An Overview of AI Development and Its Location Relationship in Agricultural Supply Chains

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***Abstract*—The paper explores artificial intelligence (AI) in agricultural (Ag) supply chains (SCs) and presents a new typology to understand AI-based solutions in Ag SCs. Previous research has not focused on examining the connection between the drive to integrate AI technology and where the SC's AI is being integrated. A literature review approach was adopted and follows a series of different analyses. Using the findings from the analyses, the authors propose a typology created on the foundation of two dynamics, the location of AI applications in Ag SCs and the driving values to integrate the AI applications. The typology is presented in the form of a granular numeric scale; the typology aims to create a tool of measurement to infer AI technology's relation in the Ag SC and create a new viewpoint to investigate and provide insights for predictions of AI's future in Ag SCs. In addition, the new typology should aid Ag firms in understanding and capturing potential synergies stemming from the driving values of innovation. The authors found that AI applications with a strong relationship in SC provide the greatest beneficiary relationship between technology value creation and SC logistics. Furthermore, AI applications will have the strongest relationship and implementation when operating in collaboration with other SC locations and AI integrated firms.**

***Index Terms*—Artificial intelligence, agricultural supply chains, innovation creation**

I. Introduction

The agricultural (Ag) industry is a crucial division in sustaining everyday human activities. Ag practices have changed throughout history 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. However, even with advancements to the Ag industry, the industry still remains vulnerable to impending dangers.

Today Ag SCs face approaching challenges of food scarcity, depletion of recourses, and climate change. Ag SCs encounter increasingly demanding environments. However, AI technology provides opportunities for Ag businesses to enhance their SCs and meet market demands. Integration of AI can help improve Ag productivity and work as an indirect mechanism to empower farmers to make informed decisions [1]. While AI applications are not a new notion, it is still an emerging solution and foreign to many working in Ag.

The unfamiliarity of AI for Ag industry stakeholders can be connected to the lack of study of AI-related to Ag SCs. AI alone has received extensive attention from researchers, but AI and its impacts on Ag SCs have not received the same attention. The study of the adoption and diffusion of AI technology is just in the beginning stages [1]. The Ag industry is unlike other traditional industries and faces unique risks and regulations that other industries are not confronted with. 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 [2].

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. 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 agriculture's different layers and intricate features.

Similar work of AI implementation in other industries can be found in the journal *Application of machine learning and artificial intelligence in the oil and gas industry* [3], where authors analyzed AI implementation dynamics in the oil and gas industry. The study's authors reviewed artificial intelligence applications and limitations in various supply chain sectors of the oil and gas industry. They found that creating an intelligent SC system through AI integration could work to eliminate the risks and maintenance costs for the oil and gas industry [3]. Additionally, another research study from *Artificial intelligence (AI)-enhanced medical drones in the healthcare supply chain (HSC) for sustainability development* [4] was conducted assessing the opportunities of AI implementation in the healthcare industry. Researchers found that executing AI-enhanced medical drone applications in healthcare SC shows promise to improve the public's social and economic lives and would work to contribute to the long-term corporate sustainability of the healthcare industry [4].

Motivated by the need of innovation in the Ag industry and the opportunities AI technology presents, the focus of this study was directed towards reviewing the AI's location dynamics in the Ag SC and the value received from the integration of the AI applications. To further understand the relationship between AI technology and Ag SCs, the authors of this study searched to find a connection between the location of the SC the impact of the AI technology. The authors guided their search and scope of their work by the following three questions:

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

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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?

Artificial intelligence technology provides opportunities for agriculture businesses to enhance their SCs and meet market demands as threats to the industry increase Ag businesses look to advancements to mitigate and prevent threats to their supply chains. This overview aimed to answer many questions that the Ag industry has regarding how AI can improve the supply chain.

II. Methodology

The authors in this work utilized an integrative literature review, explicitly focusing on analyzing published papers with an unbiased examination of AI in Ag SCs. The beginning research stage search centered on finding articles containing the keywords "AI in Ag SCs". Publications found in the beginning explorations introduced broad ideas of AI and its capabilities related to Ag. Fig. 1 below outlines the framework of the literature review process of this study including an established criterion questionnaire, guiding questions, and keywords utilized in the literature collection process.

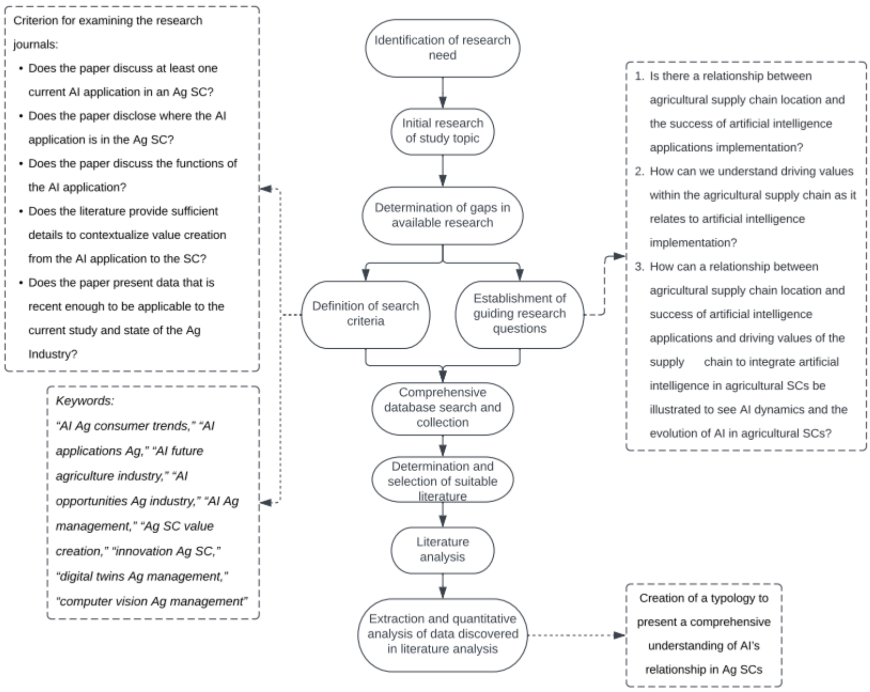


Fig. 1. Framework for literature review.

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 Ag SCs and why the AI applications are being integrated.

After establishing this gap in the current research, the literature review directed attention to collecting secondary data from papers that reviewed existing AI applications operating in various locations in Ag SCs. The review's objective was to find 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 "AI in Ag SCs" was exhausted, the paper proceeded using different search terms to widen the exploration and collect more data to find AI applications in the Ag industry.

Throughout the entirety of the literature review, eighty-five papers were examined. The eighty-five papers were scrutinized to determine if viable to use for data collection of AI applications in Ag SCs. From the original eighty-five reviewed research papers, thirty research papers were determined to contain the necessary information. The publication dates of the research papers range from 2015 to 2022.

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, it was discovered that existing research primarily concentrates on AI in the early stages of Ag SCs.

When adjusting the search to examine other SC 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 SC.

The data was evaluated and critiqued using different quantitative analysis techniques following the secondary data collection phase with an integrative literature review approach. 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 the 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 Ag SCs.

III. Literature Review and Analysis for AI Location and Driving Values in AG SC

The authors in this study reviewed eighty-five papers, and the research focused on collecting information on current AI applications operating in various Ag SCs. From the original reviewed eighty-five papers, thirty papers were identified discussing current AI in Ag SCs. From the thirty research papers, 112 AI applications were distinguished. The applications uncovered in the research review are in current use in various Ag SCs. The SCs that were reviewed varied in locations globally. Please reference Appendices A, B, and C to find complete lists of AI applications cited in this paper 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 SC. The second perimeter focused on researching the motivations influencing Ag businesses to integrate the AI applications into the SC.

A. *Agriculture Supply Chain Location Review*

The review analysis breakdowns the Ag SC 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 down-stream sector's operations include distribution/trade, retail/e-commerce, food safety, and consumer consumption. Fig. 2 below outlines some key processes in each division of a standard Ag SC.

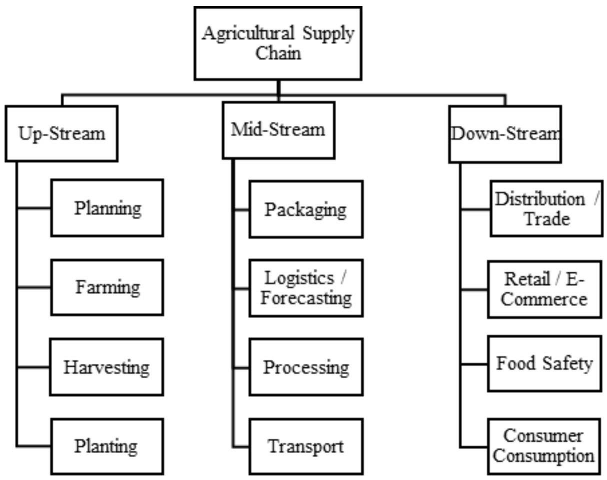


Fig. 2. Agriculture supply chain divisions.

After defining the three SC locations, the 112 AI applications identified in the research review were sorted into their respective locations. The location was determined by the position at which the AI application operates in the SC. Eighty-seven applications were observed operating in the up-stream processes, thirty-three in the mid-stream, and nineteen in the down-stream. Fifteen of the AI applications were found conducting operations in multiple areas of the SC. These results actively prove that the AI application has operating control in multiple sectors. Twelve applications were found operating in all three locations up-stream, mid-stream, and down-stream, and three applications were found operating in both the mid-stream and down-stream. Fig. 3 below depicts the locations at which the AI applications were supporting and performing operational functions. In Fig. 3, applications that were found in various locations were counted in each location that the technology was conducting operations.

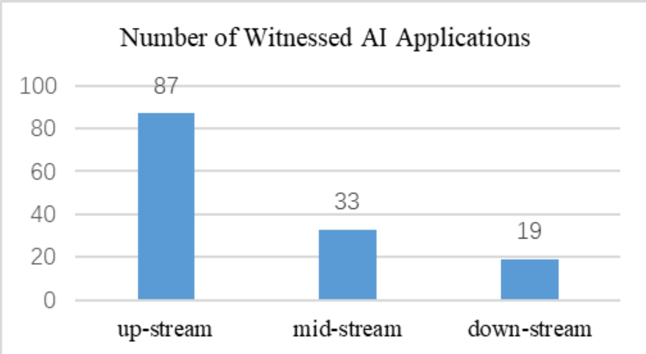


Fig. 3. Locations that witness AI application support.

The intention of the literature review was 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 Ag SCs. The literature review revealed that the least explored area of AI application in Ag 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 Ag activity, as operations in the down-stream of the Ag SC can overlap with other various industries. Another potential factor that could lead to this research gap is that generally when discussing Ag, 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 Ag processes and involve multiple parameters that require modeling, planning, and control.

In Ag SCs, the up-stream sector generally contains the majority of activities and operations performed in the SC. The down-stream and mid-stream sectors are often found to perform fewer activities, but they are almost equal in the number of activities and processes they serve in the SC. With this knowledge, our researchers were not surprised that the up-stream had received more publication attention than the down-stream and mid-stream. However, our researchers were surprised to discover that the down-stream literature was notably disproportionate to its mid-stream counterpart.

B. Values of Artificial Intelligence Applications

The next analysis 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 Ag SCs could be separated into two main innovation-driving categories, operation-oriented values and customer-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. Whereas in the customer-oriented values category, the attention is on innovating the SC technology to benefit the consumers' experience. Customer values focus on product safety, SC transparency, consumer wants, and market prediction. With the two categories established, the AI applications were inspected to determine what driving innovation value stems from integrating the AI technology into Ag SCs. Fig. 4 illustrates the findings from categorizing the AI applications by their primary innovation driving value. From the 112 reviewed applications, 106 observe operation-oriented values, and nine observe customer-oriented values. In addition, three applications were cited having both operation-oriented and customer-oriented innovation value drivers.

It was observed that the majority of the examined AI are driven by operation-oriented values. Based on this observation it can be suggested that the AI applications in the SCs predominantly focus on improving operations within the SC.

Next, the study observed the AI applications in their respective locations in the SC to determine each SC location's value drivers of innovation. Defining the main innovation drivers of each location provided additional insight into the SC's desires and needs. The study sought to develop a comprehensive understanding of each SC location's driving innovation value category, as this knowledge can help spearhead further discoveries outside of this dimension.

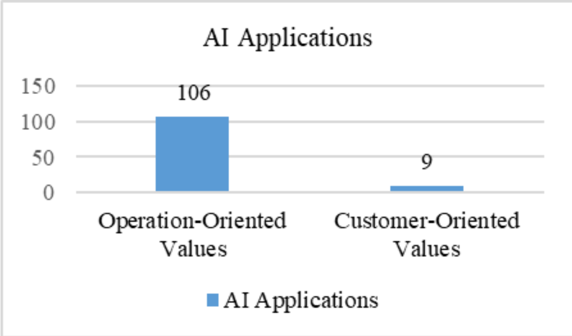


Fig. 4. AI Applications from literature research's driving innovation values.

Fig. 5 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. In the up-stream location, the primary innovation driving value comes from operation-oriented values. The up-stream found 94.4% of AI applications had operation-oriented values and 5.56% had customer-oriented values. In the mid-stream 84.85% of AI applications had operation-oriented values, and 15.15% had customer-oriented values. Finally, the downstream location observed the AI applications having a precise spilt of 52.63% operation-oriented and 47.37% customer-oriented values.

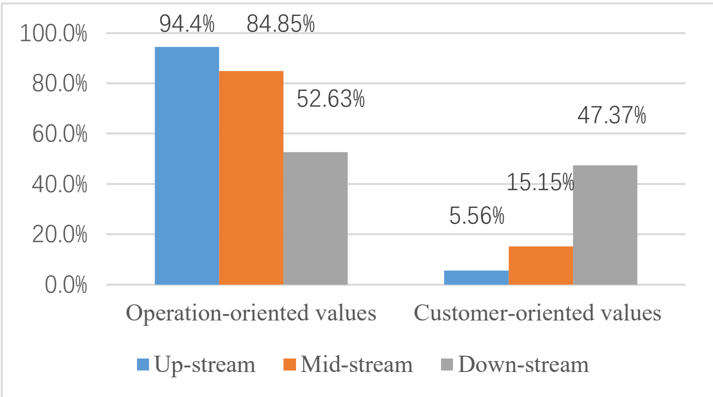


Fig. 5. Innovation drivers vs location.

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 Ag 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 Ag 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 Ag SC. Definitions of value-added activities and attributes are provided in Table I below. The values were defined based on how Ag SCs profit from the value addition. Additionally, Table I shares and expresses the value-added activities' associated innovation driving value category.

TABLE I: AG SC VALUE DEFINITIONS

Innovation Driving Category	Value-Added Attributes	Definitions of Value-Added Attributes
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 [5], detect and inform users if a product container is inconsistent in a warehouse with radiography images [6], and automatically sort and grade food [7]
	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 [8].
	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

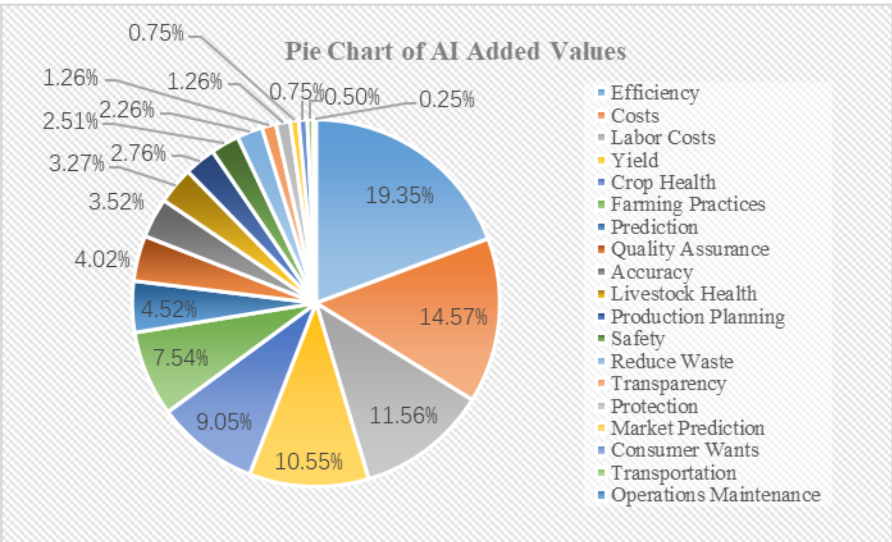


Fig. 6. Pie Chart of values from AI applications.

After the final determination of the added values, the pie chart found in Fig. 6 was created to illustrate the different added values and their frequencies, data collected from all the AI applications from every location in the SC. The pie chart highlights that over half of all witnessed values in AI applications come from just four values, including efficiency, costs, yield, and labor costs.

From this finding, it can be inferred that efficiency, costs, yield, and labor costs are the most widely observed value-added contributions from AI innovation into Ag SCs. Consequently, it can be anticipated that stakeholders are integrating AI applications into Ag SCs to improve and address problems correlated to efficiency, costs, yield, and labor costs.

Conversely, the pie chart concluded that AI applications' least commonly exhibited values are operations maintenance, transportation, consumer wants, and market prediction. Reviewing the lowest frequency added values, it was unexpected to our researchers that consumer wants and market prediction were some of the least observed value additions. These values are very fruitful to the success of many AG SCs, and these values are heavily utilized in demand and forecast planning, which works to determine supply chain production. With this knowledge, our researchers hypothesize that these values are still very impactful to the SC and the applications that have these values extend their impact across the supply chain.

Due to the various Ag SC locations all performing different operational tasks, it was determined that to fully understand the added-values from the AI applications, the values needed to be analyzed in the respected Ag SC locations. Through observing the application's values in their respective SC locations, the paper hopes to infer if any differences in value-additions exist across the SC locations.

1) Up-stream values of artificial intelligence applications

The pie chart found in Fig. 7 below represents the up-stream Ag SCs driving values from AI applications. The operational activities in this area focus primarily on farming, raw material sourcing, managing crops, and livestock. Consequently, it was anticipated that the main added values from innovation would be operations-oriented, focusing mainly on improving operation-based activities.

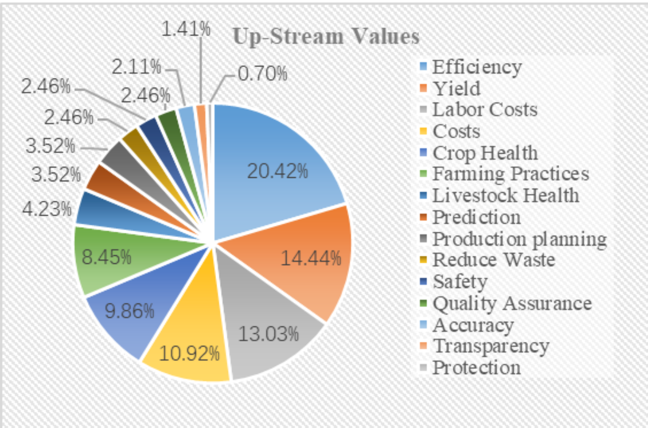


Fig. 7. Up-stream values pie chart.

Fig. 7 highlights that in the up-stream location of the SC, the main added values from the AI applications are *efficiency*, *yield*, *labor costs*, and *costs*. Efficiency, costs, and yield alone made up 47.89% of all the witnessed added values from AI integration in the Up-Stream location of Ag SCs. Conversely, the three least witnessed added values are *protection*, *transparency*, and *accuracy*. In conclusion, it was determined that the upstream SC sector is currently focused on finding 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*. 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.

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 AG SC, 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 Fig. 8. The pie chart shares the main findings of added values: *efficiency*, *quality assurance*, *costs*, and *labor costs*. Those top four values account for 59.38% of all added values to the SC from the AI technology.

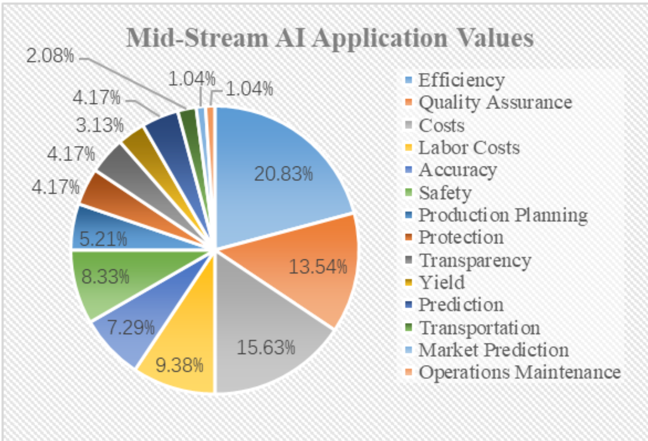


Fig. 8. Mid-stream values pie chart.

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. Instead, the AI applications in the mid-stream of the Ag SC administer to optimize operational efficiency, increase quality assurance, and lower operational and labor costs.

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 Fig. 9 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 *efficiency*, *quality assurance*, *transparency*, and *safety*. Quality assurance, transparency, and safety are all customer-oriented innovation driving values. 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.

The down-stream location of Ag 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.

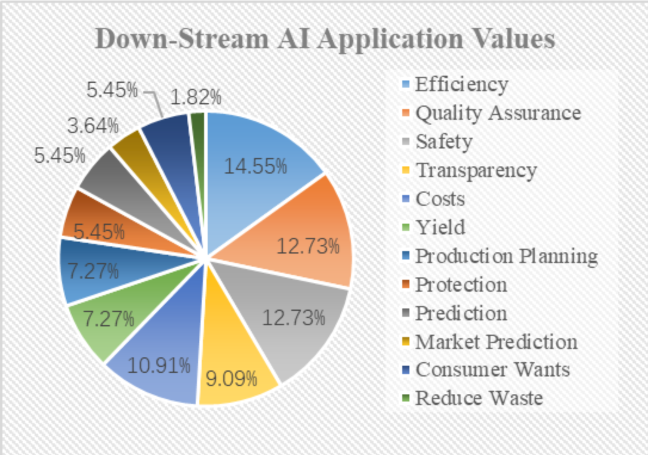


Fig. 9. Pie Chart down-stream ai added values.

IV. Agricultural Supply Chains - Artificial Intelligence Relationship Typology

The typology concept is customarily utilized to represent complicated and interrelated relationships among many variables while avoiding oversimplification [9]. Other studies have employed typologies to create a framework and classification system to describe a phenomenon. In a similar study analyzing digitalizing the global agricultural system, authors constructed a landscape 2×2 map typology to understand the implementation pathways of developing a smart farming world [10]. The researchers found that the typology led to their discovery of four potential business models and uncovered latent problems associated with utilizing a digitalized supply chain, such as issues of ownership, data control, and cyberattacks.

Insights from the presented analysis of the location versus values of AI implementation dynamics in Ag SC lead to developing a proposed typology. The typology aims at capturing such dynamics through identifying and defining two main innovation dimensions that support the development of AI in Ag SC. These dimensions are the driving *values* and the *innovation's relationship* in the Ag SC. The typology proposed exclusively attempts to capture and compare the dynamics of the added value from AI innovation to its location in Ag SCs. The framework of the typology uses a sliding measurement scale to survey the depth of AI application through a scale displayed in Table II. The scale was created to measure the depth of AI applications and distinguish the application's relationship to the Ag 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 Ag SC do not embrace the AI application's innovation and value. Other Ag 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 Ag 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 Ag SC operations and locations helping other areas to design their operations strategically.

The *Depth Rating Scale* found in Table II 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 II helps to capture and provide visual explanation for the typology.

TABLE II: Typology – 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-stream)
8	Extremely Deep	Greatly assists the entirety of the supply chain

The AI applications as whole with their Ag SC 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 AI applications within the context of their given study enables us to study and clearly understand the AI applications impact and depth in respect to the *Depth Rating Scale*. After completing the depth assessment, the chart found in Fig. 10 below was created to highlight the findings from the assessment. The bar chart visualizes the frequencies of each depth measurement found from the reviewed 112 AI applications.

From Fig. 10, it can be 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 Ag SC.

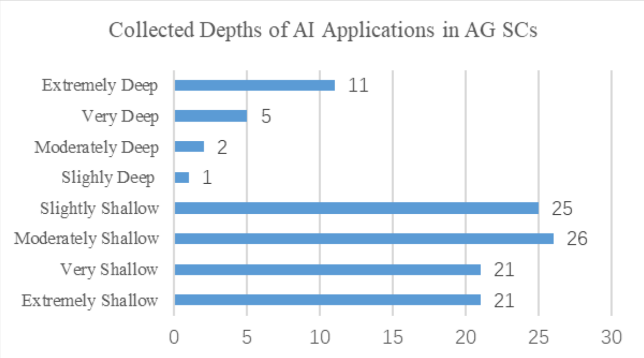
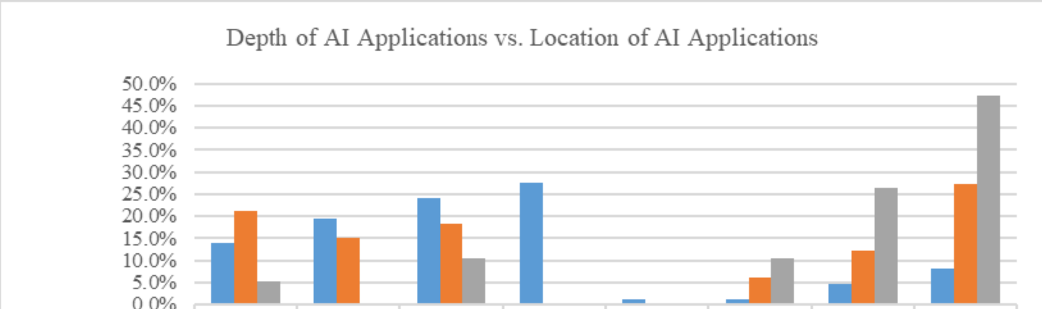


Fig. 10. Collected depths of AI applications in Ag SCs.

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 Ag 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 depths of slightly deep, moderately deep, and very deep should have been detected more as these ranges require less of a relationship with other Ag SC locations and thus have an easier entry to Ag SCs. As AI in Ag SCs is still in the early stages of integration, one can predict that it would be easier and more common for SCs to adapt AI applications with depths lower than "Extremely Deep".

After reviewing the depths relationship dynamics, the AI applications were once again reviewed within their locations in the SC to determine where the depth ratings stem from in the Ag SC. Fig. 11 below shares the depths of AI applications within their corresponding location in the Ag SC and shares the data using percentages. The figure illustrates where the majority of each location's depth lays and how the locations contrast.



	Extremely Shallow	Very Shallow	Moderately Shallow	Slightly Shallow	Slightly Deep	Moderately Deep	Very Deep	Extremely Deep
Up-Stream	13.8%	19.5%	24.1%	27.6%	1.1%	1.1%	4.6%	8.0%
Mid-Stream	21.2%	15.2%	18.2%	0.0%	0.0%	6.1%	12.1%	27.3%
Down-Stream	5.3%	0.0%	10.5%	0.0%	0.0%	10.5%	26.3%	47.4%

Fig. 11. Depth of AI application vs location of AI application.

The AI applications in the up-stream location of the SC exhibited the highest depth range of "Slightly Shallow" with 27.6% of the applications ranked in that range. Overall, 85.1% of AI applications in the up-stream location were ranked in the shallow depth range, and only 14.9% of the applications received a rating in the deep depth range. Therefore, based on the data, it can be hypothesized that the Ag 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 Ag 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 45.5% of the mid-stream applications ranking in the deep range and 54.5% in the shallow range. The analysis made the interesting discovery that none of the mid-stream applications ranked in slightly shallow or slightly deep ranges. This actively demonstrates that ***none*** of the applications was 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 27.3% of applications categorized in this range. Given this data, it can be suggested that within the mid-stream Ag SC 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 (84.2%) ranking in the deep range compared to the other locations. 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 "Extremely Deep" range. In the down-stream, 47.4% of AI applications received an "Extremely 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".

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.

V. Summary

The literature review found that researchers have primarily focused on and studied AI applications taking place and assisting the upstream locations of the Ag SC. The research review attempted to obtain as many AI applications from all Ag areas as possible, but due to available research limitations, collecting data from AI applications specifically in the Ag 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 Ag SC was restrictive.

Currently, the push to integrate innovation into Ag SCs comes from operation-oriented and customer-oriented values. Of the two value categories, the majority of the drive for innovation specifically comes from operation-oriented values. With 106 applications observing operation-oriented values, and nine observing 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 almost even spilt customer-oriented (52.6%) and operation-oriented values (47.4%).

Examining the AI applications in all areas of the SC it was determined that efficiency, cost, labor costs, and yield are the most observed value-added contributions from the 112 reviewed AI applications. However, because the number of AI applications found in the three different SC locations (up-stream, mid-stream, down-stream) varies so drastically, it was concluded that looking at the SC and the AI applications as a whole would mask potential discoveries.

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 paper moved forward in constructing a new 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 Ag 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 Ag SCs. The typology consisted 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 AI technology integration, and the driving values of innovation into Ag SCs related to AI implementation.

The typology provided a guide for the paper to review the AI applications to determine the dynamics of AI and its evolution in Ag 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 twenty-three applications.

As previously stated, AI is in the early stages of introduction into the Ag 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 [11].

A. Conclusions

AI's role in Ag SCs is quickly expanding. Even since beginning the composition of our study, new case studies have since published. The authors carried out the study, analyzing literature published from 2015 to November 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. AI is just at the foreground in the Ag industry, and the need to innovate is only growing stronger as threats to the industry grow larger.

Looking into the future of AI and its role in Ag 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 Ag industry stems from operation-orientated values. However, in the future, it can be hypothesized that the push to innovate the Ag 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 Ag SCs that skilled specialty works are helping with the AI operations.

The current need and drive to implement AI into the Ag 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 paper draws the following conclusions:

- AI can make the Ag SCs more efficient, environmentally friendly and safe, and make the Ag industry's SCs more traceable and transparent.
- The Ag 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 AI applications create value for Ag 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.

B. Proposed Recommendations

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

1) Recommendations for Ag business development

The author’s typology proposed will help Ag businesses examine the current state of AI applications and operations in their SC. The typology allows Ag 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 can help to 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 Ag 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. 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 analysis results 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.

2) Recommendations for Ag industry data sharing

The typology determined that AI applications that have the greatest degree of value creation across the Ag SC rely on data sharing to other locations in the SC. However, the reviewed literature confirms that 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 [12].

Due to the current state of the Ag industry’s data management, the paper suggests 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 and industry leaders 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, authors proposes that government agencies initiate preferential policies to incentivize large-sized agriculture firms to participate in data-sharing to grow AI development.

The paper 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 [13].

3) Recommendations for artificial intelligence in the Ag SC 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. 84.2% 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 Ag SC processes.

4) Recommendations for global development

Lastly, the paper recommends that the typology is to be 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 and leverage AI innovation.

Using the typology to analyze the current state of AI in different countries will unearth gaps and find weaknesses in the global Ag 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 paper 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.

C. 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.

APPENDIX

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	[14]
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	[15]
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	[15]
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	[15]
All areas	Procurement	AI based platform	That offers procurement optimization and yield prediction solution for the agriculture sector	[16]
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	[2]
All areas	All sectors	RFID and IoT sensors	Used to track the traceability system for the perishable food	[17]

			supply chain. Is able to track product movement and monitor the temperature and humidity conditions of the product through out the supply chain.	
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.	[18]
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.	[18]
All areas	Supply Chain Traceability	Deep AI algorithms (convolutional neural networks)	Intello Labs' technology system uses deep AI algorithms to track the movement of product throughout the supply chain.	[18]
All Areas	Demand Management	Machine Learning	Using machine learning algorithms to understand and predict demand and improve production planning	[19]
All Areas	Food Inspection	IoT Sensors	Utilizing large spectral databases and trained models - IoT sensors assess the authenticity of food and inspect quality	[20]
Up-stream	Soil Management	Machine Learning	ML algorithms are utilized to learn about soil properties and use that understanding to improve farming decisions	[21]
Up-stream	Irrigation Management	Machine Learning	Using ML algorithms researchers were able to create simulations and optimization models for predicting and mitigating drought scenarios	[21]
Up-stream	Crop Management	Machine Learning	ML algorithms utilized to improve crop yield prediction, prediction of soil properties and irrigation management	[19]
Up-stream	Crop Management	Machine Learning	ML algorithms utilized in weather prediction, disease and weed detection through predictive analysis	[19]
Up-stream	Livestock Management	AI sensors	AI sensors implemented to monitor and track the conditions of livestock in real time	[22]
Up-stream	Irrigation Management	IoT-based systems	IoT-based irrigation and fertilization systems implemented to enhance the efficiency of irrigation processes and minimize waste	[22]
Up-stream	Irrigation Management	Automation	Self-managing irrigation	[15]
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	[23]
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.	[24]
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.	[25]
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.	[1]
Up-Stream	Grape crop	Neural Network and sensors	An AI system developed to predicted grape disease beforehand. The system used various sensors to collect data and send the gathered data to the system database. From a Wireless System Network (WSN) was able to detected upcoming diseases in the grapes.	[26]
Up-Stream	Irrigation Management	Neural Network ANN model	This model was used to estimate soil moisture Paddy fields.	[26]
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	[26]
Up-Stream	Wheat	Image processing	The system utilizes two machine algorithms SVM and neural networks to be able to classify different wheat variations.	[26]
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	[27]
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	[18]
Up-Stream	Milking Animals	AG robotics	EU foresight study predicts that around 50% of all European herds will be milked by robots by 2025	[11]

Up-Stream	Livestock	Autonomously monitoring	For livestock and collecting field data	[11]
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 modeling of crops over time, for example, tracking the development of the crop canopy, and thus improved prediction of future growth patterns	[11]
Up-Stream	Crop monitoring	Machine Vision	Phenotyping, classifying when individual plants are ready for harvest, and quality analysis	[11]
Up-Stream	Animal Monitoring	Machine Vision	Animal monitoring, e.g. for weight estimation, body condition monitoring and illness detection in pigs, cattle, and poultry.	[11]
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	[11]
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	[28]
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	[28]
Up-stream	Potato Crops	Digital Twin - monitoring, predictive, and prescriptive	Grow and harvest potatoes	[14]
Up-stream	Cow, heard	Digital Twin - monitoring and predictive	Milk production	[14]
Up-stream	Weeds, lettuce crops, field, weeding machine, harvested lettuce	Digital Twin - monitoring, predictive, prescriptive, and recollection	Grow and harvest lettuce	[14]
Up-stream	Pig, farm, slaughterhouse	Digital Twins - monitoring and predictive	Fatten and slaughter pigs	[14]
Up-stream	Irrigation Management	Machine Learning	Irrigation scheduling and management cater to the spatial assessment of when, where, and how much to irrigate	[8]
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	[8]
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	[8]
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	[8]
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	[8]
Up-Stream	Fruits, Vegetables, etc.	Artificial neural	Application uses an artificial neural network to detect and diagnose disease	[29]
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	[15]
Up-Stream	Cotton	AG robotics	Blue River Technologies developed “See & Spray” which monitors and sprays weed on cotton plants	[15]
Up-Stream	Harvesting, Planting, Seeding	AG robotics	Robots can preform these tasks that would otherwise require human labor efforts	[15]
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	[15]
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.	[15]
Up-Stream	Farmers	Digital Assistants (AI algorithms to translate	Can also be used to help with capturing information from farmers and farm workers - such as spoken instructions,	[15]

		and extract knowledge)	requests, observations or even measurements	
Up-Stream	Farmers	Chat-bots Artificial narrow intelligence (ANI)	Help farmers to receive the information they need	[15]
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.	[15]
Up-Stream	Farm	Automation	Driverless farm vehicles	[15]
Up-Stream	Planting	Automation	Variable application rate planters	[15]
Up-Stream	Pest and Weed management	Automation	Precision spraying, precision picking	[15]
Up-Stream	Cow	Digital Twin	Can help to determine the probability of cattle	[15]
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	[16]
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	[16]
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	[16]
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	[16]
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.	[16]
Up-Stream	Farming	Drones	Equipped with multi-spectral and photo cameras that can monitor crop stress, plant growth and predict yield	[16]
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.	[16]
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	[16]
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	[30]
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	[31]
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.	[32]
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.	[33]
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.	[33]
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.	[33]
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	[33]
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	[33]
Up-Stream	Livestock	Digital Twin	BeeZon is a digital twin application that replicates bee colonies, allowing beekeepers to remote monitor and control the colonies	[33]

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	[34]
Up-Stream	Dairy disease detection	Computer vision and robots	Robotics test milk from cattle for disease using laser scanner, ultrasound, and Optical Guidance System	[35]
Up-stream	Milking and Cow Feeding	Autonomous robots	Robots used to identify cattle with an electronic tagging system. The robots cattle feed and then attach to milk the cow	[35]
Up-Stream	Wine Grape examination	Computer vision System and ML	Used to identify spoiled and defective grape clusters which are unable to produce wine	[35]
Up-Stream	Apple Classification	Deep learning and Computer Vision	Classify the type of apples with datasets, pattern recognition, and decision making	[35]
Up-Stream	Fruit Grading	Convolutional Neural Network and Computer Vision	Computer vision utilized with digital imaging to test and grape different varieties of fruits, this technique to reduces the rate of misclassification	[35]
Up-Stream	Crop Management	AI and data science	Using an AI and data science-based program to create a in-depth imaging replication of the farm's microclimate to provide insight as to when to plant, irrigate, feed, and protect crops across a range of varying conditions	[20]
Up-Stream	Crop Management	AI based cloud computing program	AI program used to predict disease outbreaks and generate pest control solutions in greenhouses	[20]
Up-Stream	Weed Control	Machine Vision	Using machine vision and AI technology to recognize weeds, autonomous machinery targets and removes weeds without the use of chemicals	[20]
Up-Stream	Fruit Harvest	AI robotics	Using a real-time detection system and stereo vision, AI robotics are used to harvest apples without harming the fruit	[20]
Up-stream	Farming	Machine Learning Algorithms and Drones	Monitor farmland health and generate insights about crop health and quality	[20]

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	[14]
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	[15]
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	[15]
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	[15]
All areas	Procurement	AI based platform	that offers procurement optimization and yield prediction solution for the agriculture sector	[16]
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	[2]
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.	[17]
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.	[18]
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.	[18]
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.	[18]
All Areas	Demand Management	Machine Learning	Using machine learning algorithms to understand and predict demand and improve production planning	[19]
All Areas	Food Inspection	IoT Sensors	Utilizing large spectral databases and trained models - IoT sensors assess the authenticity of food and inspect quality	[20]
Mid-stream &	Transportation	Machine	Genetic algorithm and focused on vehicle routing, minimizing the	[8]

Down-Stream		Learning Algorithms	product damage, travel distance, and preserving the product quality	
Mid-stream & Down-Stream	Transportation	Autonomous vehicles	Driverless cars. Would save labor costs	[15]
Mid-stream & Down-Stream	Transportation	Autonomous Robots	Study found that utilization of unmanned aerial vehicles, and remote sensors are deemed helpful for transportation, storage, inventory, and retailing	[19]
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	[6]
Mid-stream	Warehouse	Autonomous Robots	Automatic unloading	[6]
Mid-stream	Operations - Incoming inventory	Neural Network	Supports the delivery of mails and parcels for high inventory places. AI extracts individual fields from an address in raw text format and provides a standardized representation the automatic	[6]
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	[6]
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	[6]
Mid-stream	Demand Managenment	Machine Learning Algorithms	Precise demand prediction of food requirements helps to avoid overstocking, overproduction, and overutilization of resources	[8]
Mid-stream	Production Planning	Machine Learning Algorithms	ML algorithms help inefficient production planning through the reduction of setup time and better demand sensing	[8]
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%	[7]
Mid-stream	Packaging	Automation	Smart processing and packing systems	[15]
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	[5]
Mid-stream	Meat Grading	ML algorithms and imaging	ML algorithms are able to grade and rate meat carcasses with high accuracy.	[36]
Mid-stream	identify produce defects	Deep AI algorithms (convolutional neural networks)	Intello Labs' technology system uses deep AI algorithms to identify produce defects and improve customer-level quality of produce	[18]
Mid-stream	Dairy transportation	wireless sensor network with induced artificial intelligence	Monitors milk temperature to prevent spoilage	[35]
Mid-stream	Quality Analysis of Cheese	Computer vision System	Use to analysis the quality attributes of cheese including texture, nutritional quality, defects from some pesticides, rotten material, and shelf life protection	[35]
Mid-stream	Lactose Removal in Milk	Artificial Neural Networks	Used to detect and remove lactose in milk	[35]
Mid-stream	Beer Fermentation	AI Monitoring	Used to regulate the fermentation process of beer	[35]
Mid-stream	Bread Making	Robotics	Utilizing an AI automated control system with robotics the system supports managerial decision making and monitors the bakery conditions and bread making process	[35]
Mid-stream	Quality and Food Safety	"MUSE-TECH" a Computer Vision System	This program uses computer vision to reduce the risk of potato chips developing toxic polar compounds during the cooking process through a network of imaging sensors.	[20]

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	[14]

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	[15]
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	[15]
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	[15]
All areas	Procurement	Artificial Intelligence based platform	that offers procurement optimization and yield prediction solution for the agriculture sector	[16]
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	[2]
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.	[17]
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.	[18]
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.	[18]
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.	[18]
All Areas	Demand Management	Machine Learning	Using machine learning algorithms to understand and predict demand and improve production planning	[19]
All Areas	Food Inspection	IoT Sensors	Utilizing large spectral databases and trained models - IoT sensors assess the authenticity of food and inspect quality	[20]
Down-Stream & Mid-Stream	Transportation	Machine Learning Algorithms	Genetic algorithm and focused on vehicle routing, minimizing the product damage, travel distance, and preserving the product quality	[8]
Down-Stream & Mid-Stream	Transportation	Autonomous vehicles	Driverless cars. Would save labor costs	[15]
Mid-stream & Down-Stream	Transportation	Autonomous Robots	Study found that utilization of unmanned aerial vehicles, and remote sensors are deemed helpful for transportation, storage, inventory, and retailing	[19]
Down-stream	Consumer Analysis	Machine Learning (deep learning and ANN)	Used in food retailing to predict consumer demand, perception, and buying behavior	[8]
Down-stream	Customer Service	AI Chatbots	Chatbots utilize ML and natural language processing to provide automated and personalized client service to assist restaurants and collects payment and orders	[35]
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	[15]
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.	[5]

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Samantha Ault and Ahmed Deif constructed the research idea and designed a framework for the study. Samantha Ault collected the data, developed the typology, and performed the computations. Ahmed Deif supervised the findings of this work and was a reviewer of paper throughout.

All authors discussed the results and contributed to the final manuscript and approved the final version.

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