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HOW ARTIFICIAL INTELLIGENCE IMPROVES AGRICULTURAL PRODUCTIVITY AND SUSTAINABILITY: A GLOBAL THEMATIC ANALYSIS

Siddhartha Vadlamudi

AT & T Services Inc., Vintech Solutions, Plano, TX, **USA**

*Email for Correspondence: vadlamudisiddhartha@gmail.com

Abstract

In the face of the agricultural sector's challenges, food security with an increasing human population and high demand for food is a significant problem. Traditional methods used by farmers have not been sufficient to meet the food requirements of the growing population. As a result, the agricultural sector has begun to deploy artificial intelligence to meet the demand for food and sustainability. This study was conducted to examine how AI improves farmers' productivity and sustainability. Data were analyzed using centering resonance analysis, t-test, ANOVA, and text mining news articles from 2014-2019 in Africa, Asia, Europe, and North America. Results show that AI is used primarily to increase productivity and efficiency and secondarily to address labor shortages and environmental sustainability concerns. The results at the regional level reflect the active adoption of AI in North America and Europe, with increasing efforts in Asia and Africa.

Key words

Environmental sustainability, Artificial intelligence, Agricultural productivity, Thematic analysis

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INTRODUCTION

In recent decades, agricultural systems have faced immense global challenges, such as climate change, a decrease in the availability of water, increased production costs, and a decrease in agricultural labor. These factors challenge the environmental and economic sustainability of current and future systems of the food supply. (Andersen et al., 2018). Although agriculture continues to evolve, essential innovations will be required to keep pace with ongoing global challenges (Hatfield et al., 2014).

However, the incorporation of information technology (IT) into agricultural operations, also referred to as agricultural information technology (AIT), has made significant progress over the last 20 years (Wang, Jin, and Mao, 2019). Recently, Artificial Intelligence (AI) has drawn tremendous interest from the agricultural sector because it is now readily accessible for the exploitation of big data from Unmanned Aircraft Systems (UAS). Thus, Artificial intelligence continues to evolve, creating the most commonly available development niche from the laboratory. Recent research shows that most large organizations are rapidly implementing artificial intelligence (AI) technologies or preparing to deploy them (Donepudi, 2018). Hence, UAS provides an unparalleled opportunity for advanced analytics of agricultural system management to enhance production systems' resilience and efficiency (Coble et al., 2018).

Moreover, AI is increasingly prevalent in business and industry nowadays. It can revolutionize the way we discover, read, work, interact and operate. It has tremendous economic and societal potential (National Artificial Intelligence Research and Development Strategic Plan, 2016). The rise in precision agriculture is a new approach that uses data-intensive techniques and instruments to revolutionize agriculture, which has led to the corporation of IT into agricultural production (Donepudi, 2014a). Thus, an essential aspect of precision farming is artificial intelligence

(AI), which uses a vast amount of data to guide farm decisions and value-added farming. Hence, to generate value by improving crop yields and addressing sustainability problems, the agricultural sector implements AI and Machine Learning (ML) applications (Donepudi, 2017).

However, There are several AI concepts, and over time, they have been updated. Mostly, AI solves complex human intelligence-related cognitive problems. AI identifies issues and develops solutions for the benefit of technology, people, and society. However, the central principle of AI has been the continuous development of machines that can think like humans (Marr, 2018). Thus, Artificial Intelligence (AI) can assist farmers in getting more out of the soil while using energy more sustainably. Also, big data refers to a vast volume of information from cameras, IoT, GPS, aerial photography, and so on (Sjaak et al., 2017). Hence, In addition to traditional methods of political and economic action, Artificial Intelligence (A.I.) plays a growing role in the eyes of scientists and governments in their efforts to address challenges facing food security (Cortés and Sànchez-Marrè, 2000; Gelb et al., 2008).

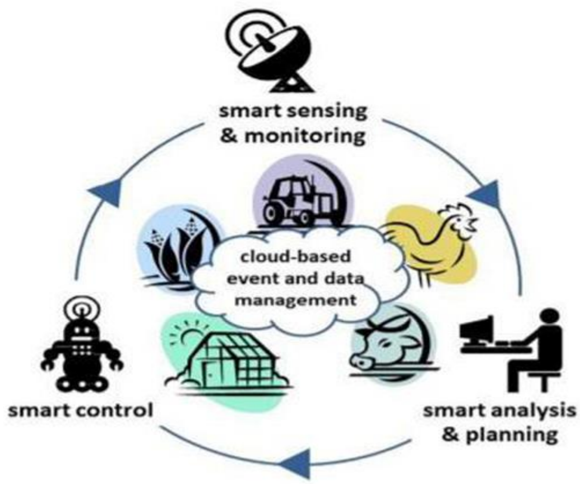

Fig 1: The Smart farm Conceptual framework (Wolfert et al., 2017)

Furthermore, Scholars and professionals have a greater interest in artificial intelligence technology in the last 20 years (AI). First, several attempts to describe AI have been made. For AI, some authors describe the ability of a "machine" in a versatile configuration to interpret the inputs generated by the environment in a "clever" way or to decode external variables better (Kaplan, Haenlein, 2019; Nilsson, 1983). Thus, AI represents a modern way of generating and handling information in an adequately rethought business model (Mikalef et al., 2017; Sachs et al., 2019), including the link between innovation and sustainability.

Also, dramatic changes in the agricultural sector are needed to achieve the UN Sustainable Development Goals for zero hunger by 2030. The disturbances in agricultural practices due to unpredictable weather, global water shortages, and greenhouse gas emissions pose serious concerns. Thus, Transitioning from traditional farming practices to a sustainable way of growing food will contribute to a healthier environment and social and economic equity. Therefore, it is becoming a priority to accelerate agricultural production while minimizing negative environmental impacts.

However, the emergence of artificial intelligence (AI) is shaping a growing range of sectors. For example, it affects global productivity (Acemoglu and Restrepo, 2018), equality and inclusion (Bolukbasi et al., 2016), environmental outcomes (Norouzzadeh et al., 2018), and several other areas, both in the short and long term (Tegmark, 2017). Thus, By promoting food, health, water, and energy provision to the people, AI can act as an enabler for all objectives. It can also underpin low-carbon systems, such as by promoting the creation of circular economies and smart cities that make efficient use of their resources (International Energy Agency, 2017).

According to Ullah et al. (2017), there are technologies useful for precision farming such as GPS/GNSS, mobile devices, robotics, driverless tractor, irrigation, Unmanned Arial Vehicle (UAV), Internet Of Things (IoT), sensors, variable rate seeding, weather modeling. However, AI is used when robots and drones, and other devices, operating in the fleet (Ribeiro et al., 2015). AI is also used for classification based on the quality characteristics of the product at the time of harvesting (Oppenheim and Shani, 2017). However, one of the significant areas of computer science research is Artificial Intelligence (AI). AI is increasingly becoming more widespread with its rapid technological growth and a wide variety of applications due to its strong applicability to specific problems humans and traditional computing structures cannot resolve (Rich and Kevin Knight, 1991).

This research seeks to determine how agricultural organizations, both globally and within different geographical regions, use AI to create value and address sustainability concerns. Thus this study is divided as follows. The following sections follow as Literature reviews, methodology, results, and discussion, conclusions, and recommendations.

LITERATURE REVIEW

Agriculture is essential to our livelihood and is vital to the economies of many countries. Thus, increasing agricultural productivity in a disrupted climate and limited resources are increasingly demanding. Hence, to meet farm challenges and increase food demand, computer, satellite, internet, mobile, and social media technology are used. It is expected that the combination of IT and agricultural techniques will result in increased output, perhaps up to 60% (Donepudi, 2014b).

However, with the introduction of technology, companies have undergone dramatic changes across many industries globally (Kakkad, Patel, Shah, 2019). Thus, the Agricultural sector being the least digitized industry has seen tremendous growth in the development and commercialization of agricultural technologies. Hence, Artificial Intelligence is entering daily life by augmenting our possible perceptions and changing how we interact with our environment (Vadlamudi, 2016).

In Agricultural sector, AI is getting implemented. The utilization of AI in agriculture has revolutionized the modern agricultural system. What this technology has enabled is increased crop production, more significant real-time streamlining of harvesting, processing, and marketing (Yang et al., 2007). Thus, farm management operations involve complex problems characterized by high uncertainty and multiple action courses (Recio et al., 2003). Hence, current IT innovations provide farmers with adequate support when making decisions and other operations (Aubert et al., 2012).

Furthermore, new automated systems technology using agricultural robots and drones has contributed to the agro-industry. Various high-tech computer systems, such as weed detection, yield detection, crop quality, and many other techniques, are designed to recognize different important parameters (Liakos et al., 2018). AI-based technologies help increase productivity in all areas and also handle the challenges faced by various industries, including agricultural sectors such as crop yield, irrigation, identification of soil content, monitoring of crops, weeding, the establishment of crops, and so on (Kim et al., 2008).

According to Panpatte (2018), artificial intelligence allows farmers to compile large quantities of data from websites and to provide farmers with solutions to many problems of uncertainty, as well as to provide the farmer with smart agricultural practices that will increase farm yield. However, shortly, agriculture will be a combination of technical and biological skills due to artificial intelligence, which will not only act as a better quality outcome for all farmers but will also minimize their losses and workloads. Thus, to reduce the pressure on farmers. Agricultural AI can automate a variety of procedures, minimize risks and provide reasonably simple and successful farming for farmers.

However, Adoption is defined as a decision to continue full use of innovation while the adoption process is a decision-making process (Ekong, 2003). Thus, farmer's adoption of new technology is due to factors such as the influence of peer's (Fox et al., 2018), farm size, location, farmer's level of education and age, the complementarity of technology, and access to information sources (Auernhammer, 2001; Kitchen et al., 2002; Daberkow, and McBride,2003; Fountas et al., 2005). Initial adoption decisions are reflected in the attitudes and behaviors of the adopters; while technology enthusiasts actively adopt technology, unwilling users maintain traditional farming practices (Cavallo et al., 2014). Several factors could drive the adoption process. Low or non-adoption could be conditioned by institutional and structural factors, such as social networks and the market structure of AI (Akinola et al., 2010). Moreover, to increase productivity, technology must be adopted in the production process. The rate of adoption of new technology is subject to its profitability, degree of risk associated with it, capital requirements, agricultural policies and socioeconomic characteristics of farmers (Shideed and Mohammed, 2005). Thus, farmers' perception and preference for particular attributes influence their actions in choosing one crop or variety over another. Hence, perception and knowledge guide decision-making and, consequently, farmers' actions (Kisauzi et al., 2012).

However, the focus of AI is different from that of the past 60 years (Yunhe, 2016). It is starting to become an essential feature of almost all industries (Bollier, 2017). The concept of AI consists of a comprehensive set of training computers that aim to do tasks involving human intelligence. AI encompasses many different aspects, including machine learning, deep learning, expert systems, and robotics (Purdy and Daugherty, 2016). Also, their are different factors that can affects the adoption of AI in the agricultural sector. The first is environmental barriers. The environmental barrier categories include consumer trust and regulatory acceptance (Grosz et al.,2016; (Ransbotham et al., 2017).

Contrary to the benefits of AI technology (Ransbotham et al., 2018), the technology followers have expressed similar digital innovation that depends on both customer data and customers' trust. The AI characteristic like mimic human intelligence, creates new management issues for legal activities. Furthermore, government regulatory issues have not yet cove with AI technology. AI offers a new strategic approach towards business decision-making resulting in new ways to create value, which are not well understood (Chui and Francisco, 2017; Ransbotham et al. 2018).

According to the Mckinsey Global report (2018), the implementation of AI in organizations poses crucial challenges that cut across developers, government, and employees (Chui et al., 2018). Therefore, we suggest that government regulation is essential to building trust in AI. However, there are organizational barriers. The organizational barrier categories are related to a lack of top management support, a lack of AI skills and employee fear of change (Bughin et al., 2001; Ransbotham et al., 2017; Sikka, 2017). Thus, there is also a lack of top management support, which is interpreted as a lack of managerial skills associated with managing organizational adaptations to AI. Strong top management support goes hand-in-hand with AI adoption (Chui and Francisco, 2017). Hence, the technological barrier category includes security and limited technology capabilities (Bughin et al., 2017; Ransbotham et al., 2017).

According to Chan et al. (2003), AI could be applied to reducing environmental pollution, conservation and recycling since natural resources are significant social and environmental concerns. On a comprehensive account, the areas of artificial intelligence are classified into sixteen categories, (Vadlamudi, 2017; Chen and Van Beek, 2001; Hong, 2001; and Stone et al., 2001). These are reasoning, programming, artificial life, belief revision, data mining, distributed AI, expert systems, genetic algorithms, systems, knowledge representation, machine learning, natural language understanding, neural networks, theorem proving, constraint satisfaction, and theory of computation (Peng and Zhang 2007; Zhou et al. 2007;Wang et al. (2007).

Artificial Intelligence (AI) is a combination of numerous varieties of methods and phenomena, among which two major concepts called Neural Networks (NN) and Deep Learning (DL) are responsible for AI to attain such an outstanding advancement (Norvig, 2002). The Availability of data related to food and edible products made researchers explore the field of food with AI lenses (Kagaya et al., 2014).

Thus, another application of AI in agriculture will help farmers obtain the information they need in the right way. For example, language-translation AI can deliver to farmworkers the information they want in the language that works best for them, such as helping deliver agricultural advice to farmers working in areas where people speak different languages. Such capabilities could significantly improve the spread of good agricultural advice, leading to improved agricultural practices more widely. Chat-bots, where an interacting agent is simply a machine, could also help farmers receive the information they need (Kannagi et al., 2018). Furthermore, AI will provide more and better information about a situation on the farm to enable the farmer to look at it, think and decide on management actions. Close or exact analogs are being realised in much of the precision-agriculture applications already being deployed on farms, such as animal-activity trackers (Vadlamudi, 2018) and high-resolution field maps (Vasisht et al., 2017).

Also, a primary recent agricultural application of AI has involved data capture through devices such as movement sensors on, or even in, farm animals, to enable reporting of their behaviours, health and condition farm sensors' (Rutten et., 2013)). One of the earliest examples is pedometers to detect oestrus in cows (Galon, 2010)which can both reduce manual labour of having to observe oestrus onset but also can improve the chances of obtaining the specific sex of calf desired by better timing of insemination. Artificial intelligence is also being used to improve information extraction from satellite and aerial imagery (Sirosh, 2018). AI is already having impacts in agriculture through improving robotics and mechanisation (Duckett et al., 2018). However, Sustainable agricultural technology for Nigeria is essential for the country's effort at achieving food security (Ladebo, 2004). Thus, boosting agricultural productivity has been an issue of paramount importance to development institutions across the globe and in order to achieve this, the use of technological improvements have played a key role (Maertens and Barrett, 2013). Agricultural innovations also play a significant role in fighting poverty, lowering per-unit production costs (Kassie et al., 2011), boosting rural incomes and reducing hunger (Maertens and Barrett, 2013).

METHODOLOGY

This study uses content analysis to determine how Artificial Intelligence improves agricultural productivity and sustainability. However, all materials, methods, and objectives of this study, including the software tools used, will be listed and explained.

Data Gathering Method

The tool and procedure for collecting data for this study are secondary data. Secondary data was used for convenience and completeness and was accessible to provide a basis for comparison.

Research Instrument

This study was analyzed using the Centering text analysis tool. Centering Resonance Analysis (CRA) is an approach with text analysis that utilizes the centering theory premises (Corman et al.,2002). Thus, CRA analyzes the text by developing word networks of the main concepts, influence, and relationship (McLaren et al., 2007). Hence, a complex content analysis approach is Centering Resonance Analysis (CRA) (Corman et al., 2002).

However, CRA analyzes terms and phrases in a significant way in order to form a network and illustrate their influence and their relationship (Corman et al., 2002; McPhee et al., 2002). Hence, words in the text are more influential if it draws other words together in a text network, reflecting some meaning (Canary and Jennings, 2008).

Furthermore, several types of content analysis are available for applying to the text of several job postings. Thus, the approach appropriate for this scenario is a particular form of content analysis called Centering Resonance Analysis (CRA). CRA is a method of analyzing a computerized text, where the text is depicted as a network. CRA is based on the Centering Principle, which states that, by concentrating their comments on discussion centers, capable authors or speakers produce locally coherent statements. To recognize centers (noun phrases) in text and connect the word part (tokens) to a network, it uses natural language processing (Rossetti et al., 2011). Although other similar methods use the word co-occurrence in the visualization window of a given software to identify these units, CRA unites and links words based on linguistic theory, which considers how the texts are produced. Therefore, the CRA is based on a systematic behavioral perspective (Freitas et al.,2018). According to Corman et al. (2002), Crawdad is a useful tool to determine CRA. Crawdad provides enhanced information retrieval, network visualization, and secondary analysis, surpassing earlier text analysis tools. (Lee & James, 2007). Thus, Crawdad has been used in various scholarly and research journals and reports (Corman et al., 2002; Dooley, Corman, McPhee, & Khun, 2003; Lichtenstein, Dooley, & Lumpkin, 2006; McPhee et al., 2002). Hence, the acceptance of Crawdad and CRA into various academic fields and renowned journals has increased (Tate, Ellram, & Kirchoff, 2010).

Furthermore, Crawdad Desktop 2.0 was used for this study, consistent with other research (Augustin-Behravesh, and Dooley, 2018). Thus, Crawdad highlights the presence, influence, and resonance of codewords (Corman and Dooley, 2006) and creates network maps of the words for every sampled article. Influence values between 0 and 1 are assigned to words based on the principles of CRA, as explained above. An influence value of 0.01 is considered to be important, while a value above 0.05 is considered to be very important (Tate, Ellram., and Kirchoff, 2010)

Data Analysis

Data analysis is a process of inspecting, cleansing, transforming, and modeling data to highlight useful information suggesting conclusions and supporting decision making. This study divided the analysis into two parts because there are many different words in the four geographical regions. The Crawdad parameters were set to identify the 250 most influential words common across the four geographical regions. Articles were converted into readable texts and repetitive terms were eliminated to avoid ambiguity whenever possible (Tate et al., 2010). Thus, each word file was converted into a CRA File, and then a Network Map and influential words were generated from it by using Visualizer.

However, the second analysis revealed what words were important in the training data sample. To measure the similarity and differences in the influential words across the four regions, we calculated the average influence score of the words with greater than or equal to a 0.1 influence (Rossetti and Dooley, 2010) for the four data samples. To prevent biases due to a word with a higher impact value but a lower appearance in texts, we limited the study to the terms that appeared in at least 20 papers (Rossetti and Dooley, 2010). Next, through the four data sets, we searched for identical terms. Agriculture, for instance, appeared in all four data sets and had an effect value above 0.1. As an indicator of random variation, the variance of a word's impact value across the texts within a dataset was used. We then ran an ANOVA to test whether a word's average impact on the dataset was different. Continuing with the previous example, the results of ANOVA for agriculture showed that the average impact of agriculture across the four data sets was significantly different. We ran t-tests to assess where the significant difference was, if significant ($p<0.05$). Across the four data sets on which we ran ANOVA, we found 52 identical or related terms.

RESULTS

Table 1 showed the Analysis of 52 commonly used and most essential words revealed 23 words, which differed across four regions. The word *agriculture* had a higher influence score (0.080) in the African context, followed by Asia (0.063), North America (0.028) and Europe (0.026). Table 3 showed the t-tests for the word *agriculture* and suggested significant differences between the four different regions. The word *agriculture* is more prominent in the trade press from Asia than Europe, given Asia is a developing and agricultural-centric economy. Hence the focus is on ensuring sustainability by protecting traditional occupation and protecting the agricultural sector.

Thus, the word precision had more influence value in the context of Europe (0.056) as compared to Asia (0.014) and North America (0.011), hence suggest a more active use of precision agriculture in Europe. In Asia, as compared to other regions, AI provides a platform for researching (0.041) and finding solutions (0.028) to the problems in agriculture. However, all the influence scores for each word per region are not provided due to space limitations. Thus, this study provides how influential words in each region uses AI in agriculture.

Table 1: Top Influential and Similar Words

The 52 most influential and similar words across the four data sets	agriculture, agricultural, ai, application, area, big, business, company, crop, data, development, event, farm, farmer, farming, field, food, global, good, government, industry, information, innovation, land, machine, market, new, platform, precision, product, production, project, report, research, robot, sector, sensor, soil, software, solution, state, start-up, system, technology, time, tractor, university, vegetable, water, way, world, year
Significant 23 words per region	
North America	event, farming, new, precision, robot, soil, system, tractor
Europe	ai, big, business, data, startup, time, way, world
Asia	platform, report
Africa	agriculture, state, solution, research, vegetable

Thus, Compared to the other three regions, in Europe, AI has emerged as a highly effective term, indicating that AI applications in Europe are more pronounced, creating a variety of forms for expansion and agriculture transition. Higher size and data value affect the use of data-intensive methods and data to create value in agricultural activities. Such techniques minimize repetitive activities, which allow farmers to spend their time on their business as a whole. Hence, this correlates to the growth in Europe contexts of a start-up that exercises considerable influence. AI-based and business-context data applications provide a fertile basis for the growth of agro-tech start-ups. The values of the word robots and land influence were strong in the North -American context, as opposed to European. Thus, this will mean a more robust implementation of AI. To increase productivity and profitability, North-American farms deploy robots to make farming productive and cost-effective, with attention to monitoring soil conditions through ML applications. As a modern form of sustainable farming, precision farming is gaining popularity. Besides, various events to promote new AI-enriched products, such as automated tractors and robots, are being organized by suppliers.

Unlike Europe and North America, AI in emerging economies is at an early stage, i.e., Africa and Asia. Influential keywords in these regions imply that research activities that support AI and agriculture knowledge and growth are more prevalent in Africa. The findings point to the growing deployment of AI to solve major agricultural problems such as low production and crop losses in the Africa context. AI is seen as a forum for achieving economic goals in agricultural research in the Asian context. Studies are underway reporting on the need and value of the implementation of AI in the Asian agricultural sector.

Table 2: Statistical tests of the influence of agriculture across the four data sets ANOVA value

Cases	Homogeneity Correction	Sum Of Squares	DF	Mean Square	F	P	η^2
Id	None	0.140	3.000	0.047	7.691	<.001	0.023
Id	Brown-Forsythe	0.140	3.000	0.047	8.354	<.001	0.023
Id	Welch	0.140	3.000	0.047	7.604	<.001	0.023
Residual	None	5.967	986.000	0.006			
Residual	Brown-Forsythe	5.967	414.041	0.014			
Residual	Welch	5.967	221.116	0.027			

Table 3: Post-HocComparison-ID

	Countries	*Mean Difference*	*SE*	*T*	*P*
1	**2**	**0.013**	**0.012**	**1.790**	**0.265**
	3	**0.053**	**0.012**	**3.746**	**<.001**
	4	**0.041**	**0.014**	**2.781**	**0.026**
2	**3**	**0.013**	**0.008**	**3.756**	**<.001**
	4	**0.013**	**0.009**	**1.794**	**0.263**
3	**4**	**-0.008**	**0.009**	**-1.118**	**0.665**

1 Africa, 2* Asia, 3* Europe, 4*North America*

Conclusion

This study analyzed how AI improves agricultural productivity and sustainability using the Centering Resonance Analysis, t-test and ANOVA. The results of this study help to shed more light on how understanding the application of AI to the agriculture sector can address the sustainability challenges in agriculture and help inform AI solutions in other similar sectors. However, agriculture is essential in ensuring global food security and therefore ensuring food security and sustainability AI can create modern ways to address environmental and food security challenges. The study, therefore, recommends that the emphasis should be placed on developing AI applications in agriculture in order to address agricultural issues such as the productivity of farmers and also to address some of the serious environmental challenges needed to ensure sustainability. Efforts should also be made to further research on adopting the AI application in Agriculture by major stakeholders through primary data. Primary data can better determine farmers' productivity and food sustainability.

References

Acemoglu, D. and Restrepo, P. (2018). *Artificial Intelligence, Automation, and Work. NBER Working Paper No. 24196 (National Bereau of Economic Research, 2018).*

Akinola, A. A., A. D. Alene, R. Adeyemo, D. Sanogo, A. S. Olanrewaju, C. Nwoke, G. Nziguheba, and J. Diels. (2010). "Determinants of Adoption and Intensity of Use of Balanced Nutrient Management Systems Technology in the Northern Guinea Savanna of Nigeria.". *Quartely Journal of International Agriculture* , 49(1):25-45.

Andersen MA, Alston JM, Pardey PG, Smith A. (2018). A century of U.S. productivity growth: a surge then a slowdown. *Am J Agric Econ* , 93:1257-1277.

B. Recio, F. Rubio, and J.A. Criado, (2003). "A decision support system for farm planning using AgriSupport II." Decision Support Systems, vol. 36, no.2,, pp.189-203.

B.A. Aubert, A. Schroeder, and J. Grimaudo, (2012). "IT as enabler of sustainable farming: an empirical analysis of farmers adoption decision of precision agriculture technology," Decision Support System, vol. 54, pp. 510-512.

Bollier, D. (2017). Artificial intelligence comes of age. The promise and challenge of integrating AI into cars, healthcare and journalism. The Aspen Institute Communications and Society Program.Washington, DC.

Bolukbasi, T., Chang, K.-W., Zou, J., Saligrama, V. & Kalai, A. (2016). Man is to computer programmer as woman is to homemaker? Debiasing word embeddings. *Adv. Neural Inf. Process. Syst.* , 29, 4349–4357.

C.L. Rossetti, and K.J. Dooley,. (2010). Job types in the supply chain management profession. *Journal of Supply Chain Management, vol.46, 2010, pp. 40–56.*

Canary, H. E., and Jennings, M. M. (2008). Principal and influence in codes of ethics: A centering resonance analysis comparing pre-and post – Sarbanes-Oxley Codes of ethics. *Journal of Business Ethics,* , 80(2), 263–278.

Cavallo, E., E. Ferrari, L. Bollani, and M. Coccia,. (2014). Attitudes and Behaviour of Adopters of Technological Innovations in Agricultural Tractors: A Case Study in Italian Agricultural System. *Agricultural Systems,* , vol.130, pp.44–54.

Chan, C. W. and Huangb, G. H., (2003). Artificial intelligence for management and control of pollution minimisation and mitigation processes. *Engineering Applications of Artificial Intelligence,* Vol. 16 Issue 2, pp.75-90,.

Chen, X. and Van Beek, P., (2001). Conflict-directed backjumping revisited. *Journal of Artificial Intelligence Research,* Vol. 14, pp.53-81,.

Chui, M. and Francisco, S.,. (2017). Artificial intelligence the next digital frontier?. Company Global Institute,.

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P. and Malhotra, S.,. (2018). NOTES FROM THE AI FRONTIER INSIGHTS FROM HUNDRED OF USE CASES.pp.2-7.

Coble KH, Mishra AK, Ferrell S, Griffin T. (2018). Big data in agriculture: a challenge for the future. . *Appl Econ Perspect Policy* , 40:79-96.

Corman, S., Kuhn, T., McPhee, R., & Dooley, K. (2002). Studying complex discursive systems: Centering resonance analysis of communication. . *Human Communication Research*, 28, 157-206.

Donepudi, P. K. (2014a). Technology Growth in Shipping Industry: An Overview. *American Journal of Trade and Policy, 1*(3), 137-142. https://doi.org/10.18034/ajtp.v1i3.503

Donepudi, P. K. (2014b). Voice Search Technology: An Overview. *Engineering International, 2*(2), 91-102. https://doi.org/10.18034/ei.v2i2.502

Donepudi, P. K. (2017). AI and Machine Learning in Banking: A Systematic Literature Review. *Asian Journal of Applied Science and Engineering, 6*(3), 157–162. http://doi.org/10.5281/zenodo.4109672

Donepudi, P. K. (2018). AI and Machine Learning in Retail Pharmacy: Systematic Review of Related Literature. *ABC Journal of Advanced Research, 7*(2), 109-112. https://doi.org/10.18034/abcjar.v7i2.514

Duckett T, Pearson S, Blackmore S, Grieve B, Smith M . (2018). *White paper – agricultural robotics: the future of robotic agriculture. In 'EPRSC, 2018 international robotics showcase'.* . Retrieved from Available at http://eprints.uwe.ac.uk/36839

E. Gelb, A. Maru, J. Brodgen, E. Dodsworth, R. Samii, V. Pesce. (2008). Adoption of ICT* Enabled Information Systems for Agricultural Development and Rural Viability, Atsugi Japan, p. 4-5.

E. Rich and Kevin Knight. (1991). *"Artificial intelligence", .* New Delhi: McGraw-Hill, .

Freitas, J. S., Ferreira, J. C. A., Campos, A. A. R., de Melo, J. C. F., Cheng, L. C., and Gonçalves, C. A. . (2018). Methodological roadmapping: A study of Centering Resonance Analysis. *RAUSP Management Journal,*, 53(3),459–475. https://doi.org/10.1108/RAUSP-04-2018-005

G. Fox, J. Mooney, and P. Rosati,. (2018). "Towards an understanding of farmers mobile technology adoption: a comparison of adoption and continuance intentions," AMCIS, New Orleans, .

Galon, N. (2010). The use of pedometry for estrus detection in dairy cows in Israel. *The Journal of Reproduction and Development*, 56, S48–S52. https://doi.org/10.1262/jrd.1056S48

Grosz, B., Weinstein, S., and Joshi, A. (1995). Centering: A framework for modeling the local coherence of a discourse. *Computational Linguistics*, 21,203-225.

Grosz, B.J., Altman, R., Horvitz, E., Mackworth, A., Mitchell, T., Mulligan, D. and Shoham, Y.,. (2016). *Artificial Intelligence and life in 2030: One hundred year study on artificial intelligence. Stanford University.*

H. Auernhammer,. (2001). "Precision farming - The environmental challenge," Computers and Electronics in Agriculture, vol.30, 2001, pp. 31–43.

H. Kagaya, K. Aizawa, M. Ogawa, . (2014). Food detection and recognition using convolutional neural network, in: Proceedings of the 22nd ACM International Conference on Multimedia, 2014, pp. 1085–1088.

Hatfield J, Takle G, Grotjahn R, Holden P, Izaurralde RC, Mader T, Marshall E, Liverman D: Ch. 6. (2014). *: Agriculture. In Climate change in the United States: The Third National Climate Assessment. Edited by Melillo JM, Richmond T, Yohe GW. U.S. Global Change Research Program:50-174.*

Hong, J. (2001). Goal recognition through goal graph analysis, Journal of Artificial Intelligence Research,Vol. 15, pp.1-30,.

International Energy Agency (2017). *International Energy Agency. Digitalization & Energy .*

Kakkad, V., Patel, M., Shah, M.,. (2019). Biometric authentication and image encryption for image security in cloud framework. Multiscale and Multidiscip. Model. Exp. and Des., 1–16. Retrieved from https://doi.org/10.1007/s41939-019-00049-y

Kannagi L, Ramya C, Shreya R, Sowmiya R . (2018). Virtual conversational assistant: 'The FARMBOT'. *International Journal of Engineering Technology Science and Research* , 5, 520–527.

Kaplan, A.; Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz. 2019, 62, 15–25.*

Kassie M, Shiferaw B, Muricho G . (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. . *World Dev* , 39(10):1784–1795.

Kim, Y.J., Evans, R.G., Iversen, W.M.,. (2008). Remote sensing and control of an irrigation system using a distributed wireless sensor network. . *IEEE Trans. Instrum. Meas.*, (pp. 57 (7), 1379–1387).

Kisauzi, T., Mangheni, M. N., Sseguya, H. and Bashaasha, B. (2012). Gender dimensions of farmers' perceptions and knowledge on climate change in Teso Sub - Region, Eastern Uganda. *African Crop Science Journal*, 20(2): 275 – 286.

Ladebo, O. (2004). Job Behaviour and Attitude of Agricultural Faculty: Beyond the influence of Biographical factors. . *Journal of extension system* , 20 (2)), pp. 89 – 103.

Liakos, K., Busato, P., Moshou, D., Pearson, S., Bochtis, D.,. (2018). Machine Learning in Agriculture: A Review. Sensors 18 (8), 2674. Retrieved from https://doi.org/10.3390/s18082674

Maertens A, Barrett CB. (2013). Measuring Social Networks' Effect on Agricultural Technology Adoption. . *Am J Agric Econ* , 95(2):353–359.

Marr, B. (2018). *What is artificial intelligence and how will it change our world?* *Retrieved from* https://www.bernardmarr.com/default.asp?contentID=963

McLaren, T., Vuong, D., & Grant, K. (2007). Do you know what you don't know? Critical reflection and concept mapping in an Information system strategy course. communications of the Association for Information Systems. 20,892-908.

McPhee, R. D., Corman, S. R., and Dooley, K. (2002). Organizational knowledge expression and management. . *Management Communication Quarterly*,, 16(2), 274–281.

Mikalef, P.; Framnes, V.A.; Danielsen, F.; Krogstie, J.; Olsen, D. (2017, 16-20 July). *Big Data Analytics Capability: Antecedents and Business Value. In Proceedings of the Pacific Asia Conference on Information Systems, Langkawi Island, Malaysia; p. 136.*

N.R. Kitchen, C.J. Snyder, D.W. Franzen, W.J. Wiebold. (2002). "Educational needs of precision agriculture,". *Precision Agriculture*,, vol.3, pp.341–351.

National Artificial Intelligence Research and Development Strategic Plan. (2016, october). *Executive office of the president of the United States. National Science and technology Council and Networking and information technology Research and development subcommitee.* Retrieved from https://www.nitrd.gov/PUBS/national_ai_rd_strategic_plan.pdf

Nilsson, N.J. (1983). *Artificial intelligence prepares for 2001. AI Magazine, 15 December 1983; p. 7.*

Norouzzadeh, M. S. et al. . (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. . *Proc. Natl Acad. Sci. USA 115, E5716–E5725.*

Norvig, P. (2002.). *, S.A. Intelligence, A Modern Approach, Prentice Hall,.*

Oppenheim, D. and Shani, G. (2017). Potato Disease Classification Using Convolution Neural Networks. ECPA. 244–249.

Panpatte, D.G.,. (2018). Artificial Intelligence in Agriculture: An Emerging Era of Research. Intutional Science, CANADA, pp. 1–8.

Peng Y. and Zhang X. (2007). Integrative data mining in systems biology: from text to network mining,. *Artificial Intelligence in Medicine*,, Vol. 41, No. 2, pp.83-86,.

Purdy, M., and Daugherty, P. 2016. (n.d.). "Why Artificial Intelligence Is the Future of Growth," Remarks at AI Now: The Social and Economic Implications of Artificial Intelligence Technologies in the Near Team). pp.1-72.

Ransbotham, S., David Kiron, Philipp Gerbert and M. Reeves. (2017). *Reshaping Business With Artificial Intelligence. MIT Sloan Management Review.*

Ransbotham, S., Gerbert, P., Reeves, M.A.R.T.I.N., Kiron, D.A.V.I.D. and Spira, M.I.C.H.A.E.L.,. (2018). *Artificial Intelligence in Business Gets Real. MIT Sloan Management Review .*

Ribeiro, A.–Fernandez-Quintanill, C.–Dorado, J.–Lopez-Granados, F.–Pena, J. M.–Rabatel, G.–Perez-Ruiz, M.–Conesa-Mufi, J.–Gonzalez deSantos, P. (2015). A fleet of aerial and ground robots: a scalable approach for autonomous site-specific herbicide application. ECPA . 167-173.

Rossetti, C. L., Handfield, R., and Dooley, K. J. (2011). Forces, trends, and decisions in pharmaceutical supply chain management. *International Journal of Physical Distribution & Logistics Management.*, 41(6), 601–622. https://doi.org/10.1108/09600031111147835

Rutten CJ, Velthuis AGJ, Steeneveld W, Hogeveen H. (2013). Invited review: sensors to support health management on dairy farms. *Journal of Dairy Science*, 96, 1928–1952. https://doi.org/10.3168/jds.2012-6107

S. Corman, and K. Dooley. (2006). “Crawdad text analysis system 2.0”. Chandler, AZ: Crawdad Technologies, LLC,.

S. Fountas, S. Blackmore, D. Ess, S. Hawkins, G. Blumhoff, J. Lowenberg-Deboer, et al. (2005). “Farmer Experience with Precision Agriculture in Denmark and the US Eastern Corn Belt,”. *Precision Agriculture,* , vol. 6, pp. 121–41.

S.A. Augustin-Behravesh, and K. Dooley. (2018). “Differentiating Sustainably": Relating organizational culture to corporate sustainability strategies,” AOM, Chicago.

S.G. Daberkow, and W.D. McBride,. (2003). “Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the US,” . *Precision Agriculture,* , vol.4, no.2,, pp.163-177.

Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Messner, D.; Nakicenovic, N.; Rockström, J. (2019). Six Transformations to achieve the Sustainable Development Goals. Nat. . *Sustain.* , 2,805–814.

Shideed KH, Mohammed E . (2005). *Adoption and Impact Assessment of Improved Technologies in Crop and Livestock Production Systems in the WANA Region. The Development of Integrated Crop/Livestock Production in Low Rainfall Areas of Mashreq and Maghreb Regions(Mashreq/Maghreb Project).*

Singer, J., Gent, I. P. and Smaill, A., . (2000). Backbone fragility and the local search cost peak, . *Journal of Artificial Intelligence Research,* , Vol. 12, pp.235-270.

Sirosh, J. (2018). Planet-scale land cover classification with FPGAs. In ‘Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery and data mining’, 19–23 August. pp. 2877–2877. (ACM: London).

Sjaak Wolfert, Lan Ge, Cor Verdouw, and Marc-Jeroen Bogaardt, (2017). “Big data in smart farming–a review, ″ *Agricultural Systems,* , 153, 69 .

Stone, P., Littman, M.L., Singh, S., Kearns, M., ATTAC-. (2001). An adaptive autonomous bidding agent, . *Journal of Artificial Intelligence Research,* , Vol. 15, pp. 189-206.

Tate, L.M. Ellram., and J.F. N Kirchoff, . (2010). W.L.“Corporate social responsibility reports: a thematic analysis related to supply chain management,” . *Journal of Supply Chain Management, vol. 46, pp. 19-44.*

Tegmark, M. (2017). Life 3.0: Being Human in the Age of Artificial Intelligence (Random House Audio Publishing Group,).

U. Cortés & M. Sànchez-Marrè (Eds.). (2000). *Workshop Notes on 2nd ECAI Workshop on Binding Environmental Sciences and Artificial Intelligence, European Conference on Artificial Intelligence Berlin.*

Ullah, A., Ahmad, J., Muhammad, K., Lee, M.Y.,. (2017). A Survey on Precision Agriculture: Technologies and Challenges. The 3rd International Conference on Next Generation Computing(ICNGC2017b.

Vadlamudi, S. (2016). What Impact does Internet of Things have on Project Management in Project based Firms?. *Asian Business Review*, *6*(3), 179-186. https://doi.org/10.18034/abr.v6i3.520

Vadlamudi, S. (2017). Stock Market Prediction using Machine Learning: A Systematic Literature Review. *American Journal of Trade and Policy*, *4*(3), 123-128. https://doi.org/10.18034/ajtp.v4i3.521

Vadlamudi, S. (2018). Agri-Food System and Artificial Intelligence: Reconsidering Imperishability. *Asian Journal of Applied Science and Engineering*, *7*(1), 33-42. Retrieved from https://journals.abc.us.org/index.php/ajase/article/view/1192

Vasisht D, Kapetanovic Z, Won J, Jin X, Chandra R, Sinha SN, Kapoor A, Sudarshan M, Stratman S. (2017). FarmBeats: an IoT platform for datadriven agriculture. In 'Proceedings of the 14th USENIX Symposium on Networked Systems (NSDI '17)', 27–29 March 2017, Boston, MA.pp.515-529.

Wang S., Wang Y., Du W., Sun F., Wang X., Zhou C. and Liang Y., . (2007). A multi-approaches-guided genetic algorithm with application to operon prediction, Artificial Intelligence in Medicine, Vol. 41,No. 2, pp.151-159, 2007.

Y. Wang, L. Jin, and H. Mao, . (2019). "Farmer cooperatives intention to adopt agricultural information technology- mediating effects of attitude,. *" Information Systems Frontiers,* , pp.1-16.

Yang, H., Liusheng, W., Junmin, X. Hongli, Jan. (2007). Wireless Sensor Networks for Intensive Irrigated Agriculture, . *Consumer Communications and Networking Conference, 2007. CCNC 2007. 4th IEEE. pp. 197–201 Las Vegas, Nevada.*

Yunhe, P. (2016). Heading toward artificial intelligence. . *Engineering Journal,* , 2, pp.409-413.

Zhou X., Liu B., Wu Z. and Feng Y. (2007). Integrative mining of traditional Chines medicine literature and MEDLINE for functional gene networks. *Artificial Intelligence in Medicine*, Vol. 41, No. 2,pp.87-104.

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