Investigation of the Effects of Smart Farming on Decision-Making in Agriculture

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

The Internet of Things (IoT) can be described as the network of every physical device that connects to the internet and can process, store, and communicate data (Clark, 2016). At the end of 2020, the IoT market had over 35 billion devices connected, largely due to its capabilities for collecting data and gathering insights (Maayan, 2020). The term “SMART” is an acronym for “Self-Monitoring Analysis and Reporting Technology” and is a marketing term that broadly implies connection to the IoT (Anderson, 2020). IoT has been associated with smart home technology, healthcare, smart cities, and recently has been gaining attention in agriculture. The American Farm Bureau Federation surveyed farmers, and states that “smart farming” can reduce costs for resources by an average of 15% and increase crop yield by an average of 13%.

The first recorded instances of IoT implementation within agriculture can be dated back to the 1980s, when a Geographical Information System (GIS) was used to gather geographic data on farmland (Brase, 2005). Newer technologies that have emerged in recent years within smart farming include smart sensors, climate control, and livestock tracking (IOT Solutions World Congress, 2019). These technologies gather and backhaul large amounts of data, and allow decisions to be made based on predictive analytics. Specifically on farms, a wireless IoT protocol that is becoming more and more prevalent is LPWAN (Low-Power Wide-Area Networks), as it works in areas with poor wireless coverage, extends battery life, and reduces costs (Senet, 2020). IoT and its recent production of sensory big data in farming applications is moving the human decision-making process to be increasingly facilitated by the logic of algorithms (Marquis, 2020). This work will examine the effects of smart technologies on human impact in decision making among different stakeholders, specifically within agriculture.

This paper will cover the concept of technological momentum, and how IoT, specifically in farming, has progressed in its implementations. It will also examine agriculture's transition from farmer-controlled decision-making to big data-controlled decision-making. This research will investigate how smart farming technologies have influenced farmers' influence in active decision making by exploring case studies of different agricultural technologies.

Analysis of Technological Momentum in Smart Farming

Technological momentum is a concept that fuses elements of social determinism and technological determinism. On a broad scope, social determinism is the idea that people are what they are, or make their decisions, based on social factors that shape their environment (Markman, 2011). Technological determinism, also on a broad scope, is the idea that technology and society are linked in a causative relationship (Hallström, 2020). Thomas Hughes argues that time is a crucial factor in technological momentum as a technology grows from social determinism to technological determinism over time (Hughes, 2000). As technological systems become more complex over time, which in the case of farming is the rapid increase in available data and connected devices, systems tend to be more shaping of society and less shaped by it (Hughes, 1987). Where the farmers have to be careful is with normative technological determinism, if and when the system of smart farming becomes so complex and common that it is no longer amendable to social control (Winner, 1980). Agriculture is becoming more automated, and this can be seen in recent innovations and adoptions in the industry like the hub capstone project. This automation in decision-making is contributing to and leading to a technological system that shapes farming when they may not even realize it.

Technological Determinism persists in the reactions experienced when confronted with new ways of doing things, as seen with new ways of utilizing IoT over the years (Wyatt, 2008). IoT in farming may have caused farmers to feel a sense of relief at a time where food production has a need to increase exponentially. Farmers have gone from the use of simple GIS to understand the land, to nearly fully autonomous farms and predictive analytics, and they've adopted these technologies at alarming rates due to their effectiveness. Over time, farmers are reacting by gaining trust of smart technology's decision-making. A 2020 survey by Purdue University reported that 44% of farmers follow analytics closely, while 53% follow analytics somewhat closely (DeLay, 2020). This use of IoT allows farmers to innovate and progress on a scale never seen before, however, it can be dangerous in many ways if they become over-dependent on the capabilities of data.

As stated before, LPWAN in IoT is a growing market, and in addition to current stakeholders, there are a number of new stakeholders that are attracted to the idea of big data and get support from big tech investors (Wolfert, 2017). With the introduction of new stakeholders and changes in current stakeholder roles, the farmers will be affected in terms of issues with data ownership, data quality, analytics, and changing business models. This investment to big data in agriculture will provide unprecedented decision-making capabilities within the industry, and these decisions may not be up to the farmers themselves. A 2014 survey revealed that over 82% of farmers and ranchers said they were unclear on how companies intended to use their data (American Farm Bureau Federation, 2014). Changes in decision-making not only result from explicit IoT data insights, but can also be taken away from farmers in the form of contractual agreements with tech companies.

Algorithm decisions and farmer decisions are linked in a causal relationship through the usage of IoT on farms. In an article from a precision farming consultant, Ian Beecher-Jones, an overview is provided to farmers who are looking to get into precision agriculture, or smart farming. He argues that the most difficult part of precision agriculture is the human decision making, or deciding what inputs to vary, such as the amount of fertilizer to increase or decrease. He also argues that, based on his experiences, the process requires human interaction with the interface, but once programmed correctly, can be automated within their given parameters (Beecher-Jones, 2017). However, 47% of farmers don’t understand farm data software (DeLay, 2020). It is up to the farmers whether or not they will make the effort to keep up with the technological changes that are inevitably happening to their industry, or if they will take the risks of allowing companies and algorithms to make their decisions for them.

The smart technology developed in this context is a direct consequence of the transition from social determinism to technological determinism associated with IoT data usage over time. As farming becomes more integrated with smart technologies, farmers are gaining efficiency, but losing their decision-making power.

Companies and algorithms are both making decisions for smart farmers as opposed to physical inspection and analysis like it was done in the past. This is representing the growth of IoT in agriculture from social determinism to technological determinism. In order to keep up with the companies and algorithms involved in these solutions, farmers now must educate themselves on the software in these systems and the legal issues involved, or they risk to lose all their decision-making prowess.

Case Context

This case was brought to my attention by technology like my capstone project's, which is a modular gateway that uses LPWANs to provide sensory data in farming among other applications. In relation to the case, many farmers have now adopted hub technologies very similar to the one we are creating. By working on this project, it gives direct context into the research of this paper from the producer perspective as opposed to the farmer perspective. LPWANs like in this hub provide optimal solutions to use cases that require devices to send small amounts of data, such as a sensor's temperature reading, periodically over remote networks that span many miles and use battery-powered devices that need to last many years (Wedd, 2020). A number of LPWAN solutions, such as LoRa, Sigfox, and NB-IOT grew at over 100% over 2019 to reach 231 million global connections (Pasqua, 2020). Farmers have experienced this first hand with the increasing number of sensors and sensory data available that can accommodate needs from temperature and weather condition monitoring, to geospatial livestock tracking and binary fence status. The ability to inexpensively enable remote sensor monitoring over a greater range has proven to be a valuable and popular addition to the family of IoT solutions, and is a large contributor to the growth in farming.

Due to increased investment from different industries, integrated IoT solutions are now being implemented by companies who have never had influence in agriculture before (Ayaz, Ammad-uddin, Sharif, Aggoune, & Mansour, 2019, pp. 2–3). For example, Microsoft is supporting FJ Dynamics, which is a company that specializes in artificial intelligence, and is now using data and automation to augment the decision-making and work farmers do (Microsoft, 2020). They're not only using sensory data to gain decision insights, but they are working to implement full automation in smart farming vehicles like tractors and transplanters. Also, IBM is now using artificial intelligence combined with IoT data to provide global insights about planning, plowing, and harvesting crops (Medori, 2019). IBM states that the average farm generates an estimated 500,000 data points daily, and this number is expected to reach 4 million data points by 2036. These growing data give opportunity for technology companies to expand their influence in agriculture through the use of smart farming.

In more common uses, integrated IoT data collection would use various sensors to detect any irregularities in the farm's fields, or provide the data needed for analytical insights on the backend. For example, a farmer can have a sensor placed in their soil, around their fencing, and on the crop shade. All three of these sensors would send data to a system, and it would aggregate the data and send it to the cloud. Once in the cloud, the farmers will get insights into all the metrics they need to address like "Use Less Fertilizer" or "Spray Crop Shade". Within the scope of this research, automation in farming can now physically complete these commands for the farmers as well. In the past this would be done through physical inspection and passed down knowledge, whereas now companies are creating solutions that utilize sensory data to enhance decision making, and blindly trusting the results provided from the data.

Research Question & Methods

The question I will investigate is: How has farmers' impact in agricultural decision making been affected by smart farming, and how will it be affected? This question will allow me to investigate the different stakeholders and technologies that are involved in smart farming that were discussed in this paper. The results will hopefully provide insight as to what IoT solutions may help farmers, and what solutions may hurt them. With the implementation of IoT in farming growing at a rapid rate, farmers may be in immediate danger of losing their independent decision-making. Based on my capstone project's contribution to this, it is necessary for me to research this question from an engineer's perspective and from a social perspective to get a holistic view of the potential benefits and dangers to farmers.

Data from two public surveys given to farmers regarding their involvement and views on smart farming and precision agriculture will provide a consumer perspective. One of these surveys was done by Purdue University, and asks farmers various questions about data privacy with smart farming, farmer education, and making decisions based on analytics. The other survey was published by the University of Guelph, and includes surveys of farmers concerning decision-making changes, stakeholder relations, and trust in the technology with smart farming. To supplement these surveys, three separate case studies offer evidence that cover big data decisions, the learning curve with this technology, and the different trust between stakeholders. These case studies were chosen based on them being issues that are relevant to the decision-making farmers and technology producers, and have all experienced changes with the further use of IoT technologies in farming. This will allow me to understand what decisions are made by which stakeholders, and where the line is drawn as far as those who bear the risk and those who control the risk.

The data was analyzed by comparing the survey results to the case studies, and seeing if the data matches the different real-world examples in agriculture. The ultimate goal was comparing and tracing the producers to the farmer, to find how each stakeholder interacts. This allowed me to analyze the farmer perspective, and how they make decisions based on both technology changes, and the producer choices that affect said technology changes.

Results

Stakeholder dynamics, decision-making, and distribution of benefits within agriculture has experienced a number of changes due to the implementation of smart farming technologies. Smart farming has changed agricultural stakeholder dynamics in that farmers are losing their individual active decision-making power while the decisions are being made by a technological system. A large percentage of farmers are highly influenced by their data, though many don't have a full understanding of the data, and there is a lack of trust between the farmers and the companies whose technology they use.

I began with the first survey I analyzed by Purdue University, and I looked into the results on farmer education and understanding of software, their decisions they make based on that software (DeLay, 2020). To go over some of the important highlights of the survey, they report that 93% of farmers are somewhat influenced or highly influenced by big data when making fertilizer decisions, and 40% who aren't already collecting data plan to collect soil data in the future. The survey also reports that those with no formal college education are 16% less likely to collect data. In that same regard, over 35% of those surveyed are unsure of how to use the data that is collected.

In the second survey by University of Guelph, I looked into the results on farmers' big data perceptions, and stakeholder trust dynamics between farmers and tech companies in agriculture (Marquis, 2020). Looking into these categories, over 30% of the farmers surveyed believe that precision agriculture technologies will result in automation that would make traditional farming skills obsolete, and 83% believe that farmers are becoming more dependent on this technology for results. 27% of the same sample also believe that these technologies will reduce farmers' connection to the land. At the same time, only 49% believe that these big data technologies are giving unbiased recommendations, and 30% are unsure of who actually owns their data.

Both of these surveys portrayed similar results, and between both of their results indicate three main points of emphasis that are relevant to the research question in this paper. The first being big data decisions, the second being the education or learning curve associated with these technologies, and the third being trust. To supplement and confirm the findings in these surveys, three case studies are done below that cite real world examples of these issues.

Case Study 1: Big Data Decisions

This case study aims to show how farmers have changed their decision-making as far as following data insights and show that this data may be giving them less control over their farms instead of more. Within smart farming, there are a growing number of ways of gathering data as more devices are added to the IoT (Dowell, 2015). Associated with this is a sharp increase in data availability, and thus data analytics are being used to optimize farming inputs. The market for this type of agriculture software is predicted to jump 14% between 2019 and 2025 (Fakhruddin, 2017). With the increase in data, artificial intelligence (AI) has now begun playing a major role in other areas such as pest control, risk management, and harvesting robots. The adoption of more AI within agriculture has led to less people working in the primary sector, and a greater need for technical experts (Walch, 2020). As less primary sector workers are involved in agriculture, more and more decisions are being made by those technical experts and their automation technologies within farming. As stated in the survey above, there is a large percentage of farmers who are highly influenced by big data recommendations, and they believe this number will only increase over time (Marquis, 2020). This shows how decision-making in farming is now becoming more autonomous as the technology becomes more autonomous.

Case Study 2: Learning Curve

This case study will show farmers are deciding to deal with the need for up-to-date technology, and how they understand and interpret the technology they use. As seen in the survey by Purdue, there is a large percentage of farmers who don't understand the big data that they gather, and have no choice but to trust the optimizing technology, which puts them at risk of following biased results. Farmers realize though that these technologies can greatly increase efficiency, and in order to keep up with the technologization of farming they must implement them into their systems. However, using these technologies without being familiar with the IoT can be dangerous, and can be intimidating when the practices they're trying to improve have been done differently for a number of years. This brings to light the learning curve of the robots in smart farming as well. Robots require their own form of learning in machine learning, and while they are very efficient now, they can still be greatly improved as more farmers adopt smart farming (CIOReview, 2019). These new farming technologies are needing more skills to operate effectively, and farmers are now required to understand data analysis and information technology. According to the Purdue survey, 35% don't understand how to utilize their collected data, so there is work to be done in tackling this learning curve for data agriculture. Farmers are in a dilemma where they need to use these technologies, but first have to make the decision to either educate themselves on how IoT devices and systems work, or blindly trust the algorithms.

Case Study 3: Trust between Stakeholders

This case study aims to shed light on the distribution of benefits and decision-making power between technology companies and farmers. As seen in the University of Guelph survey results, farmers are worried about who owns their data. There have been many examples of mistrust between technology companies and farmers, especially as the technology becomes more complicated and more proprietary. John Deere’s tractors have become so complex with the integration into IoT that farmers have no choice but to go to a specialist to have them repaired. With this requirement came repair costs that weren’t affordable, so many farmers started to implement a Ukrainian firmware hack in order to fix their tractors (Gotbaum, 2017). Current limitations in digital infrastructure are creating data ownership issues as well, and technology companies understand this and they find loopholes to utilize farmer data (Jakku et al., 2019). These types of issues create a lack of trust between stakeholders, and puts farmers in a poor position for making decisions. This can relate to the survey results in that farmers don’t want their data to be shared, but at the same time the technology companies need as much data as possible in order to have efficient algorithms (Leader, 2018). They now must decide whether to trust the technology they are working with and the companies providing it, when this had rarely been an issue in the industry before smart technology.

Discussion

Technological momentum is seen in the movement from active to passive decision-making within smart agriculture. IoT as a whole would be considered at the momentum stage in the evolution of large technological systems, due to its mass technical and organizational components, and the accelerating growth rate in its implementation (Hughes, 1987). With the current state of IoT in agriculture, it is at the growth, consolidation, and competition stage, and moving towards momentum. There are new standards to which the agriculture industry is capable of, and companies are now competing to gain the trust and business of farmers across the U.S. In time, the various interests of different stakeholders (i.e., engineers, farmers, policymakers, agricultural associations) will create more momentum within the smart farming industry, as they all compete and further the growth of the system. However, current trust between stakeholders is acting as a reverse salient for the system, thus preventing it from achieving its development goals as of now (Hughes, 1987). The research done in this paper can be seen as a reflection of how the entire IoT landscape is today, whether it be trust in data ownership within social media applications, or artificial intelligence passively making decisions for people in everyday life.

Limitations of this study were not hard to come by, largely due to my lack of direct connections with farmers who use these technologies and their stakeholders. Not having these connections prevented me from gathering my own original survey data, so I had to use previous surveys and back them up with case studies on the different topics. Farmers have been proven to be difficult to reach with mail surveys in the past as well, so the surveys used have relatively small sample sizes (Pennings, Irwin, & Good, 2002). Even so, the surveys lacked data from the producer perspective, so the results in this paper related to their side were more qualitative. Also, smart farming is still a relatively new revolution, so there is still a lack of long-term data surrounding its use. This lack of detail and documentation on technology development in smart farming prevented me from going into more detail on specific technologies within the case study topics.

If I had the resources, in the future I would connect with a survey company, and create a survey of my own to send out to farmers and to any producers who would be willing to participate. I would also do more research into the industry stakeholders like the producers of the technology to understand their perspective more. I would go outside the scope of the current research as well to cover the whole digital agriculture life cycle, from before, during, and after farming. This would allow for a better understanding of the relationships between stakeholders, and a better understanding of the decision farmers would make outside of the farm.

Currently, this research is allowing me to advance my engineering practice by giving me a consumer perspective with the technology I am creating in my capstone project. I've now taken into account the different risks and benefits that could be associated with it. In the future of my engineering work, I'll now be more cognizant of how a technology can have unforeseen risks, and how important it is for work, especially in IoT, to be transparent and fair to all parties.

Conclusion

This research shows the implementation of IoT in farming from the views of different stakeholders, and goes in detail on the social implications of this revolution. The work done here can be used to illustrate how digital farming has recently been making giant leaps in conjunction with the broader scope of IoT implementation among other industries. The type of issues prevalent in the farming implementation may be seen in other industries as well, and this study can help bring those to light.

To further this study, one could survey the producers as well in order to get their perspective on data privacy concerns and the other ethical implications they are battling. This could help allow for transparency and help farmers learn more about the technology they're using, so that they can make the best decisions for themselves. Looking into the accuracy and bias of current smart farming algorithms could be useful as well in order to improve the system for those who have already implemented these technologies.

Farmers have been thrown into the mouth of the IoT revolution at a very fast pace, and have been forced to adapt and understand this technology to keep up. With the increasing capabilities of artificial intelligence and data in smart farming technologies, the automation is at risk of spreading to the decision-making of farmers. There is still a way to go with the development of many of these automation technologies, as the algorithms are trained to learn on past systems, and as more farmers implement the technologies, the new data improves them. This creates a data dilemma between producers and farmers where they need each other to have the most efficient technology. However, socially there is a clear lack of trust between stakeholders, which may stem from lack of understanding perspectives on both ends, and lack of a clear digital infrastructure between them (Dowell, 2015). Farmers now need to understand the technological repercussions and understand their data so they can be active decision-makers in the entire agriculture life cycle.

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