collected from all the AI applications from every location in the SC. Reviewing the AI applications in all areas of the SC, it can be inferred that efficiency, costs, yield, and labor costs are the most widely observed value-added contributions from AI innovation into agriculture SCs.
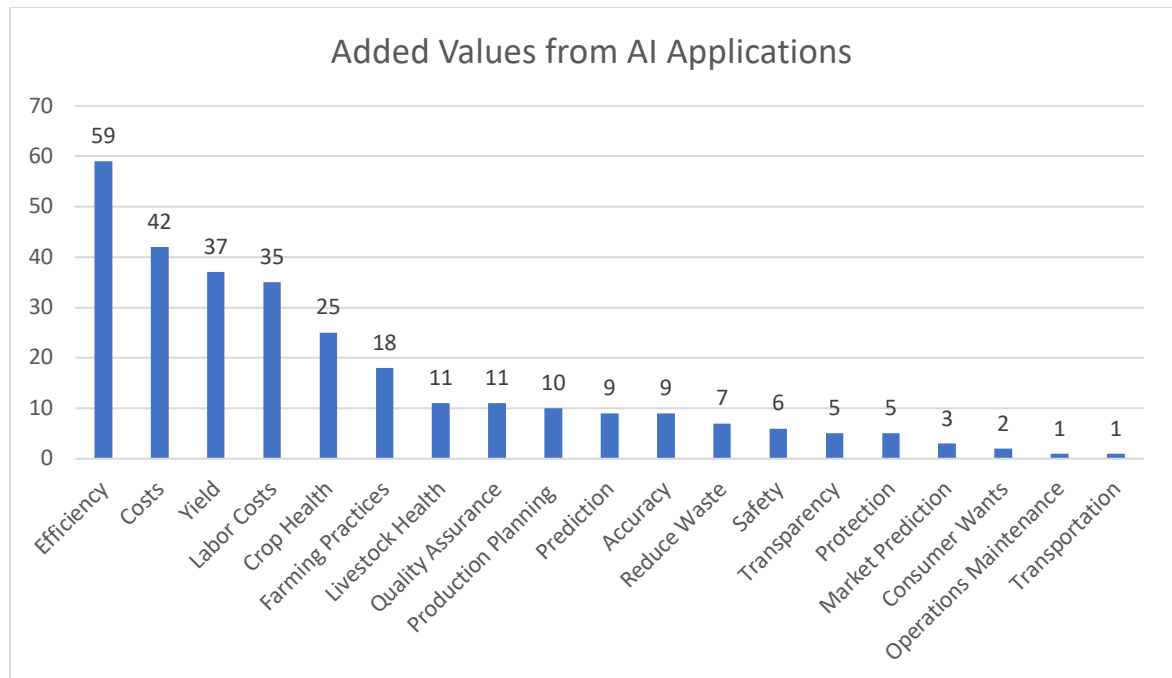
Figure 9: Values from AI Integration

The driving values frequencies were used to create the Pareto chart in figure 10 below with the records obtained from figure 9. The Pareto chart helped to determined what values hold the most considerable impact on the SC. From studying the Pareto chart in figure 10, it was discovered that 72.7% of that data stems from 31.6% of the individual values. At 31.6%, most data come from efficiency, costs, yield, labor costs, crop health, and farming practices. Consequently, it can be anticipated that stakeholders are integrating

AI applications into Ag SCs to improve and address problems correlated to efficiency, costs, yield, labor costs, crop health, and farming practices.
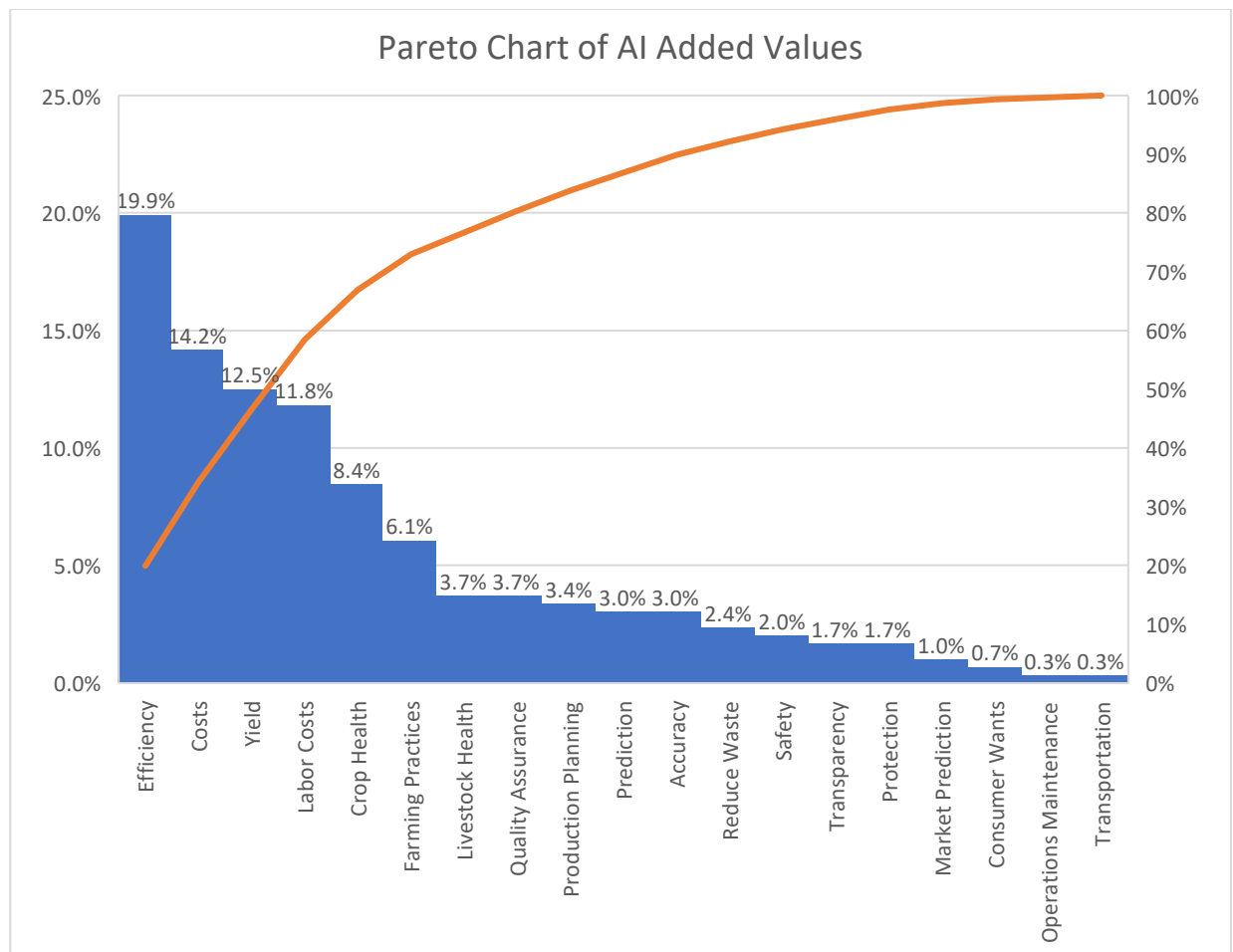
Figure 10: Pareto Chart of AI Added Values

Broadening the analysis of AI application value-added activities, the data accumulated from figure 9 *Values from AI Integration* was utilized to create the pie chart in figure 11. The pie chart shows which values from the AI application have the most significant impact on the Ag SCs. Moreover, observing the values on a pie chart can help identify which values are more niche and are not exhibited in multiple applications. In particular, the pie chart highlights that over 50% of all witnessed values in AI applications come from just four values, including efficiency, costs, yield, and labor costs. Conversely,

the pie chart concluded that AI applications' least commonly exhibited values are transportation, operations maintenance, consumer wants, and market prediction.
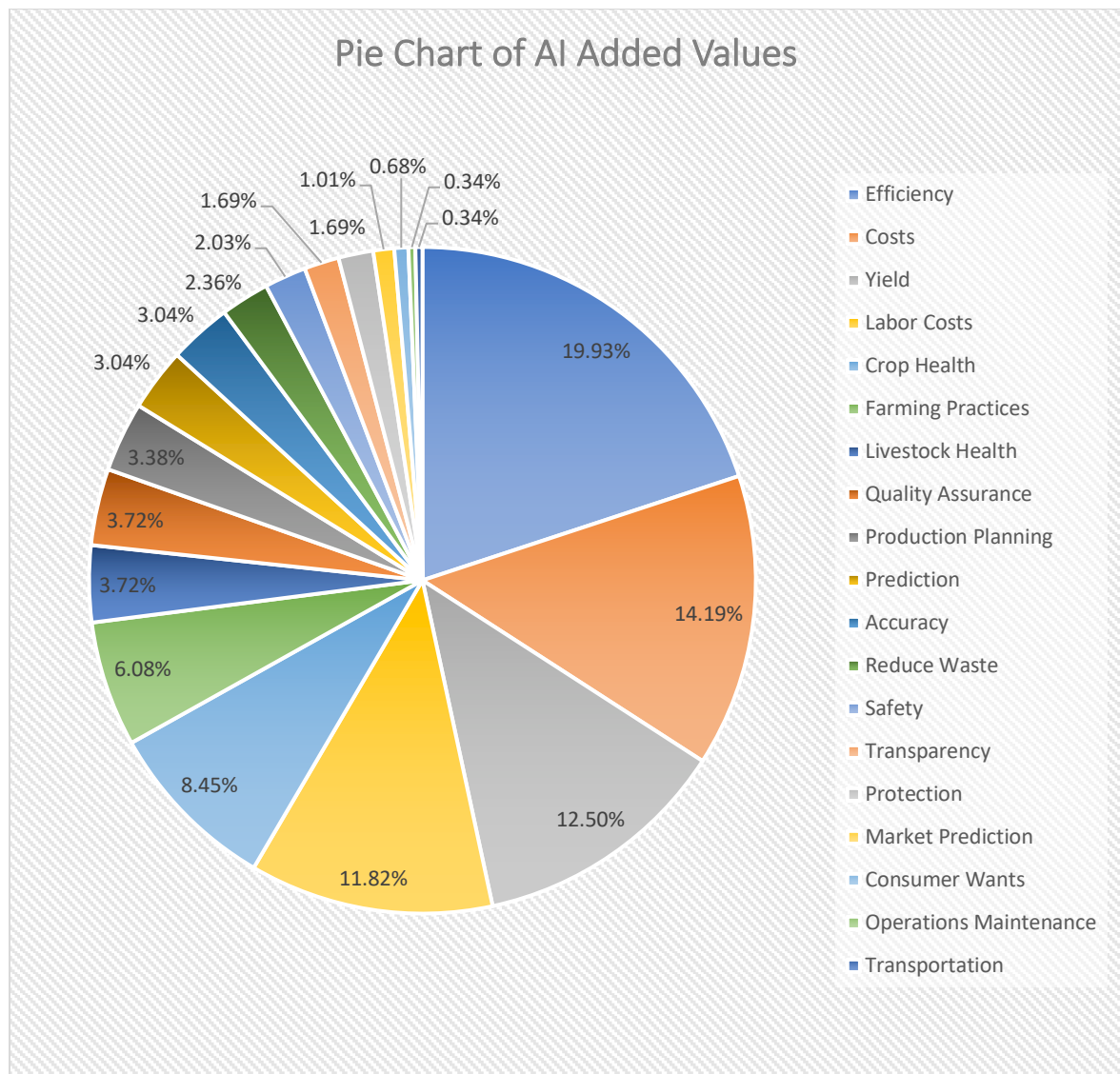
Figure 11: Pie Chart of Values from AI Applications

It can be hypothesized that the main concerns that stakeholders look to address in the agriculture industry relate to operating efficiently, optimizing yields, occurring operational costs, and occurring labor-related costs. Therefore, the least observed values could indicate that stakeholders are not looking to address problems relating to these values

or that they have not had success implementing AI applications to address problems in these areas. Furthermore, information from the pie chart and the Pareto chart can help identify and match other sectors, areas, and stakeholders within agricultural SCs that would benefit from the AI application's derived values.

Due to the various SC locations (up-stream, mid-stream, and down-stream) all performing different operational tasks, it was determined that to fully understand the added-value from the AI applications in the agricultural SCs, the values needed to be analyzed in the respected SC locations. By looking at the application's values in their respective SC locations, the research hopes to infer if any differences of value-additions exist across the SC locations.

3.2.1 Up-Stream Values of Artificial Intelligence Applications:

The pie chart found in figure 12 below represents the up-stream SCs driving values from AI applications. The up-stream location has received the most attention from researchers studying AI's influence and effect on the agricultural industry. The operational activities in this area focus primarily on farming, raw material sourcing, managing crops, and livestock. Therefore, the main driving values of innovation in the up-stream sector are operations-oriented, focusing mainly on improving operation-based activities. The earlier data results gathered from figure 8 found that 93.06% of applications in this sector exhibited operation-orientated innovation driving values.

Up-Stream Values

Legend
Efficiency
Yield
Costs
Labor Costs
Crop Health
Farming Practices
Livestock Health
Prediction
Production planning
Reduce Waste
Safety
Quality Assurance
Transparency
Accuracy
Protection
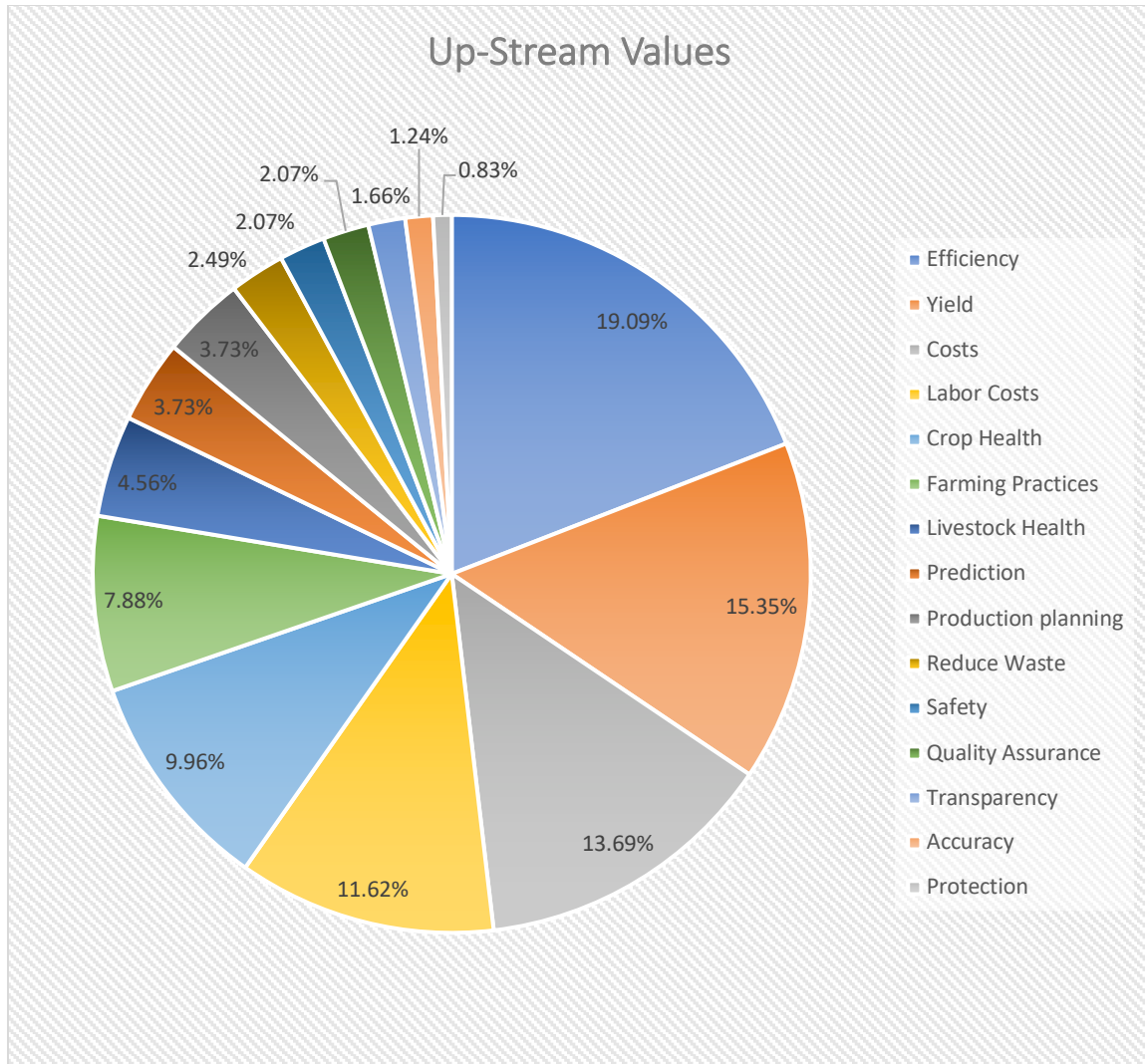
Figure 12: Up-Stream Values Pie Chart

Figure 12 highlights that in the up-stream location of the SC, the main added values from the AI applications are ***efficiency, yield, costs,*** and **labor costs**. Efficiency, costs, and yield alone made up 47.94% of all the witnessed added values from AI integration in the Up-Stream location of agricultural SCs. Conversely, the three least witnessed added values are ***accuracy, protection,*** and ***quality assurance,*** making up only 3.72% of witnessed AI added values.

As previously expressed, the up-stream location's most significant driving innovation value is operation-oriented values. Operation-oriented values focus primarily on improving activities that influence operation and production functions and increase company profits. The focus of operation-oriented values aligns with the findings that the leading AI added values are *efficiency, costs*, and *yield*. In conclusion, the up-stream SC is currently focused on finding AI applications that will increase *efficiency,* lower *costs*, and improve *yields*.

Another finding during the value versus location analysis is that **none of the AI applications** in the Up-Stream of the SC witness added values of **market prediction, consumer wants, operations maintenance, and transportation**. These findings are illustrated in figure 13 below. Reviewing the none witnessed values, it was remarked that market prediction and consumer wants are primarily customer-orientated values. Although this sector of AI technology primarily focuses on operational value additions, it was unexpected that market prediction and consumer wants are not among the primary goals of AI in the up-stream location. Market prediction and consumer wants are values that help understand what products will sell and avoid overproduction, which is essential data for up-stream stakeholders when planning production.
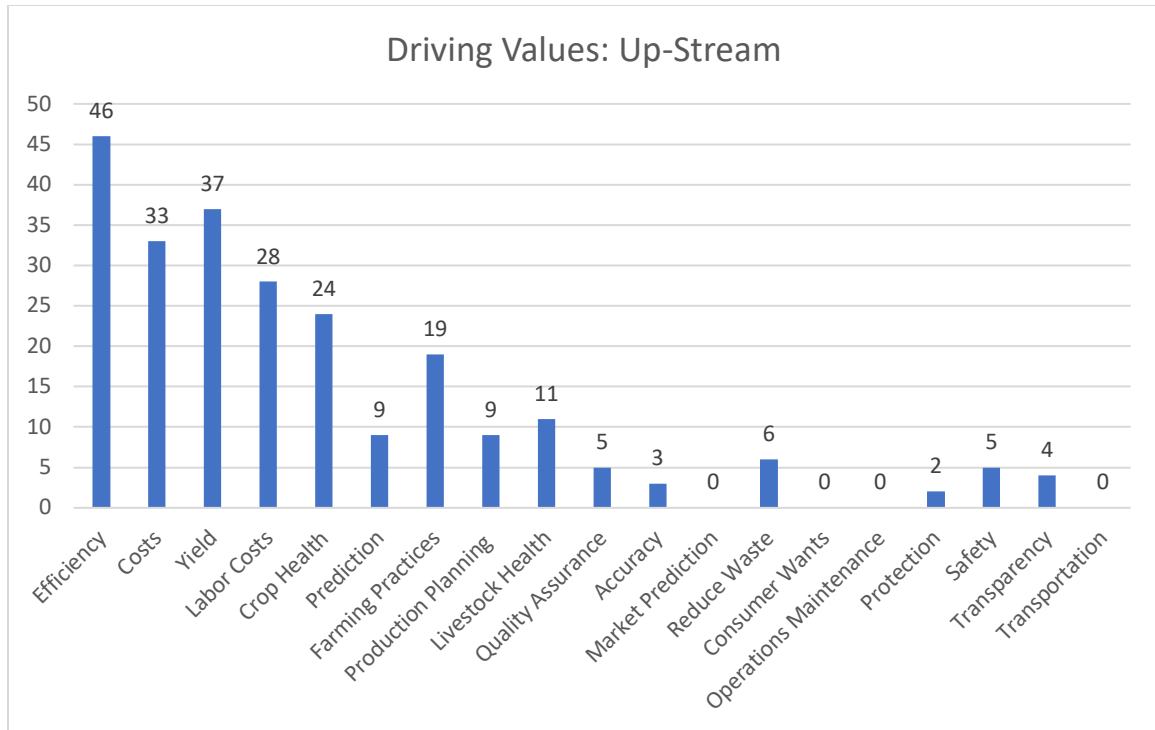
Figure 13: Up-Stream Added Values

3.2.2 Mid-Stream Values of Artificial Intelligence Applications:

Next, the AI applications in mid-stream location of the SC were studied to distinguish which values are derived directly from the AI applications. In agricultural SCs, mid-stream location activities typically include processing raw materials, packaging, logistics/forecasting, and transport. The findings from the mid-stream AI application's added values are shared below in the pie chart found in Figure 14. The pie chart shares the main findings of added values: *efficiency, quality assurance, costs,* and *labor costs*, which account for 58.2% of all added values to the mid-stream location from the AI technology. The three least witnessed added values from the mid-stream sector AI applications are *market prediction, operations maintenance,* and *transportation* making up only 4.41% of witnessed AI added values.
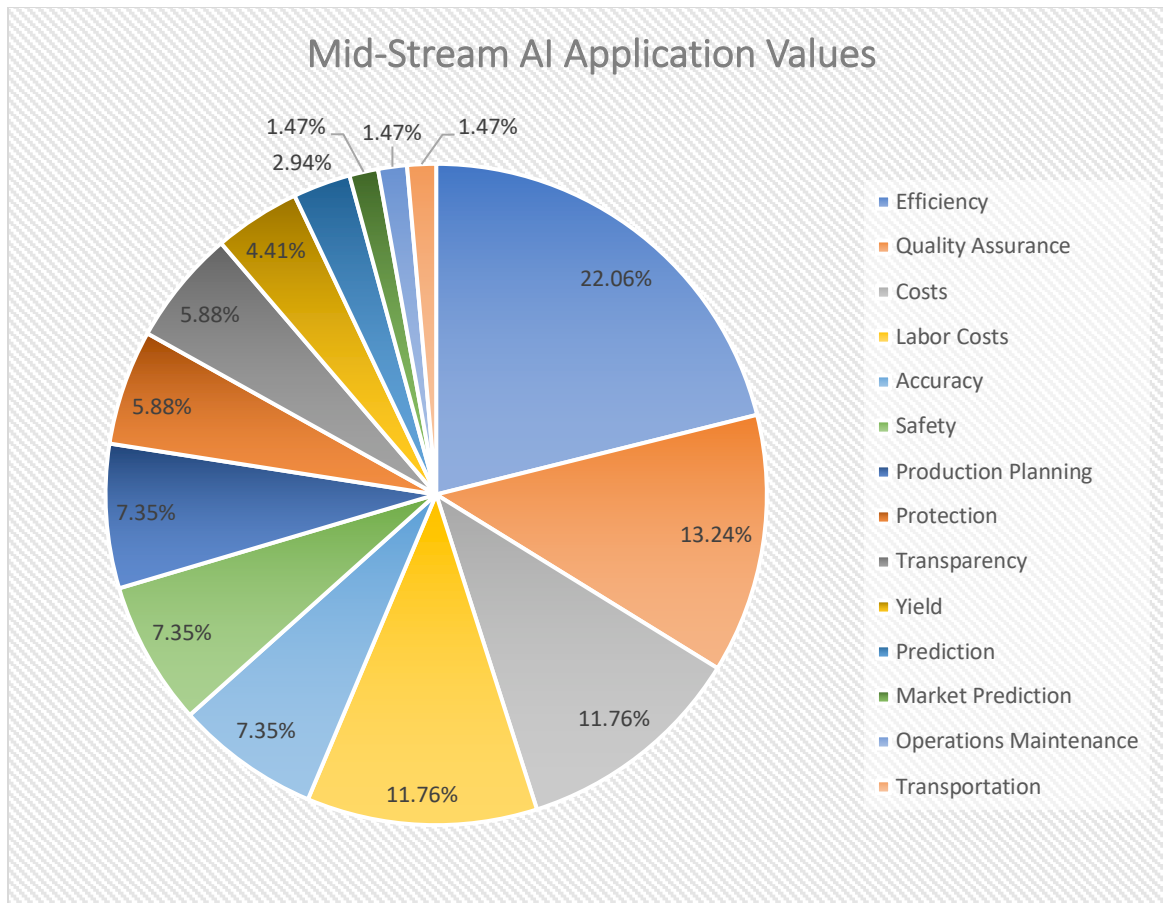
Figure 14: Pie Chart Mid-Stream AI Added Values

When comparing the mid-stream to the up-stream location, a significant difference is that the mid-stream area receives no added value relating to farming management activities. This finding is highlighted in figure 15 below. ***None of the AI applications*** in the mid-stream of the SC perform any added values activities contributing to ***crop health, farming practices, livestock health, reduce waste,*** and ***consumer wants***. Typically, the mid-stream location would not perform actions in association with farming management. Instead, the AI applications in the mid-stream of the agricultural SC administer to optimize operational efficiency, increase quality assurance, and lower operational and labor costs.
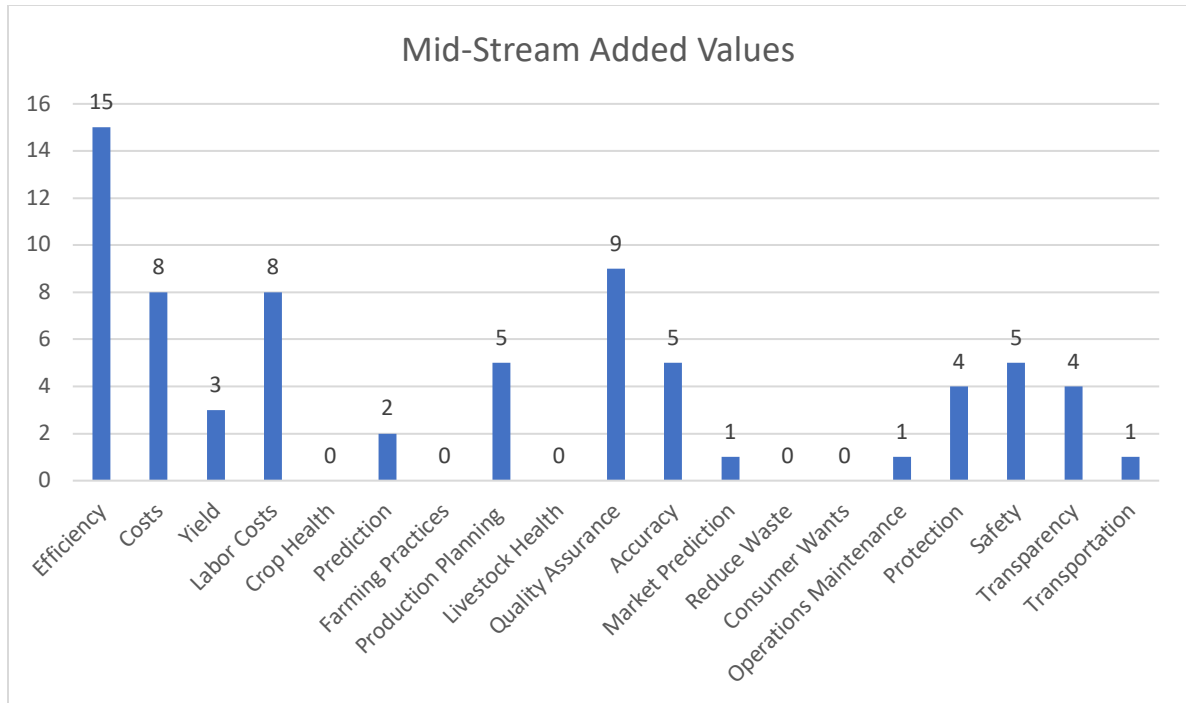
Figure 15: Mid-Stream Added Values

3.2.3 Down-Stream Values of Artificial Intelligence Applications:

Finally, to conclude the location versus added values comparison, the down-stream division of the SC was assessed. With the pie chart found in figure 16 below, the down-stream AI applications were evaluated to find and highlight the main added values. The primary added values from the AI applications are ***quality assurance, safety, transparency,*** and ***efficiency.*** These added values account for 50% of all the witnessed added values from AI integration in the down-stream location of the Ag SCs. Of the four primary added values, three are customer-oriented innovation driving values (quality assurance, safety, and transparency) and create value for consumers. It was discovered that the downstream location of the SC is the only location that witnessed approximately equal quantities of AI applications possessing innovation driving values in both categories.

40

In the down-stream sector, four added values were witnessed the least. The second least witness added value was determined to be a draw between three values. The least witnessed added values are ***reduce waste, consumer wants, prediction,*** and ***market predictions*** making up 15.92% of witnessed AI added values.
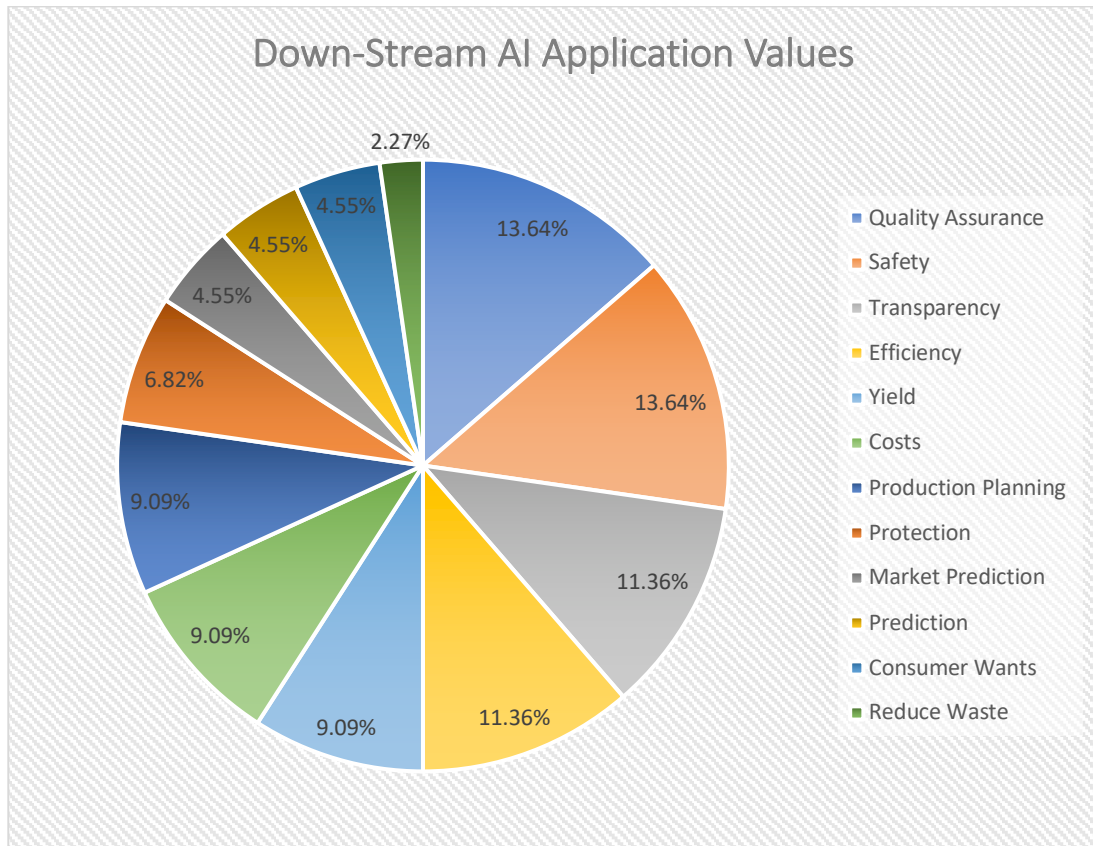
Figure 16: Pie Chart Down-Stream AI Added Values

The down-stream location of agricultural SCs focuses on operational activities supporting distribution/trade, retail/e-commerce, food safety, and consumer consumption. AI applications in this location concentrate on ensuring the SC enhances quality assurance, product safety, SC transparency for consumers, and operating efficiently. It was determined that the down-stream location is the only location to primarily receive added values that stem from consumer-orientated innovation driving values. In figure 17 below

alternative perspective is provided to critique to the down-stream application values data and highlight absent values in the down-stream sector.
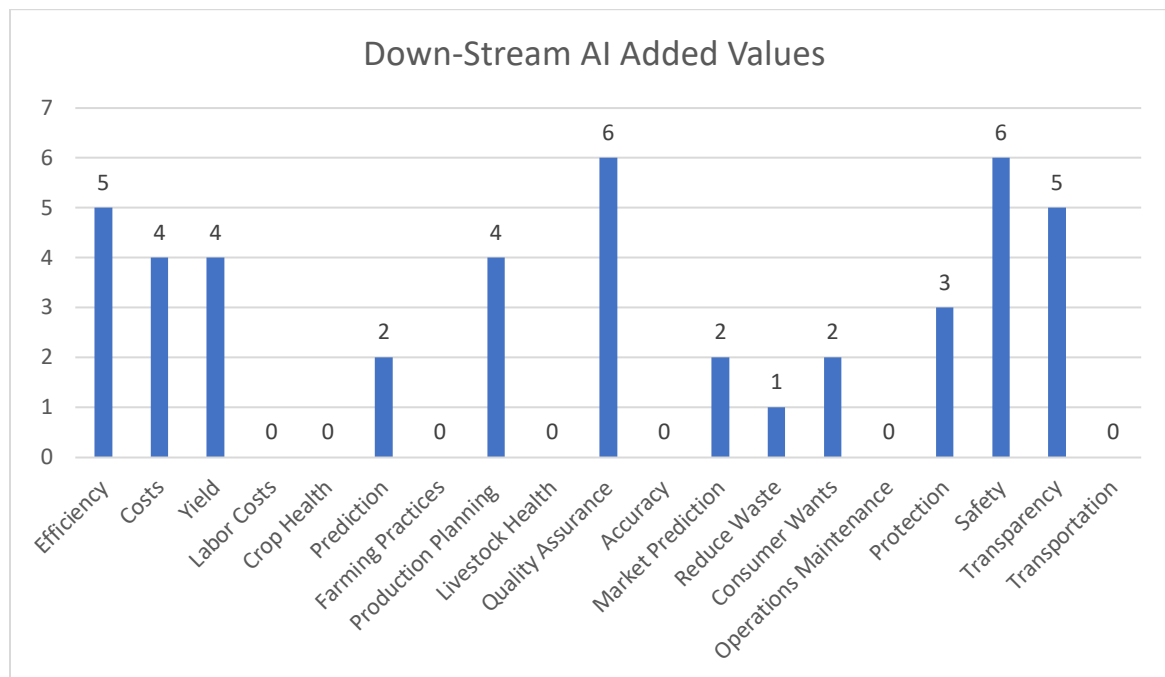
Figure 17: Down-Stream AI Added Values

From figure 17, it was determined that ***none of the downstream AI applications*** provide added value activities associated with ***labor costs, crop health, farming practices, livestock health, accuracy, operations maintenance, protection,*** and ***transportation***. The values not present are all related to farming management processes. The absence of those values can be attributed to the fact that the downstream sector does not have a direct role in farm-related operations.

In summary, from evaluating the AI applications added values into the Ag SC from the applications' respective locations in the supply chain, it was discovered that the locations experience different values additions from the AI applications. These findings were anticipated as each supply chain sector is responsible for different logistical activities

and witnesses different imposing threats. Therefore, Ag managers would select AI applications that provide value-added benefits for the individual needs of the SC sectors. The up-stream and mid-stream sectors predominantly consist of AI applications that create value derived from operation-orientated innovation value drivers. In contrast, the down-stream sector comprises AI applications that primarily create value originating from customer-orientated innovation value drivers.

Chapter 4

4.0 Typology:

This typology identifies and defines two main innovation dimensions that support the development of artificial intelligence in agricultural SCs. These dimensions are the driving values and the innovation's relationship in the SC. The typology proposed exclusively attempts to capture and compare the dynamics of added value from AI innovation to its location in agricultural SCs. The typology was created by analyzing locations of AI technology found in agricultural SCs and the added value received into the SCs from the technology. The framework of the typology uses a sliding measurement scale to survey the depth of AI application. The scale, which can be found in table 2 below, was constructed to analyze the AI technology in agricultural SCs through the two main innovation dimensions.

The scale was created to measure the depth of AI applications and distinguish the application's relationship to the SC. The further the relationship expands in the SC, the deeper the depth of the application. In the shallow levels, AI applications remain confided, and other areas of the SC do not embrace the AI application's innovation and value. Other SC sectors are not able to form a beneficial relationship with technology. Having a deeper depth entails that the AI application has a vast and sturdy relation between the different sectors and operations in the SC. As the relationship deepens, the other areas of the SC begin to work together with the technology, eventually establishing a robust relationship that other domains look to and rely on the technology to improve. At deeper levels, information is shared between SC operations and locations. Shared information is an invaluable asset as it can be used for other areas to design their operations strategically.

To determine the current state of AI in agricultural SCs the applications reviewed in the thesis were evaluated using the established *Depth Rating Scale*. The scale found in table 2 was created using the data previously collected during the literature review of the AI applications in the review, but scale was developed unbiasedly and until this point the individual applications were not considered when contrasting the typology. The sliding scale uses a numeric range from one to eight. Utilizing a wide numeric scale creates a further granular approach to analyzing the AI applications and provides heightened explanation to the SCs' relationship with AI technology. The scale generates a quantitative method for data entry to create ease of use for future research and users and permits for large scale use with bigger sample sizes. Furthermore, table 2 helps to capture and provide visual explanation for the typology.

Table 2: Depth Rating Scale

Rating Value	Rating	Definition
1	Extremely Shallow	Only supports one operation
2	Very Shallow	Supports two-three operations (in the same supply chain location)
3	Moderately Shallow	Whole sector of supply chain location
4	Slightly Shallow	Lightly assists another location of the supply chain
5	Slightly Deep	Assists another location of the supply chain
6	Moderately Deep	Greatly assists another location of the supply chain
7	Very Deep	Assists whole supply chain (Up, Mid, Down)
8	Extremely Deep	Greatly assists the entirety of the supply chain

The AI applications as whole with their location were used to devise the measuring system. To begin the assessment of applications all the applications were carefully reviewed within the context of their research study. Reviewing the context AI applications within the context of their given study enable to study to clearly understand the AI applications impact and depth in respect to the *Depth Rating Scale.* After completing the depth assessment, the chart found in figure 15 below was created to highlight the findings from the assessment. This bar chart visualizes the frequencies of each depth measurement found from the reviewed eighty-six AI applications.
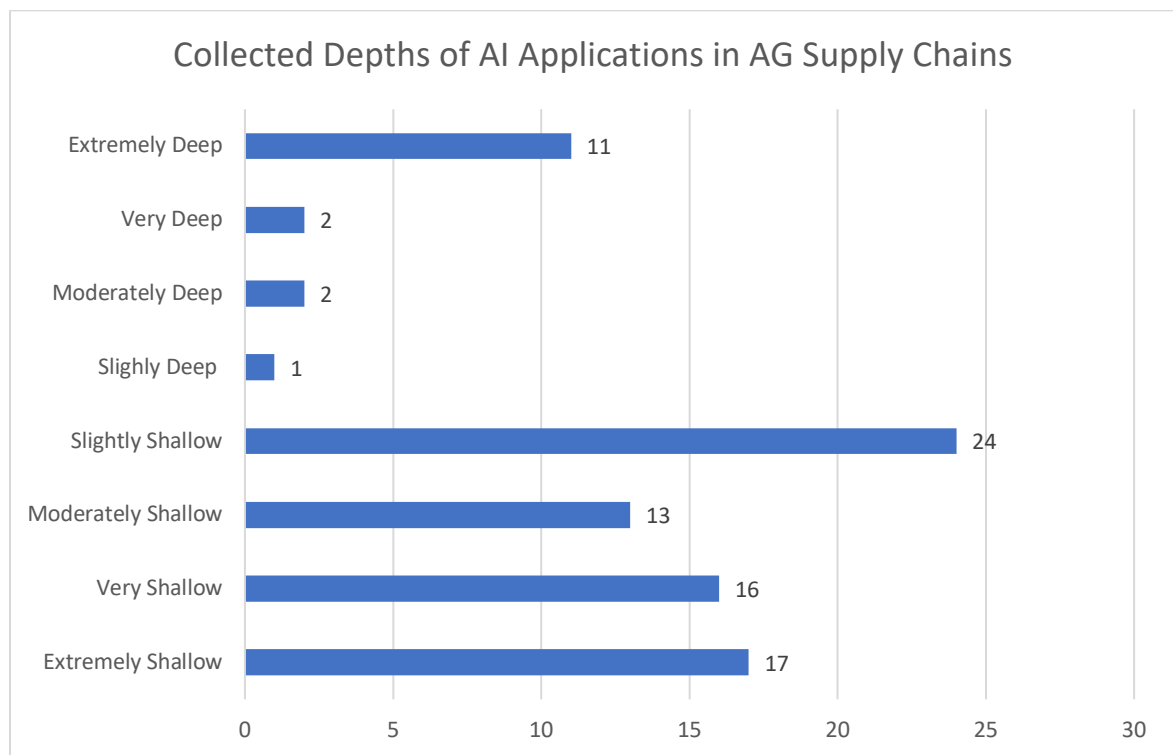
Figure 18: Collected Depths of AI Applications in AG Supply Chains

From this chart the overall depths sightings can be seen. In the chart it seen that majority of the AI applications have a depth range in the shallow territory. The least

observed depth ranges are that of slightly deep, moderately deep, and very deep. The slightly deep, moderately deep, and very deep ranges represent AI applications that begin to expand the relationship of the application to other areas in the SC.

Witnessing that the slightly deep, moderately deep, and very deep ranges have the lowest frequencies it was unanticipated to discover that that the depth range "Extremely Deep" is significantly higher. The extremely deep measurement is given to AI applications that greatly assists the entirety of the SC and provides the maximum possible support to the whole SC.

For AI applications to receive the assists the entirety of the SC and provides the maximum possible support to the whole SC. At extremely deep depth AI applications have a developed supporting relationship with the other SC relationships and stakeholders. It could be hypothesized that the other deeps of slightly deep, moderately deep, and very deep should have been detected more as these ranges require less of a relationship with other SC locations and thus have an easier entry to Ag SCs. As AI in Ag SCs is still in the early stages of integration it would be predict it would be easier and more common for SCs to adapt AI applications with depths lower than "Extremely Deep."

After concluding reviewing the depths, the AI applications were once again reviewed within their locations on the SC to determine where the depth ratings stem from in the SC. In figure 19 below the depths of applications are provided in within their corresponding location in the SC.
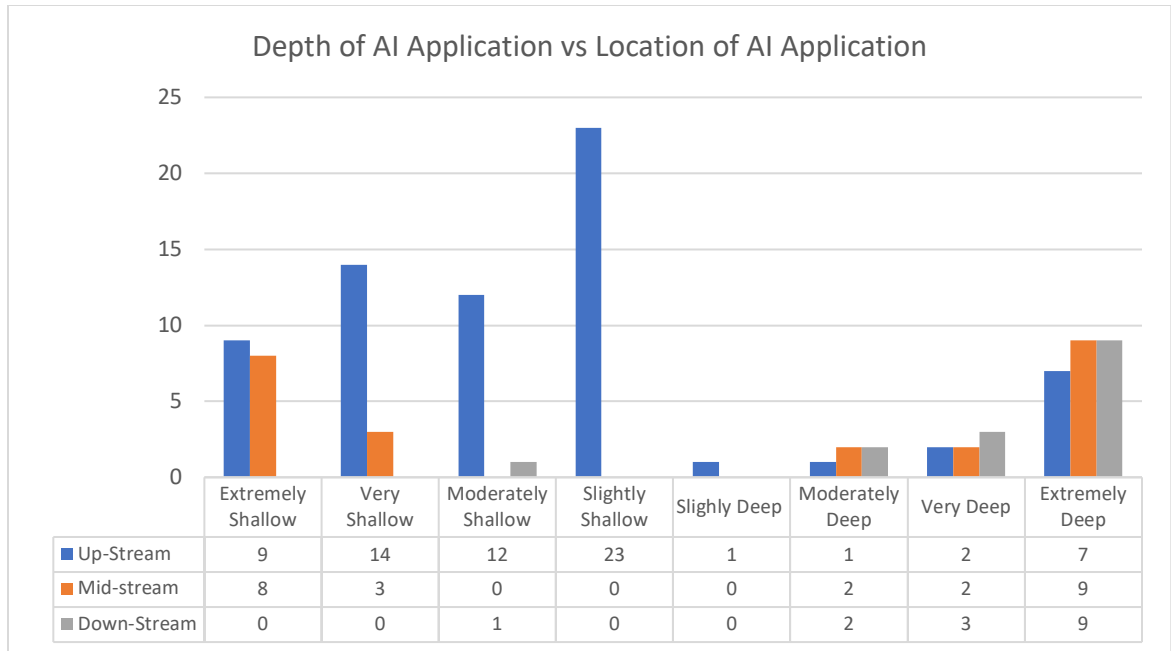
Figure 19: Depth of AI Application vs Location of AI Application

Similar to figure 19, figure 20 shares the depth of AI application within their corresponding location in the SC shares the data using percentages. The percentages allowed for enhanced comparison of the locations' depths, as the number of AI applications found within each location is inconsistent. Figure 20 illustrates where the majority of each location's depth lays and how the locations contrast.

Depth of AI Application vs Location of AI Application

	Extremely Shallow	Very Shallow	Moderately Shallow	Slightly Shallow	Slighly Deep	Moderately Deep	Very Deep	Extremely Deep
Up-Stream	13.04%	20.29%	17.39%	33.33%	1.45%	1.45%	2.90%	10.14%
Mid-stream	33.33%	12.50%	0.00%	0.00%	0.00%	8.33%	8.33%	37.50%
Down-Stream	0.00%	0.00%	6.67%	0.00%	0.00%	13.33%	20.00%	60.00%
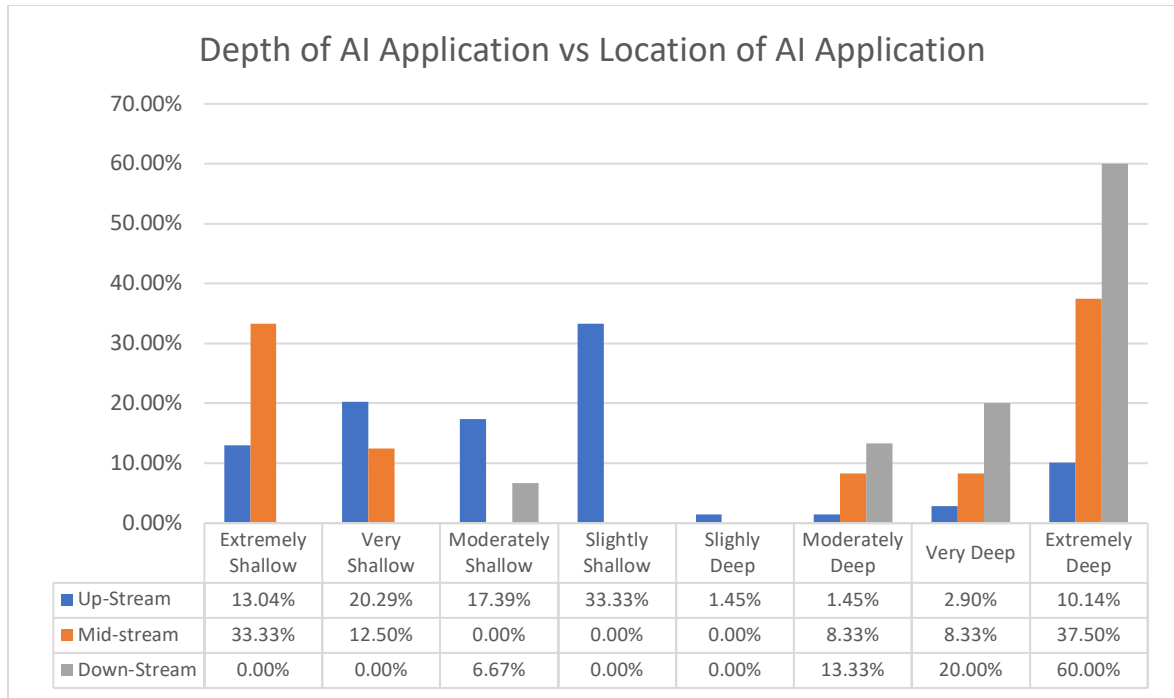
Figure 20: Depth of AI Application vs Location of AI Application (Percentage)

The AI applications in the up-stream location of the supply exhibited the highest depth range of "Slightly Shallow," with 33.33% of the applications ranked in that range. The up-stream applications that rank in the "Slightly Shallow" range support the whole up-stream sector and lightly assist another SC location. Overall, 84.05% of AI applications in the up-stream location were ranked in the shallow depth range, and only 13.04% of the applications received a rating in the deep depth range. Therefore, based on the data, it can be hypothesized that the agricultural industry has not yet entered a state where AI applications in the up-stream have the necessary infrastructure and connectivity to provide extensive support to other SC locations.

Not having the infrastructure and connectivity to form relationships with the AI applications to other SC locations could be tied to a lack of information sharing, standardization, education, technology, etc. In addition, the up-stream location typically

faces more barriers to entry, on account that this location often lacks urbanization and advanced industrialization with many farms residing in rural regions.

The AI applications located in the mid-stream were discovered to be the most evenly dispersed over the depth ranges compared to the other two SC locations. With 54.17% of the mid-stream applications ranking in the deep range and 45.83% in the shallow range. The analysis made the significant discovery that none of the mid-stream applications ranked in slightly shallow or slightly deep ranges. This activity demonstrates that none of the applications were categorized as "lightly assists another location of the SC" or "assists another location of the SC." The AI applications here were witnessed either only perform and assist operations in the mid-stream location or the applications strongly support both the mid-stream location and other SC locations.

The mid-stream location's AI applications ranked the highest in the "Extremely Deep" depth range, with 37.50% of applications categorized in this range. Given this data, it can be theorized that within the mid-stream sector, there is a substantial push to integrate AI applications that can significantly assist all locations and sectors within the SC. In addition, the mid-stream location has proven to have the capabilities necessary to implement applications that have influence and relationships with other SC locations.

The down-stream location was recorded to have the most AI applications ranking in the deep range compared to the other locations. Indeed, 93.33% of the applications ranked in the deep range in the down-stream location, and 6.67% were in the shallow range. Therefore, it was determined that the down-stream AI applications provide the most influence and support over the SCs compared to AI applications in other locations in the SC.

Similar to the AI applications in the mid-stream, the down-stream AI applications were recorded the highest in the "Extreme Deep" range. In the down-stream, 60% of AI applications received an "Extreme Deep" ranking, indicating that these applications display the most meaningful support for the entire SC. From the data, it was revealed that none of the down-stream applications rank in the ranges of "Very Shallow," "Slightly Shallow," or "Slightly Deep." Indicating that none of the down-stream applications classify as: "Supports 2-3 operations (in the same SC location)", "lightly assists another location of the SC," or "assists another location of the SC."

With the gathered depth data of AI applications from the down-stream location, it can be speculated that this location witnesses the greatest undertaking from stakeholders to integrate AI technology with the most extensive reach and influence on the SC. Another theory that might explain why the down-stream location's AI applications are seen as having the deepest depths is that this location may have fewer entry barriers, consequently allowing for easier SC adaption to the AI applications.

SC stakeholders aspire to create and incorporate value-added activities that expand to all areas in the SC. Therefore, it is in stakeholders' best interests to integrate AI applications with higher depth ranges to achieve their goals and improve the SC.

Chapter 5

5.0 Summary:

The literature review found that researchers have primarily focused on and studied AI applications taking place and assisting the upstream locations of the SC. The research review attempted to obtain as many AI applications from all areas as possible, but due to available research limitations, collecting data from AI applications specifically in the down-stream location proved challenging. While attempting to stay within key search criteria and avoid non-academic journals and databases, the available research material regarding AI technology in the down-stream sector of the agriculture SC was restrictive.

Currently, the push to integrate innovation into agricultural SCs comes from operation-oriented and customer-oriented values. Of the two values, the majority of the drive for innovation specifically comes from operation-oriented values. From the eight-six AI applications surveyed, eighty-one applications observe operation-oriented values, and eight observe customer-oriented values. In addition, three applications were detected having both operation-oriented and customer-oriented driving innovation values.

Both the up-stream and mid-stream AI applications predominantly stem from operation-oriented innovation driving values. However, the down-stream is the only location where both values influence the drive for innovation. As a result, down-stream AI applications observed an equal split of 50% customer-oriented and 50% operation-oriented values.

After determining the main innovation driving values of all the Ag SC AI technology applications, the applications were reviewed again to determine the value-added attributes received into the SC from AI applications. Looking at AI applications in

all areas of the SC, efficiency, cost, labor costs, and yield are the most observed value-added contributions from the eighty-six reviewed AI applications. Suppose the SC were to be analyzed as a whole. In that case, it could be concluded that the main reason for integrating artificial intelligence into agricultural SCs would be to increase efficiency, optimize yields, decrease accrued costs, and accrued labor costs. However, because the number of AI applications found in the three different SC locations (up-stream, mid-stream, down-stream) varies so drastically, looking at the SC and the AI applications as a whole would mask potential discoveries. Most AI applications were found in the upstream sector of the SC, consequently viewing the SC as a whole would essentially only reflect data found in the upstream location.

Specifically looking at added values from up-stream AI applications, the main takeaways are that AI applications in this area primarily add value related to improving efficiency, lowering cost, and optimizing yields. In the midstream location, AI applications' most significant value additions correlate to improving efficiency, increasing quality assurance, and lowering accrued costs. At the downstream location of the SC, AI applications mainly add values related to increasing quality assurance, safety, transparency, and optimizing yield. Thus, the downstream location is the first witness to the majority of leading value-added attributes associated with customer-oriented values.

Concluding the evaluation sequences of location and values, the thesis moved forward in constructing the proposed typology. The typology was created to cohesively evaluate the following two parameters:

1. The relationship between SC location and the success of artificial intelligence technology integration.

2. The driving values of innovation into agricultural SCs as it relates to artificial intelligence implementation.

With those two parameters, the typology set out to conceptualize and illustrate AI dynamics and the evolution of AI in agricultural SCs. The typology consists of a numeric sliding scale to measure and classify the depth of an AI application's relationship to the SC. The scale helps build a fundamental understanding between SC location, the success of artificial intelligence technology integration, and the driving values of innovation into agricultural SCs related to artificial intelligence implementation.

The typology provided a guide for the thesis to review the AI applications to determine the dynamics of AI and the evolution of AI in agricultural SCs. While assessing the AI applications through the typology, it became apparent that the majority of AI applications shared a shallow relationship within the SC. The AI applications that shared the deepest relationship to the SC were located in the down-stream sector. The rating that received the highest frequency was "Slightly Shallow," which had 23 applications.

As previously stated, artificial intelligence is in the early stages of introduction into the agricultural industry. Consequently, the SCs' receptiveness to AI applications is also in the beginning stages. The currently achieved depths from AI applications mainly rate as shallow on the depth scale. This observation may be related to an overall lack of AI use and accessible data sharing in the industry. Accessible data sharing furthermore will require the industry to standardization its data. Data standardization will enhance data exchanging between AI technologies, domains, farms, countries, and companies (Duckett, 2018).

5.1 Conclusions:

Artificial Intelligence's role in agricultural SCs is quickly expanding. Even since beginning the composition of this thesis, new case studies have since published. This study was carried out analyzing literature published from 2015 to March 2021. As more information becomes available about AI application's added values and locations within the SC, the typology may need to be adjusted. However, the typology can be the foundation for this discussion that will continue to unfold. Artificial intelligence is just at the foreground in the agriculture industry, and the need to innovate is only growing stronger as threats to the industry grow larger.

Continuing to grow upon the idea and construct of location and value within the SC, a recommendation for future work would be to isolate and study a single SC location at a time. With each location in the SC requiring different needs and values from AI technology, it will be challenging to accept the proposed typology as more than just a generalization of the AI technology in agricultural SCs.

During the literature review research, it was discovered that most of the published studies focus on artificial technology in the up-stream sectors of agricultural SCs. The review exposed a lack of research conducted to study AI technology in the mid-stream of Ag SCs. Even less research is available studying AI technology in the downstream Ag SCs. The lack of exploration of AI in other locations of Ag SCs proved to be a challenge when collecting AI applications for data analysis, as the goal of the data collection was to collect data that gave equal insight into all locations. If the study were to be continued in the future, isolating the SC locations may prove helpful to finding sole research on the up-stream and mid-stream locations.

Looking into the future of AI and its role in agricultural SCs based on the presented research, it can be anticipated that there will be a shift in AI driving innovation values. Currently, the main drive towards innovation in the agriculture industry stems from operation-orientated values. However, in the future, it can be hypothesized that the push to innovate the agricultural industry will come from customer-orientated values.

Once AI applications become a part of standard practice, stakeholders will better understand AI's potential in the SCs. However, AI technology is currently novel to the Ag industry. As a direct result, instruction on how to effectively utilize AI within the SC is limited. Furthermore, despite AI technology often being thought of as a self-regulating machine, it still requires skilled human interaction; many applications require manual inputs, corrections, data reading, etc. Therefore, it will be crucial to the success of AI in agricultural SCs that skilled specialty works are helping with the AI operations.

The current need and drive to implement AI into the agricultural industry are to improve operations to avoid looming threats. As AI technology becomes more accessible and established in the Ag industry, the threats that AI was integrated to defeat will diminish. The decrease of threats to the industry will enable industry players and stakeholders to utilize AI technology and integrate SC innovation to add value for consumers.
Through investigation and analysis, the thesis draws the following conclusions:

- Artificial intelligence can make the agricultural SCs more efficient, environmentally friendly and safe, and make the agricultural industry's SCs more traceable and transparent.
- The agriculture industry presently focuses on integrating AI technology that reliefs and advances operations-based activities to benefit operational-

orientated values. There are very few records of Ag SCs implementing AI applications that serve to benefit customer-orientated values.

- The magnitude at which artificial intelligence applications create value for agricultural SCs is not restricted by digitization but is limited to advanced adaptation and data sharing across the industry.

- The difficulty surrounding strengthening the relationship between AI technology and Ag SCs is not solely tied to integration obstacles but rather to the complexity of creating a platform to foster interaction, knowledge, and integration of technology and industry.

- AI technology will have the most robust relationship and best execution when operating in collaboration with other SC locations and AI integrated firms.

5.2 Proposed Recommendations:

The thesis proposes the following recommendations utilizing the typology. The provided recommendations are advantageous for businesses and policymakers in the advancement of artificial intelligence in agricultural SCs.

5.2.1 Recommendations for Business Development:

The typology proposed in this thesis will help businesses examine the current state of AI applications and operations in their SC. The typology allows businesses to create a benchmark of the current state of AI in the company's SC and summarize AI applications' relationship in the SC. The typology will review and provide insight into the extent of AI creation value on the SC and where the value is being received in the SC. The benchmark

would empower businesses to determine where AI value creation is absent or shallow in the SC. With a cross-examination of the business' operations, stakeholders can determine where AI value creation is needed. The typology will support businesses looking for continuous improvements and future innovation direction. Additionally, the typology can guide firms in the exploration to identify AI applications that will have deeper value creation relationships in the SC.

For Ag managers, the typology can assist Ag businesses in developing long-term AI investment strategies. Using the typology as a strategic tool, Ag business managers can estimate the degree of value a particular AI application will provide to the company. The typology offers profundity into where businesses should be looking to integrate AI technology into the SC and which applications will be the most advantageous for the SC. This typology will prove to be a valuable tool for Ag managers. Allowing Ag managers to discover which AI applications align with the company's priorities, motivates, and big-picture goals. With a clear conception of the business' future direction, Ag managers can identify AI applications utilizing the typology that transform the SC and reach the standards set forth by the company.

Additionally, the thesis suggests that Ag businesses in pursuit of adopting new AI technology into the SC investigate areas that currently receive no value additions and shallow value additions from AI applications. Business leaders can use the typology inversely to analyze individual SC processes and observe if the operation actively receives value from any AI application in the SC.

Furthermore, creating an investment strategy will also allow businesses to prepare for AI integration and maximize the success of the process. Along with the AI applications,

the investment proposal should include investing in necessary employee training, education, and consideration of hiring specialists to facilitate the adoption and manage the AI applications. These additional investments will promote the optimal opportunity for AI adaption in the Ag SCs.

5.2.2 Recommendations for Industry Data Sharing:

The typology determined that AI applications that have the greatest degree of value creation across the SC rely on data sharing to other locations in the SC. However, very few policies exist concerning data sharing in the agriculture industry that protects data owners' rights and allow other users to utilize the data. Due to the absence of regulation, Ag businesses have expressed hesitation regarding data sharing. The reluctance is attributed to sharing concerns and access control policies of the owners' data. As a result, AI technology data sharing is not a common practice in the Ag industry (Spanaki et al., 2021).

Due to the current state of the Ag industry's data management, the thesis concludes that data sharing is an imperative component in achieving large-scale value creation and deep relationship development between AI applications and the SC. Consequently, it is recommended that government legislators introduce policies to protect the security of data ownership and regulate data-sharing.

Larger agriculture enterprises have had the most significant advantage to AI integration due to expendable research, monetary funds, advanced education, and infrastructure. Therefore, this thesis proposes that government agencies initiate preferential policies to incentivize large-sized agriculture firms to participate in data-sharing to grow AI development.

The thesis recommends calling upon the Ag industry to standardize its data to help aid the efforts of successful data sharing. Data standardization will improve the quality of the data and ensure that the data is consistent, leading to the advancement of AI operations. Furthermore, executing data standardization in the Ag industry will heighten data integration and reusability, data sharing among businesses, and improve internal company communication. From the regulators, standpoint data sharing will additionally benefit the facilitation of regulatory inspections and audits, as a common language will be used and wildly understood by many ("Standardization to Enhance Data Sharing", 2013).

5.2.3 Recommendations for Artificial Intelligence in the Down-Stream:

The research review findings assume that AI is less prevalent in the down-stream location of Ag SCs. When analyzing the down-stream applications through the lens of the typology, it was discovered that the down-stream location represents the largest share of deep relationships between AI value addition and location, compared to the other SC locations. 93.33% of the down-stream AI applications have formed deep relationships. With this knowledge, it is recommended that agriculture businesses focus on integrating AI technology in the SC's down-stream. This sector is anticipated to hold the most ability for value creation through AI applications. Therefore, researchers should study this area of AI in the Ag SCs at greater lengths. More exploration will lead to a robust understanding of how the down-stream SC interacts with AI technology and support businesses pursuing approaches to innovate the down-stream SC processes.

5.2.4 Recommendations for Global Development:

Lastly, the thesis recommends that the typology is employed to analyze the current state of AI in different countries. Governing agencies can utilize the typology to provide insight and comparison to developed and developing countries. Insights drawn from the comparison can help mend the gap between agricultural SCs in developed and developing countries. Additionally, developing countries are challenged with the highest levels of threats and risks to the SCs, making it imperative that these regions attain AI innovation.

Using the typology to analyze the current state of AI in different countries will unearth gaps and find weaknesses in the SCs. Once the gaps and weaknesses have been identified, the typology can support governments in determining AI applications that address the countries' most important priorities. Furthermore, the typology provides a tool that allows industry leaders to deliberate and define which AI applications are the most beneficial to the progression of the SC. In summary, the thesis recommends that government agencies in developing countries apply the typology to distinguish areas of opportunity and invest in suitable AI application solutions. The typology assures the value and scope of the value received into the Ag SCs through the adopted AI applications. Exerting the typology safeguards government agencies and their AI investment decisions.

5.3 Future Work:

Future work will focus on a more empirical investigation to support the proposed typology. In addition, case studies for each configuration will be used to demonstrate the suggested innovation location dynamics and perhaps add more elements to the proposed typology's configuration classification approach.

References:

[1] ABDULLAYEVA, A. (2019). IMPACT OF ARTIFICIAL INTELLIGENCE ON AGRICULTURAL, HEALTHCARE AND LOGISTICS INDUSTRIES. *Annals of Spiru Haret University. Economic Series*, *19*(2), 167–175. https://doi.org/10.26458/1929

[2] Atul. (2020). *Ai vs Machine Learning vs Deep Learning.* [Online Image]. Edureka. https://www.edureka.co/blog/ai-vs-machine-learning-vs-deep-learning/.

[3] *A.I. technical - Machine Learning vs. Deep Learning*. Lawtomated. (2019, April 28). https://lawtomated.com/a-i-technical-machine-vs-deep-learning/.

[4] Alfian, G., Syafrudin, M., Farooq, U., Ma'arif, M. R., Syaekhoni, M. A., Fitriyani, N. L., Lee, J., & Rhee, J. (2020). Improving efficiency of RFID-based traceability system for perishable food by utilizing IoT sensors and machine learning model. *Food Control*, *110*, 107016.https://doi.org/10.1016/j.foodcont.2019.107016

[5] Anandan, T. M., R.I.A. (2020). Cultivating robotics and AI. Control Engineering, 67(6), M1-M2. Retrieved from http://ezproxy.lib.calpoly.edu/login?url=https://www-proquest-com.ezproxy.lib.calpoly.edu/trade-journals/cultivating-robotics-ai/docview/2415859023/se-2?accountid=10362

[6] Anitei, M., Veres, C., & Pisla, A. (2021). Research on Challenges and Prospects of Digital Agriculture. *Proceedings*, *63*(1), 67. MDPI AG. Retrieved from http://dx.doi.org/10.3390/proceedings2020063067

[7] *Artificial Intelligence (AI) - Overview, Types, Machine Learning*. Corporate Finance Institute. (n.d.). https://corporatefinanceinstitute.com/resources/knowledge/other/artificial-intelligence-ai/#:~:text=Artificial%20Intelligence%20(AI)%20is%20a,would%20otherwise%20require%20human%20intelligence.

[8] Chaganti, S. Y., Ainapur, P., Singh, M., Sangamesh, & R., S. O. (2019). Prediction Based Smart Farming. *2019 2nd International Conference of Computer and Informatics Engineering (IC2IE)*. https://doi.org/10.1109/ic2ie47452.2019.8940834

[9] Cook, Peter and O'Neill, Felicity. (2020). Artificial Intelligence in Agribusiness is Growing in Emerging Markets.

[10] Delta News Hub. (2020, January). *Nothing artificial about this intelligence: Delta's industry-first machine learning platform minimizes customer inconvenience during tough operations*. Delta News Hub. https://news.delta.com/nothing-artificial-about-intelligence-deltas-industry-first-machine-learning-platform-minimizes.

[11] Denis, N., Dilda, V., Kalouche, R., & Sabah, R. (2020, October 15). *Agriculture Supply-Chain Optimization and Value Creation*. McKinsey & Company. https://www.mckinsey.com/industries/agriculture/our-insights/agriculture-supply-chain-optimization-and-value-creation.

[12] Di Vaio, A., Boccia, F., Landriani, L., & Palladino, R. (2020). Artificial Intelligence in the Agri-Food System: Rethinking Sustainable Business Models in the COVID-19 Scenario. *Sustainability*, *12*(12), 4851. https://doi.org/10.3390/su12124851

[13] Diksha Manaware. 2020. Artificial Intelligence: A New Way to Improve Indian Agriculture. *Int.*

[14] Duckett, T., Pearson, S., Blackmore, S., & Grieve, B. Agricultural Robotics: The Future of Robotic Agriculture. (2018). UK-RAS White papers.

[15] Dolci, R. (2017). IoT Solutions for Precision Farming and Food Manufacturing: Artificial Intelligence Applications in Digital Food. *2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC)*. https://doi.org/10.1109/compsac.2017.157

[16] Hellingrath, B., & Lechtenberg, S. (2019). Applications of Artificial Intelligence in Supply Chain Management and Logistics: Focusing Onto Recognition for Supply Chain Execution. *The Art of Structuring*, 283–296. https://doi.org/10.1007/978-3-030-06234-7_27

[17] Institute of Medicine. (2013). Standardization to Enhance Data Sharing. *Sharing Clinical Research Data: Workshop Summary* (pp. 43- 55). Washington, DC: The National Academies Press. doi: 10.17226/18267.

[18] Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, *2*, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004

[19] Lin, W., Lin, M., Zhou, H., Wu, H., Li, Z., & Lin, W. (2019). The effects of chemical and organic fertilizer usage on rhizosphere soil in tea orchards. *PLOS ONE*, *14*(5). https://doi.org/10.1371/journal.pone.0217018

[20] Lakshmi, V., Corbett, J. How Artificial Intelligence Improves Agricultural Productivity and Sustainability: A Global Thematic Analysis. AI Sustain. Use AI Sustain. Initiat. 2020, 4, 10.

[21] Facts & Factors. (2021, January 12). *Global AI in Agriculture Market Size & Share Estimated to Reach USD 2,400 million by 2026: Facts & Factors*. GlobeNewswire News Room. https://www.globenewswire.com/en/news-release/2021/01/12/2156893/0/en/Global-AI-in-Agriculture-Market-Size-Share-Estimated-to-Reach-USD-2-400-million-by-2026-Facts-Factors.html.

[22] Farhadi, M., Abbaspour-Gilandeh, Y., Mahmoudi, A., & Mari Maja, J. (2020). An Integrated System of Artificial Intelligence and Signal Processing Techniques for the Sorting and Grading of Nuts. *Applied Sciences*, *10*(9), 3315. https://doi.org/10.3390/app10093315

[23] FAO. 2017. *The future of food and agriculture – Trends and challenges*. Rome. ISSN 2522-722X

[24] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

[25] Fernando, J. (2021, February 4). *Learn what stakeholders are and the roles that they play*. Investopedia. https://www.investopedia.com/terms/s/stakeholder.asp.

[26] Manaware, D. (2020). Artificial Intelligence: A New Way to Improve Indian Agriculture. *International Journal of Current Microbiology and Applied Sciences*, *9*(3), 1095–1102. https://doi.org/10.20546/ijcmas.2020.903.128

[27] Marcin, M. (n.d.). *History of Agriculture*. Resources-Light. https://www.crestcapital.com/tax/history_of_agriculture#:~:text=Humans%20invented%20agriculture%20between%207%2C000,the%20development%20of%20metal%20tools.

[28] Mathanker, S. K., Weckler, P. R., Bowser, T. J., Wang, N., & Maness, N. O. (2011). AdaBoost classifiers for pecan defect classification. *Computers and Electronics in Agriculture*, *77*(1), 60–68. https://doi.org/10.1016/j.compag.2011.03.008

[29] Goutham, R. (2020). A beginner's guide to understanding the buzz words -AI, ML, NLP, Deep Learning, Computer Vision, and Data Science. https://medium.com/swlh/a-beginners-guide-to-understanding-the-buzz-words-ai-ml-nlp-deep-learning-computer-vision-a877ee1c2cde

[30] Penning, B. W., Snelling, W. M., & Woodward-Greene, M. J. (2020). Machine Learning in the Assessment of Meat Quality. *IT Professional*, *22*(3), 39–41. https://doi.org/10.1109/mitp.2020.2986123

[31] *Precision farming: what is it and what benefits does it offer?* McCormick. (2021, January 27). https://www.mccormick.it/us/precision-farming/.

[32] Pothen, Z., & Nuske, S. (2016). Automated Assessment and Mapping of Grape Quality through Image-based Color Analysis. *IFAC-PapersOnLine*, *49*(16), 72–78. https://doi.org/10.1016/j.ifacol.2016.10.014

[33] Ren, D., & Martynenko, A. (2018). GUEST EDITORIAL: ROBOTICS AND AUTOMATION IN AGRICULTURE. *International Journal of Robotics and Automation*, *33*(3). https://doi.org/10.2316/journal.206.2018.3.206-0001

[34] Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., & Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research*, *119*, 104926. https://doi.org/10.1016/j.cor.2020.104926

[35] Smith, M. J. (2018). Getting value from artificial intelligence in agriculture. *Animal Production Science*, *60*(1), 46. https://doi.org/10.1071/an18522

[36] Spanaki, K., Karafili, E., & Despoudi, S. (2021). AI applications of data sharing in AGRICULTURE 4.0: A framework for ROLE-BASED data access control.

International Journal of Information Management, *59*, 102350.
https://doi.org/10.1016/j.ijinfomgt.2021.102350

[37] Sujatha, R., Chatterjee, J. M., Jhanjhi, N. Z., & Brohi, S. N. (2021). Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*, *80*, 103615. https://doi.org/10.1016/j.micpro.2020.103615

[39] Tzachor, A. (2020) Artificial intelligence for agricultural supply chain risk management: Constraints and potentials. CGIAR Big Data Platform

[40] Verdouw, C., & Kruize, J. W. (2017). Digital twins in farm management: illustrations from the FIWARE accelerators SmartAgriFood and Fractals. *Journal of Precision Agriculture Digital*. https://doi.org/10.5281/zenodo.893662

[41] Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021, January 28). *Digital twins in smart farming*. Agricultural Systems. https://www.sciencedirect.com/science/article/pii/S0308521X20309070

[42] Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big Data in Smart Farming – A review. *Agricultural Systems*, *153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

[43] Wongsriworaphon, A., Arnonkijpanich, B., & Pathumnakul, S. (2015). An approach based on digital image analysis to estimate the live weights of pigs in farm environments. *Computers and Electronics in Agriculture*, *115*, 26–33. https://doi.org/10.1016/j.compag.2015.05.004

[44] Young, S. (2020, January 9). *The Future of Farming: Artificial Intelligence and Agriculture*. Harvard International Review. https://hir.harvard.edu/the-future-of-farming-artificial-intelligence-and-agriculture/.

Appendices

Appendix A: *Up-Stream Artificial Intelligence Applications Reviewed in Research*

Area of Supply Chain	Targeted sector	Type of AI	Description of AI's role in the AG sector	Reference:
All areas	Tomato Crops, Greenhouse, Harvested Tomatoes, Tomato Trucks	Digital Twin - monitoring, predictive, and prescriptive	grow, harvest, and distribute tomatoes	(Verdouw et al., 2021)
All areas	All sectors	Machine Intelligence - Predictive Analysis	Predicting problems to stay efficient and meet stakeholder needs Example predicting transportation needs to avoid breakdowns then resulting in reducing the chance of failing to meet customer expectations	(ABDULL AYEVA, 2019)
All areas	Various logistics	AI Predictive data	Can be used to assist in crop pricing, insurance, reinsurance and trade finance have been factoring in production forecasts into their businesses for a long time	(ABDULL AYEVA, 2019)
All areas	Supply Chain Traceability	Digital traceability	It enables supply chain organizations to be clearer about the value derived from acquiring and using more data	(ABDULL AYEVA, 2019)
All areas	Procurement	Artificial Intelligence based platform	that offers procurement optimization and yield prediction solution for the agriculture sector	(Manaware, 2020)
All areas	All sectors	Digital Twin	Digital and analytics technologies is used to create a digital twin that replicates the physical supply chain. Allowing companies to run virtual simulations and optimizations of their supply chains	(Denis et al., 2020).
All areas	All sectors	RFID and IoT sensors	Used to track the traceability system for the perishable food supply chain. Is able to track product movement and monitor the temperature and humidity conditions of the product through out the supply chain.	(Alfian et al., 2020)
All areas	Farming	ML CropIn	Application that AG businesses upload to unstructured data and using ML algorithms the application generates real-time advice on risk management, sales, and warehousing. The application data can also create credit risk assessments for access to finance, and for supply chain traceability and quality control.	(Cook, 2020)
All areas	Milk Supply Chain	Stellapps - AI digital platform using machine	A digital platform that collects data and monitors milk production at all various levels. Helps companies achieve traceability and quality assurance.	(Cook, 2020)

		learning algorithm		
All areas	Supply Chain Traceability	Deep AI algorithms (convolutional neural networks)	Intello Labs' technology system uses deep AI algorithms (convolutional neural networks) to track the movement of product through out the supply chain.	(Cook, 2020)
Up-stream	Irrigation Management	Automation	self-managing irrigation	(ABDULL AYEVA, 2019)
Up-stream	Malt Crops	Digital Twin	Digital twin operates in a Malthouse analyses the correlation of the different input and output variables to make predictions and increase alcohol content in the malt	(Dolci, 2017)
Up-stream	Soil and Crops	Radar (GPR) imaging techniques and fuzzy neural network (FNN)	The radar imaging techniques help to find the correlations between soil characteristics and planting crop varieties.	(Ren & Martynenk o, 2018)
Up-Stream	Potato Crops	Real AdaBoost algorithm for potato defect classification	The algorithm was able to detect defects in potato classifications with high accuracy rates.	(Mathanker et al., 2011)
Up-Stream	Irrigation Management	ML algorithms	The algorithms analyze the soil moisture and provide adequate irrigation strategies depending on the crop, soil types, and environmental conditions. Using data collected from the algorithms, the machine able to make predictions that help preserve water and increase output.	(Lakshmi, V. 2020)
Up-Stream	Grape crop	Neural Network and sensors	An AI system developed to predicted grape disease beforehand. The systemused various sensors the would send the gathered data to the system database. From there the data with a Wireless System Network (WSN) was able to detected upcoming diseases in the grapes.	(Jha et al., 2019)
Up-Stream	Irrigation Management	Neural Network ANN model	This model was used to estimate soil moisture Paddy fields.	(Jha et al., 2019)
Up-Stream	Mango and Cassava Crops	Artificial neural networks	The system worked to identify the dryness in the given fruits. Allowing farmers to determine better management needs	(Jha et al., 2019)
Up-Stream	Wheat	Image processing	The system utilizes two machine algorithms SVM and neural networks to be able to classify different wheat variations.	(Jha et al., 2019)

Up-Stream	Farmers	Language translation Chat Boxes	Language translation AI can deliver to farm workers the information they want in the language that works best for them	(Smith, 2018)
Up-Stream	Farmers	Stellapps - AI digital platform using machine learning algorithm	The technology provides a credit score rating of their personal data and cow data (health, nutrition, fraud proofing). The credit score helps farmers work with lenders get loans and other financing help	(Cook, 2020)
Up-Stream	Milking Animals	AG robotics	EU foresight study predicts that around 50% of all European herds will be milked by robots by 2025	(Duckett, 2018)
Up-Stream	Livestock	autonomously monitoring	For livestock and collecting field data	(Duckett, 2018)
Up-Stream	Crop monitoring	data fusion and SLAM techniques Multispectral Imaging (MSI) data	Using both land-based and aerial platforms accurately added to the management of crops using data fusion and SLAM techniques Long-term data collection will further enable the modelling of crops over time, for example, tracking the development of the crop canopy, and thus improved prediction of future growth patterns	(Duckett, 2018)
Up-Stream	Crop monitoring	Machine Vision	Phenotyping, classifying when individual plants are ready for harvest, and quality analysis	(Duckett, 2018)
Up-Stream	Animal Monitoring	Machine Vision	animal monitoring, e.g. for weight estimation, body condition monitoring and illness detection in pigs, cattle and poultry.	(Duckett, 2018)
Up-Stream	Animal Monitoring	Machine Vision	Individual animal identification allows for more targeted precision care and timely interventions for individual animals. Helping improve animals health and optimize farm production	(Duckett, 2018)
Up-stream	Vegetation	Bio-Remotely Sensed imagery	Help to measure the plant's stress, moisture content, and stage of the growing cycle, health, spatial variability from the soil or irrigation systems, leaf density, crop height, and other factors of overall crop health	(Chaganti et al., 2019)
Up-stream	Soil	Soil Moisture Sensors	Measures the moisture content of the soil and pH sensor probe which measures the pH content of the soil Can help to manually predict which crops can grow in what soil	(Chaganti et al., 2019)
Up-stream	Potato Crops	Digital Twin - monitoring, predictive, and prescriptive	grow and harvest potatoes	(Verdouw et al., 2021)

Up-stream	Cow, heard	Digital Twin - monitoring and predictive	milk production	(Verdouw et al., 2021)
Up-stream	Weeds, lettuce crops, field, weeding machine, harvested lettuce	Digital Twin - monitoring, predictive, prescriptive, and recollection	grow and harvest lettuce	(Verdouw et al., 2021)
Up-stream	Pig, farm, slaughterhouse	Digital Twins - monitoring and predictive	fatten and slaughter pigs	(Verdouw et al., 2021)
Up-stream	Irrigation Management	Machine Learning	Irrigation scheduling and management cater to the spatial assessment of when, where, and how much to irrigate	(Sharma et al., 2020)
Up-stream	Weather Prediction	Machine Learning	The weather forecasts such as sunlight, rainfall, humidity, and moisture guide the optimal use of water for crop irrigation scheduling and planning	(Sharma et al., 2020)
Up-stream	Weed Detection	Machine Learning with machine vision	Used for weeds removal. Weeds have distinct spectral reflectance that is different from regular crops. ML algorithms uses color, texture, and shape features in crops to compare to the weeds. Early detection of Weeds reduces the usage of weedicides and enhances agricultural sustainability	(Sharma et al., 2020)
Up-stream	Crop Health	Machine Learning with machine vision	Works to protect crops by identifying early and diagnosing biotic stress factors and abiotic stress factors	(Sharma et al., 2020)
Up-stream	Livestock Management	Machine Learning Algorithms	Monitors animal welfare, animal behavior tracking, and livestock production helping the farmers in evidence-based decision-making focused on real-time data monitoring and information systems	(Sharma et al., 2020)
Up-Stream	Fruits, Vegetables, etc.	Disease detection and diagnosis using Artificial neural		(Ferentinos, 2018)
Up-Stream	Crops	"aWhere" Predictive Analysis	Uses machine learning along with satellites to predict weather and to check whether the crop has disease. Also through ML algorithms predictions can be made about various environmental impacts to crop yields	(ABDULLAYEVA, 2019)
Up-Stream	Cotton	AG robotics	Blue River Technologies developed "See & Spray" which monitors and sprays weed on cotton plants	(ABDULLAYEVA, 2019)
Up-Stream	Harvesting, Planting, Seeding	AG robotics	Robots can preform these tasks that would otherwise require human labor efforts	(ABDULLAYEVA, 2019)

Up-Stream	Livestock	AI sensors	Movement sensors and other devices that report on the behaviors, health and conditions of livestock these devices can be placed or even inserted in the farm animals	(ABDULL AYEVA, 2019)
Up-Stream	Farmers	Artificial narrow intelligence (ANI) - Language translation	AI can deliver to farm workers the information they want in the language that works best for them. This extremely helpful in creating an efficient SC as the AG industry is international language barriers can occur.	(ABDULL AYEVA, 2019)
Up-Stream	Farmers	Digital Assistants (AI algorithms to translate and extract knowledge)	Can also be used to help with capturing information from farmers and farm workers - such as spoken instructions, requests, observations or even measurements	(ABDULL AYEVA, 2019)
Up-Stream	Farmers	Chat-bots Artificial narrow intelligence (ANI)	Help farmers to receive the information they need	(ABDULL AYEVA, 2019)
Up-Stream	Various "Growth Forecasts"	Machine Intelligence - Predictive Analysis	Real time forecasts of crop or animal status as they develop: factors such as size, development stage and nutritional status. Such a capability would enable farmers to optimize their activities.	(ABDULL AYEVA, 2019)
Up-Stream	Farm	Automation	driverless farm vehicles	(ABDULL AYEVA, 2019)
Up-Stream	Planting	Automation	variable application rate planters	(ABDULL AYEVA, 2019)
Up-Stream	Pest and Weed management	Automation	precision spraying, precision picking	(ABDULL AYEVA, 2019)
Up-Stream	Cow	Digital Twin	Can help to determine the probability of cattle	(ABDULL AYEVA, 2019)
Up-Stream	Crop Health Monitoring	AI technologies using high resolution weather data, remote sensing data, and an AI platform	Assessment of the health of the crop as well as early detection of crop infestations is critical to ensuring good cultural productivity. Ai can be used to predict advisories for crops	(Manaware, 2020)
Up-Stream	Sowing (planting seeds)	Cloud-based predictive analytics	ICRISAT developed a sowing application for farmers to advise them on the best time to sow crops depending on weather conditions, soil and other indicators	(Manaware, 2020)

Up-Stream	Soil Health Monitoring	Deep Learning Models	Image recognition and deep learning models have enabled distributed soil health monitoring without the need of laboratory testing infrastructure. Helps farmers to take immediate possible action to restore the soil health	(Manaware, 2020)
Up-Stream	Soil Monitoring - Soilsens	AI sensors	The system is embedded with soil moisture sensor, soil temperature sensor, ambient humidity sensor and ambient temperature sensor. Based on this parameters, farmers are advised about optimum irrigation through a mobile app. The system can also help to avoid over irrigation	(Manaware, 2020)
Up-Stream	Plant Health - Plantix app	Deep Learning Application	Berlin-based agricultural tech startup PEAT has developed a deep learning application called plantix that identifies potential defects and nutrient deficiencies in soil. The app uses images to detect plant diseases and other possible defects through images captured by the user's smart phone camera. It is also offers corresponding treatment measures.	(Manaware, 2020)
Up-Stream	Farming	Drones	Equipped with multi-spectral and photo cameras that can monitor crop stress, plant growth and predict yield	(Manaware, 2020)
Up-Stream	Planting	Robot Drone Tractor	Robot will decide where to plant, when to harvest and how to choose the best route for crisscrossing the farmland. These robots are to reduce the usage of pesticides, herbicides, fertilizers and water.	(Manaware, 2020)
Up-Stream	Weather Forecasting	AI and satellite data	AI in farming along with the satellite data can be used to predict the weather conditions analyze the crop sustainability and evaluate the farms for the presences of pests and diseases	(Manaware, 2020)
Up-Stream	Pig weighing	Machine vision and supervised learning algorithms	This AI technology is a new approach to weighing pigs and can be used for other livestock without disturbing the animals and inducing stress	(Wongsriworaphon et al., 2015)
Up-Stream	Grape evaluation	Computer vision system	The system uses color image analysis grades and predict the color development of grape clusters in a vineyard	(Pothen & Nuske, 2016)
Up-Stream	Plant leaf disease detection	ML and DL systems	Research aimed to classify citrus leaf disease using both ML and DL methods. The AI systems were able to predict the type of disease, helping to take action before the plant infection worsens.	(Sujatha et al., 2021)

Up-Stream	Dairy	Digital Twin	Company Connecterra creates Digital Twins of cows that are used to remotely monitor cows. The twin monitors the cows' health and behavior.	(Verdouw & Kruize, 2017)
Up-Stream	Crops	Digital Twin	Application that farmers upload photo and a problem description of the plant and the application forms a Digital Twin of the plant. The twin provides insight to identifying disease.	(Verdouw & Kruize, 2017)
Up-Stream	Farm equipment	Digital Twin	FarmTelemetry creates Digital Twins for machinery and based on the digital twins, machinery is monitored in real time and provides detailed information on the machines and the fields.	(Verdouw & Kruize, 2017)
Up-Stream	Livestock	Digital Twin	INSYLO is an application that uses a digital twin to remotely monitor the the silos of the livestock farms and optimize the replenishment routes	(Verdouw & Kruize, 2017)
Up-Stream	Pest Control	Digital Twin with automated imaging	The application OliFLY uses automated imaging and a digital to inform farmers in real time of the olive fly (a unwanted pest) population growth, resulting in effective and optimal use of pesticides	(Verdouw & Kruize, 2017)
Up-Stream	Livestock	Digital Twin	BeeZon is a digital twin application that replicates bee colonies, allowing beekeepers to remote monitor and control the colonies	(Verdouw & Kruize, 2017)
Up-Stream	Harvesting	Robotics and Computer Vision	A robotic harvesting system that utilizes computer vision and custom end-of-arm tools allowing for grasping and extraction of produce	(Anadan, 2020)

Appendix B: *Mid-Stream Artificial Intelligence Applications Reviewed in Research*

Area of Supply Chain	Targeted sector	Type of AI	Description of AI's role in the AG sector	Reference:
All areas	Tomato Crops, Greenhouse, Harvested Tomatoes, Tomato Trucks	Digital Twin - monitoring, predictive, and prescriptive	grow, harvest, and distribute tomatoes	(Verdouw et al., 2021)
All areas	All sectors	Machine Intelligence - Predictive Analysis	Predicting problems to stay efficient and meet stakeholder needs Example predicting transportation needs to avoid breakdowns then resulting in reducing the chance of failing to meet customer expectations	(ABDULLA YEVA, 2019)
All areas	Various logistics	AI Predictive data	Can be used to assist in crop pricing, insurance, reinsurance and trade finance have been factoring in production forecasts into their businesses for a long time	(ABDULLA YEVA, 2019)
All areas	Supply Chain Traceability	Digital traceability	It enables supply chain organizations to be clearer about the value derived from acquiring and using more data	(ABDULLA YEVA, 2019)
All areas	Procurement	Artificial Intelligence based platform	that offers procurement optimization and yield prediction solution for the agriculture sector	(Manaware, 2020)
All areas	All sectors	Digital Twin	Digital and analytics technologies is used to create a digital twin that replicates the physical supply chain. Allowing companies to run virtual simulations and optimizations of their supply chains	(Denis et al., 2020).
All areas	All sectors	RFID and IoT sensors	Used to track the traceability system for the perishable food supply chain. Is able to track product movement and monitor the temperature and humidity conditions of the product through out the supply chain.	(Alfian et al., 2020)
All areas	Farming	ML CropIn	Application that AG businesses upload to unstructured data and using ML algorithms the application generates real-time advice on risk management, sales, and warehousing. The application data can also create credit risk assessments for access to finance, and for supply chain traceability and quality control.	(Cook, 2020)
All areas	Milk Supply Chain	Stellapps - AI digital platform using machine learning algorithm	A digital platform that collects data and monitors milk production at all various levels. Helps companies achieve traceability and quality assurance.	(Cook, 2020)

All areas	Supply Chain Traceability	Deep AI algorithms (convolutional neural networks)	Intello Labs' technology system uses deep AI algorithms (convolutional neural networks) to track the movement of product through out the supply chain.	(Cook, 2020)
Mid-stream and Down-Stream	Transportation	Machine Learning Algorithms	Genetic algorithm and focused on vehicle routing, minimizing the product damage, travel distance, and preserving the product quality	(Sharma et al., 2020)
Mid-stream and Down-Stream	Transportation	Autonomous vehicles	Driverless cars. Would save labor costs	(ABDULLAYEVA, 2019)
Mid-stream	Warehouse	Autonomous Robots	Bin Picking: Robots are trained to recognize what they are picking up. Using a ML algorithm they are trained with example images and detects objects based on a 3D sensor	(Hellingrath & Lechtenberg, 2019)
Mid-stream	Warehouse	Autonomous Robots	Automatic unloading	(Hellingrath & Lechtenberg, 2019)
Mid-stream	Operations - Incoming inventory	Neural Network	Supports the delivery of mails and parcels for high inventory places This AI form is capable of extracting individual fields from an address in raw text format and provide a standardized representation the automatic	(Hellingrath & Lechtenberg, 2019)
Mid-stream	Operations - Manufacturing	Neural Network	Works to detect parts to be used for remanufacturing: recognizes what parts can be used again and what parts can no longer be used	(Hellingrath & Lechtenberg, 2019)
Mid-stream	Operations - Incoming inventory	Radiography images with deep learning Neural Network	Analyzes the list of goods the container should have to Radiography images taken of the container, can defect and inform users if the container is inconsistent to it's list of containments	(Hellingrath & Lechtenberg, 2019)
Mid-stream	Demand Managenment	Machine Learning Algorithms	Precise demand prediction of food requirements helps to avoid overstocking, overproduction, and overutilization of re-sources	(Sharma et al., 2020)
Mid-stream	Production Planning	Machine Learning Algorithms	ML algorithms help inefficient production planning through the reduction of setup time and better demand sensing	(Sharma et al., 2020)
Mid-stream	Nut sorting and grading	Artificial Neural Networks	A device that sorts and grades nuts. The device is a mechanical system operated by a rolling distributor machine and an electrical system integrating audio signal processing and a neural network. System has an overall accuracy of 92.8%	(Farhadi et al., 2020)
Mid-stream	Packaging	Automation	smart processing and packing systems	(ABDULLAYEVA, 2019)

Mid-stream	Food Sorting	Optical sensors with machine learning capabilities	TOMRA Sorting Food currently one of the most advanced AI applications in the food industry. The machine uses cameras and sensors to visualize food in the same way that consumers do. Companies can set different requirements for the food. Saves time and money during production and improves the quality of the product	(Di Vaio et al., 2020)

Appendix C: *Down-Stream Artificial Intelligence Applications Reviewed in Research*

Area of Supply Chain	Targeted sector	Type of AI	Description of AI's role in the AG sector	Reference:
All areas	Tomato Crops, Greenhouse, Harvested Tomatoes, Tomato Trucks	Digital Twin - monitoring, predictive, and prescriptive	grow, harvest, and distribute tomatoes	(Verdouw et al., 2021)
All areas	All sectors	Machine Intelligence - Predictive Analysis	Predicting problems to stay efficient and meet stakeholder needs Example predicting transportation needs to avoid breakdowns then resulting in reducing the chance of failing to meet customer expectations	(ABDULLAYEVA, 2019)
All areas	Various logistics	AI Predictive data	Can be used to assist in crop pricing, insurance, reinsurance and trade finance have been factoring in production forecasts into their businesses for a long time	(ABDULLAYEVA, 2019)
All areas	Supply Chain Traceability	Digital traceability	It enables supply chain organizations to be clearer about the value derived from acquiring and using more data	(ABDULLAYEVA, 2019)
All areas	Procurement	Artificial Intelligence based platform	that offers procurement optimization and yield prediction solution for the agriculture sector	(Manaware, 2020)
All areas	All sectors	Digital Twin	Digital and analytics technologies is used to create a digital twin that replicates the physical supply chain. Allowing companies to run virtual simulations and optimizations of their supply chains	(Denis et al., 2020).
All areas	All sectors	RFID and IoT sensors	Used to track the traceability system for the perishable food supply chain. Is able to track product movement and monitor the temperature and humidity conditions of the product through out the supply chain.	(Alfian et al., 2020)

All areas	Farming	ML CropIn	Application that AG businesses upload to unstructured data and using ML algorithms the application generates real-time advice on risk management, sales, and warehousing. The application data can also create credit risk assessments for access to finance, and for supply chain traceability and quality control.	(Cook, 2020)
All areas	Milk Supply Chain	Stellapps - AI digital platform using machine learning algorithm	A digital platform that collects data and monitors milk production at all various levels. Helps companies achieve traceability and quality assurance.	(Cook, 2020)
All areas	Supply Chain Traceability	Deep AI algorithms (convolutional neural networks)	Intello Labs' technology system uses deep AI algorithms (convolutional neural networks) to track the movement of product through out the supply chain.	(Cook, 2020)
Down-Stream (and mid-stream)	Transportation	Machine Learning Algorithms	Genetic algorithm and focused on vehicle routing, minimizing the product damage, travel distance, and preserving the product quality	(Sharma et al., 2020)
Down-Stream (and mid-stream)	Transportation	Autonomous vehicles	Driverless cars. Would save labor costs	(ABDULLAYEVA, 2019)
Down-stream	Consumer Analysis	Machine Learning (deep learning and ANN)	Used in food retailing to predict consumer demand, perception, and buying behavior	(Sharma et al., 2020)
Down-stream	Supply Demand Optimization	AI deep learning	Help processors, retailers and wholesalers better forecast their consumption and what is likely to sell. Could create major efficiency savings ensuring that the supply matches demand, mitigating waste	(ABDULLAYEVA, 2019)

Down-stream	Food Safety at retail	Machine Learning with machine vision	An application that uses cameras to monitor workers and uses facial recognition and object recognition software, that determines whether workers are in proper attrite according to food safety laws.	(Di Vaio et al., 2020)