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Interrogating the Socio-Ethical Dilemmas of Precision Agriculture Technologies

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INTERROGATING THE SOCIO-ETHICAL DILEMMAS OF PRECISION AGRICULTURE TECHNOLOGIES

By

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DISSERTATION ACCEPTANCE PAGE

Ayorinde Ogunyiola

This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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This dissertation is dedicated to God Almighty.

To my parents, Timothy and Mulikat Ogunyiola.

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CONTENTS

ABBREVIATIONS

Agritech	Agricultural technology companies
EU	European Union
EULA	End-User License
FAO	Food and Agricultural Organization
FCT	Federal trade commission
GLBA	Gramm-Leach-Bliley Act
GPDR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
IoT	Internet Of Things
NGOs	Non-Governmental Organizations
PA	Precision agriculture
RI	Responsible innovation
SD	South Dakota
USDA	United States Department of Agriculture
VT	Vermont

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ABSTRACT

INTERROGATING THE SOCIO-ETHICAL DILEMMAS OF PRECISION AGRICULTURE TECHNOLOGIES

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Farming has moved into a digital age where data and information are available to farmers to make informed agronomic and financial on-farm decisions. The development of precision agriculture (PA), such as big data technologies and machine learning algorithms is transforming the agricultural food production system in diverse ways, economically, environmentally, and socially. Despite benefits afforded by PA to agricultural productivity and environmental sustainability, these technologies can raise unintended societal challenges that can also limit their adoption among farmers. PA is changing how farming is done, reconstructing farmers' social identities, and influencing relationships between farmers, agronomists, and technology developers. This dissertation attempts to explore the social and ethical implications of PA on farmers by understanding changes to their social practices and relationships with big data and technology firms. The study uses an interpretive qualitative analysis on six focus group discussions (FGDs) with 52 agricultural stakeholders in South Dakota and Vermont. The qualitative data is complemented with a follow-up survey with the FGD participants. Results highlight that the introduction of PA could necessitate farmers to learn and develop new competencies, such as flying drones and reading yield maps that are produced by data-based technologies. However, this new form of technological engagement also affects other farmers who are unable to meet the skill and competency demands of digital agriculture. This dissertation finds that

introduction of PA can change the future of agrarian labor by serving a system of data and capital accumulation that can disproportionately benefit agricultural technology firms. Therefore, it becomes crucial to understand whether public and private sector organizations and institutions are prepared and willing to address farmers' concerns about data ownership and access, privacy, and security. This dissertation concludes by suggesting possible ways through which PA could avoid exacerbating an existing social and digital divide between large-scale and small-scale farmers and between farmers and agribusiness. It proposes responsible innovation PA as a potential solution for a more inclusive design of PA.

CHAPTER 1. INTRODUCTION

The Food and Agriculture Organization (FAO) of the United Nations anticipate that farmers will need to cultivate 70% more food to match the expected 9 billion population by 2050 (FAO, 2011). Meeting production and environmental sustainability has become a daunting task for farmers and a concern for nation-states and international organizations such as the World Bank and FAO (IPES Food, 2015). The current farming reality suggests most of the farmland is already being cultivated in a manner that contributes to environmental carbon and nitrogen footprint, where large greenhouse gas emissions are produced, and water quality is hampered by dissolved nitrogen (Gilbert, 2012). These challenges necessitate farmers to switch to better farm management practices through innovative technologies to meet the growing demand for food and reduce agricultural ecological footprints. Better farming for a sustainable future will require a combination of efforts by the state, investors, farmers, and developers of agricultural innovation technologies.

New agricultural technologies are being developed to attend to the challenges of food security and ecological footprints in agriculture. This new paradigm is creating what is now referred to as “Agriculture 4.0” a process where farmers currently employ an array of technologies such as precision agriculture, remote sensing, Internet of Things (IoTs), and artificial intelligence considered as the ‘future of farming’ capable of improving farm management and profitability (Bongiovanni & Lowenberg-Deboer, 2004; Rose & Chilvers, 2018). Precision agriculture (PA) is a collection of both software and hardware farming tools which include tractors, unmanned aerial vehicles (UAVs), big data, and machine learning algorithms for the collection, analysis of farm data that provide farming

recommendations on site-specific information on the appropriate time to plant, spray, and harvest crops (Bongiovanni & Lowenberg-Deboer, 2004; Rossel & Bouma, 2016). With the potential PA can offer to farmers coupled with large-scale global investments in PA, there is optimism for driving higher agricultural productivity and improving farming's ecological footprint. For instance, across the globe, the total investment in agricultural technology (agritech) was over $1.5 billion in 2017 (Manhas, 2019). This investment has ballooned and in 2020, global venture capitalists invested $4 billion in startups in the agritech space and investments in PA are expected to increase in the coming years (Hall, 2020). Financial support for PA comes from the public sector as well. In 2019, the United States Department of Agriculture (USDA) invested $152 million in fourteen states to improve broadband services, especially among rural farmers, anticipating that it can improve farmers' adoption of PA technologies (USDA, 2019).

Despite the promise of digital innovations for farmers to improve crop productivity and reduce ecological footprints from farming, these technologies can raise their own social challenges (Bronson & Knezevic, 2019; Klerkx et al., 2019). Presently, only about 50 percent of farmers have adopted PA technology in the United States (Schimmelpfennig, 2016). There are several concerns among farmers from adopting PA. This is not surprising as previous innovation-led agricultural revolutions, such as Green and biotechnology, have not only brought economic benefits to farmers but created dependencies between farmers and agribusinesses. The introduction of hybrid seeds and GMOs has indeed exaggerated power inequities between small and large farmers and between farmers and powerful agribusinesses. Extant literature on the adoption of PA technologies has explained reasons why some farmers are more likely to adopt PA than others (see, for instance, Gardezi &

Bronson, 2020; Pierpaoli et al., 2013). Still, less is known about how the digitalization of agriculture can disrupt the social and political relationships between and among farmers, PA, and other actors in the food system value chain.

The introduction of PA is transforming the social and cultural phenomena associated with farming. This study focuses on three social and political changes: First, PA is changing farmers' social practices by reshaping their experiential knowledge and redefining what it means to be a farmer. The adoption of technologies such as big data and machine algorithms have significant impacts on the cultural formation of farming communities, such as changing how farming is done and reconstructing the social identities of farmers and how they grow, manage, and carry out farming activities (Klerkx et al., 2019). Second, changes in farming practices and knowledge systems are not occurring in a vacuum but are being driven by capital accumulation and dispossession of agrarian labor. Agritech firms are collecting data in the hope of accumulating current and future knowledge about farms and farming systems and, in this process, can replace or displace existing agrarian labor (Rotz et al., 2019). Third, and related to the second process, PA tools depend on the collection of large amounts of data and possibilities for questions about farm data and equipment ownership and concerns about farm data privacy and security (Eastwood et al., 2017; Jakku et al., 2019; Wolfert et al., 2017). While some laws and regulations protect ownership of farmland, current regulations pertaining to data ownership, security, and privacy are not strong to protect end-users. Understanding and addressing these three challenges is crucial to ensure that PA can be sustainable not only economically and environmentally but also socially for those who will be impacted by it most, such as farmers. Therefore, the central focus of this dissertation is to contribute to

the literature on the socio-ethical implication of PA by empirically examining: (1) how farmers' social practices and social identities are changing under the emergence of PA (2) how PA is dispossessing farmers of their autonomy, control of production process and the implications of PA for future agrarian labor and (3) the perceptions and expectations of stakeholders towards data and equipment ownership, data privacy and security. Addressing these socio-ethical questions is crucial to ensure that PA delivers the promise of food productivity, efficiency, and reduction in ecological footprint from farming activities.

This dissertation used a qualitative approach, specifically thematic analysis, to explore the social implications of PA in South Dakota and Vermont. I used primary data from six workshops (focus group discussions and surveys) held between October and December 2019 with a mix of US food system stakeholders comprising farmers, academia/extension personnel, non-government organization, and PA technology developers.

Dissertation outline

This dissertation is organized into six chapters. In chapter two, I detailed the methods used in this dissertation; the study site, choice of sampling frame and sample, data collection methods, and the analytical approach used to understand PA's socio-ethical implication in the US food production system.

In chapter three, I explore how the introduction of PA is changing farmers' social practices and social identities. This chapter focuses on how the adoption of big data and machine learning algorithms are rescripting and transforming farmers' traditional social

practices from a manual to a more data-driven approach and how farmers are to make sense of the world as they adopt these technologies.

In chapter four, I examine how the introduction of PA is transforming the cultural fabric of farming, exploring the implication of PA in two aspects: how PA is (1) dispossessing farmers of their autonomy and control of their production process and (2) reconfiguring future agrarian labor in the US food production system. With the adoption of PA, the current and future agricultural workforce are impacted in diverse ways, with the unskilled workers most affected by the innovation.

In chapter five, I elicit the importance of inclusion and anticipation of food system actors in developing technologies by examining the perceptions and expectations of US food system stakeholders towards farm data and equipment ownership and privacy and security under the emergence of PA. I highlight that for PA to meet societal values and needs; there needs to be an avenue to include all stakeholders in the process and design of technological development. The inclusion of stakeholders will provide an opportunity for diverse values and expectations to be captured, and the negative implications of technology can be anticipated and acted upon at an early stage and throughout the production process.

Chapter six provides a summary and conclusion dissertation. Broadly, the dissertation explores the socio-ethical effects of the introduction of PA by understanding how: (1) social practices are changing under big data and machine learning algorithms and how farmers are making sense of the world as a result of these changes and (2) PA is becoming a strategy to dispossess farmers of their autonomy and production processes and how PA might reconfigure future agrarian labor in the US food systems. These issues

necessitate understanding (and reflecting upon) perceptions and expectations of various food system actors in the US towards farm data and equipment ownership and data privacy and security in PA technologies. Findings from this dissertation help generate valuable policy lessons for reducing the technological inequity resulting from these emerging technologies.

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CHAPTER 2. METHODOLOGY

2.1 *Research design*

This chapter explains the methods used in this dissertation. A qualitative research design is chosen as a methodological approach to explore the implications of the emergence of PA on the US food production system. The qualitative research approach provides the opportunity to explore, understand, and interpret social phenomena in-depth within a natural setting (Denzin & Lincoln, 2003). Qualitatively exploring the emergence of PA in the US food production system provides insight into decision-making processes that will strengthen the design and adoption of PA. Specific approaches followed through the qualitative research design are discussed in subsequent subsections: the study region, the procedure for data collection, the codebook development process, the coding process, and the analysis of focus group discussion (FGDs) transcripts and survey data used in this dissertation.

2.2 *Study region*

The locations chosen for this study are SD and VT. These sites were selected to capture a robust difference in the ecological condition of farming and cropping systems. Farmers in SD predominantly produce export-based commodity crops, such as wheat, corn, and soybeans, on large acres. In VT, most farmers engage in the production of specialty crops, such as fruits and vegetables. Dairy farming is also prevalent in VT. Farming systems in SD are more on an industrial scale, and farmers often practice conventional monocropping practices, such as rotation of corn and soybean in alternative years. Farms in VT are primarily family-owned, organic, and farmers usually practice mixed cropping.

The average farm size in SD is 1,459 acres, while in VT is 176 acres (USDA, 2020a; 2020b). VT presently has 667 dairy farms that contribute milk and milk-based products to local and national demand. The differences in SD and VT in terms of scale and farming systems provide an interesting comparison to study how PA can influence small and large-scale farms and farm operators (Kolady et al., 2020; Purdy, 2016).

2.2.1 *Population and sampling strategy*

The target population recruited for this study are stakeholders throughout the food system value chain, including farmers, PA technology developers, university and extension professionals, and experts from government agencies and nonprofit organizations (NGOs). Participants were initially chosen through a purposive sampling procedure targeted at recruiting a wide range of US food system actors with some variance in experience, knowledge, and engagement with the development and use of PA technologies (Kerlinger & Lee, 1999; Patton, 2002). The choice of purposeful sampling technique was to effectively select participants who can provide rich and contextual information for answering this dissertation's research questions (Berg 2007). Through purposeful sampling, university and extension professionals were contacted in SD and VT who provided an opportunity to invite participants to increase the possibility of involving other stakeholders with varying levels of engagement with PA through a snowball sampling (Patton, 2002). Snowball sampling was useful in identifying participants who might have useful insights about PA technologies. The sampling frame in SD and VT included farmers, academics, extension personnel, NGO experts, and technology developers.

Fifty-two stakeholders were recruited as FGD participants. These participants can be categorized into four groups; farmers (that operate various types of farms and on

different scales in SD and VT who concentrate on farming crops and livestock), university extension personnel from academia who provide agronomic recommendations to farmers, NGO professionals and government regulators, and PA technology developers (see table 1). Participants were initially contacted through emails and a follow-up via phone to ascertain their commitment to participate in the study. The inclusion of the diverse groups of participants provides a broad perspective on the socio-ethical implication of PA.

Table 1: FGD and survey participants by categorization

Participants	South Dakota	Vermont	All participants
Farmers	4	2	6
NGO/government regulators	10	5	15
Academia/Extension	14	8	22
Technology developers	6	3	9
Total	34	18	52

Note: Some participants had multiple roles. For instance, some extension agents also farmed part-time. For this reason, participants primary occupation was used for grouping them into one of the four categories.

2.3 Data collection procedures

Focus group discussion

Data for this study comes from a mixed-method approach. The data collection was conducted in two phases. In the first stage, a qualitative approach was used to capture individual and collective perspectives of stakeholders in the US food systems, such as their engagement with PA through focus group discussions (FGDs). FGD is a data collection method that brings together individuals who share similar characteristics to interact on a particular social phenomenon of interest (Morgan & Krueger, 1993; Kitzinger, 1995). The choice of FGD comes from the fact that FGDs offer opportunities to gain multiple as well as shared or collective perspectives about the emergence and development of a social

phenomenon such as the emergence of PA in the US food production system. FGDs are an inexpensive way for participants to openly share their perception of a social phenomenon, providing researchers with an avenue to gather rich data from a group that shares similar experiences rather than interviewing participants individually (Cyr, 2019). FGDs enable participants' unique views, experiences, and behavior to be collected by a researcher on a given social phenomenon (Morgan & Krueger, 1993; Wilkinson, 1998). Within the context of FGDs, participants might reflect and provide a more practical and empirical reflection of their past and current experiences rather than an individual interview (Greg et al., 2017; Kreuger, 1994; Wilkinson, 1998). In this sense, stimulating participants through FGDs among US food system actors offered an avenue to articulate participants' perspectives and experiences vis-à-vis the development or adoption of PA technologies.

Six homogeneous FGDs were held in SD and VT between October and December 2019. Each FGD had an average of 8 participants that all represented the same group identity (farmers, PA technology developers, NGOs and regulators, and university academics & extension professionals). During the FGDs, stakeholders were motivated to expand their discussion on topics relating to the overall benefits and risks of developing and adopting PA technologies. Participants discussed how PA may (or may not) improve on-farm decision-making, what areas of crop production have PA helped improve most, and which tools may be needed to make PA more ‘successful’. The FGD sessions were audio and video recorded, each one lasting between 90 to 120 minutes. These sessions were transcribed, and for the confidentiality of participants, their group association (e.g., “a farmers from VT”) were used instead of their name and organization. Participant's organizational affiliation was also collected but removed in the analysis to ensure

anonymity. Informed consent was procured from all FGD and survey participants prior to engaging in any discussion.

Although FGDs help collects rich information about a topic from a group of participants, this data collection method is not without limitations. First, collecting data through FGDs can lead to a tendency where only certain kinds of socially acceptable opinions emerge and where specific individuals in the FGDs might domains the entire discussion or data collection process (Smithson, 2000). Second, methods of producing focused discussion constitute a limitation of using FGDs, which raise questions on the role of the moderator in data collection and the influence of the group in the data generation (Morgan, 1996). Third, data collected through FGDs are sometimes influences of the group on participants' responses. Since group interactions require mutual self-disclosure, it becomes inevitable that specific discussion topics might be unacceptable for group discussions (Morgan, 1996).

Survey data

The second stage of data collection included a follow-up survey completed by 52 FGD participants. The survey method was chosen to collect additional data, triangulating the data sources for the dissertation by asking questions regarding the overall benefits and risks associated with PA to farmers (Creswell, 2003). Surveys help to triangulate the data collected for this dissertation (Miles & Huberman,1994). Exploring a social experience from multiple methods can provide useful insights for a researcher interested in exploring the lived experiences of study participants (Maxfield & Babbie, 1998). Although both farmers and non-farmers completed the study survey, the questions in the survey focused on eliciting participants' response to how PA would impact social, economic, and

environmental relationships for farmers. Importantly for this dissertation, a series of questions on farmers' social identity were asked to understand what it meant to be 'a good farmer'. Farmer identity was measured through a series of 17 questions related to the perception of 'a good farmer.' These questions were designed to understand how PA's emergence changes farmers' views of their own identities and how other stakeholders' views articulate the social expectations of what it means to be 'a good farmer'. The survey questions design was drawn from the literature on social identity theory and literature related to what it means to be 'a good farmer' (Burton, 2004; Burton and Wilson, 2006; McGuire et al., 2013). Survey questions used in this study were modified from previous surveys designed by Arbuckle (2013) and McGuire et al. (2015). The question measuring the social identity of 'a good farmer' was answered by respondents on a five-point Likert scale from one to five, with one representing "not important" and five representing "very important." Survey questions covering farmers' social identities are detailed in Appendix 2.

2.4 Analysis

Qualitative interpretive approach

This study adopted a qualitative interpretive method to analyze FGDs, allowing the emergence of concepts based on theoretical perspectives guiding this study (social practices, social identity accumulation by dispossession, agrarian question of labor, and responsible innovation framework) and critical social science scholarship on PA. The interpretative approach is defined as the "systematic analysis of socially meaningful action through the direct detailed observation of people in natural settings to arrive at understandings and interpretations of how people create and maintain their social worlds"

(Neumann, 1997:74). The qualitative approach was chosen to understand how participants understand social phenomena, with the emergent realities associated with social life (Chamaz, 2006; Yanow, 2002). The ontological assumptions of interpretivism are rooted in how social reality can be demystified through the eyes of different participants, and these participants have their unique interpretations, creating multiple perspectives about social life (Cohen et al., 2007 p.19). Therefore, social realities tend to have various interpretations of the social world (Charmaz, 2006; Yanow, 2011).

The interpretive approach provided an appropriate method to explore the introduction of PA in US food production systems, where obtaining quantitative evidence may be complex and in-depth information will otherwise not be collected. The approach allowed for exploring and interpreting distinct contributions and perceptions of stakeholders in the US food systems on the emergence of PA. Indeed, the interpretive approach allows a researcher to present participants' construction of social realities and the researcher's interpretation of these realities (Guba & Lincoln, 1994; Neuman, 1997).

The inductive approach to coding was used in reading and interpreting FGDs aimed at developing codes and themes that emerge to answer the study questions (Backett & Davison, 1995; Boyatzis, 1998, Creswell, 2002). The choice of inductive coding was to ensure that inductive reasoning is applied to FGDs where the research findings that emerged from important themes are dominant and inherent in FGDs, without the restraints imposed by quantitative methodologies. In addition to the inductive approach, a deductive approach to coding was also utilized (Crabtree and Miller, 1999). Combining inductive and deductive approaches to coding can be seen as a hybrid coding process that allows themes to emerge from the data, literature, and theoretical frameworks that guided this study

(Fereday and Muir-Cochrane, 2006; Grbich, 2007). The mixture of inductive and deductive coding approaches relied on the study's research questions and the insight from the theoretical perspective. This hybrid approach has been used recently by Jakku et al. (2019) to code textual data (interviews) on the benefits and opportunities of smart farming among Australian grain industry stakeholders. Using a hybrid approach to coding FGDs allows for theory and literature to influence how themes emerge from the data to answer research questions.

Before coding all the FGDs, preliminary coding was finalized on one of the six transcripts, and a codebook was developed following the procedure outline by MacQueen et al. (1998). A codebook was developed by generating codes, a short description of what the codes mean, and specifying inclusion criteria for codes. The study followed Braun and Clarke's (2006; 2020) process of qualitative coding in four-step. In the first step, FGDs were transcribed verbatim. The textual data were read to get familiar with the information contained in the FGDs by identifying important text segments that highlighted research questions, literature, and theory. In the second step, systematic data coding was performed on FGDs. Data was re-read, and initial coding was performed on FGDs. The initial coding allows for multiple pages of textual data to be reduced to important and manageable segments that can be further used in analyzing the data in the next stage (Bailey, 2006). After the initial coding, axial coding was performed to identify and combine codes that emerged from the larger classifications that included multiple codes. In the third step, selective coding was applied, where themes emerged from the axial coding process following the labeling important textual segments with codes and combing codes that incorporate similar codes and categorizing them into themes. The themes that emerged

were further refined and modified in the fourth step, reflecting the FGD transcripts (see figure 1). The codebook generated after this process was applied to the remaining FGDs. The qualitative program NVivo QSR 12 software was used to organize and manage the coding process, update the codebook, and document the description of themes and codes. In addition to analyzing qualitative data, survey data responses were coded into excel and imported into STATA software for further analysis in a non-parametric analysis.

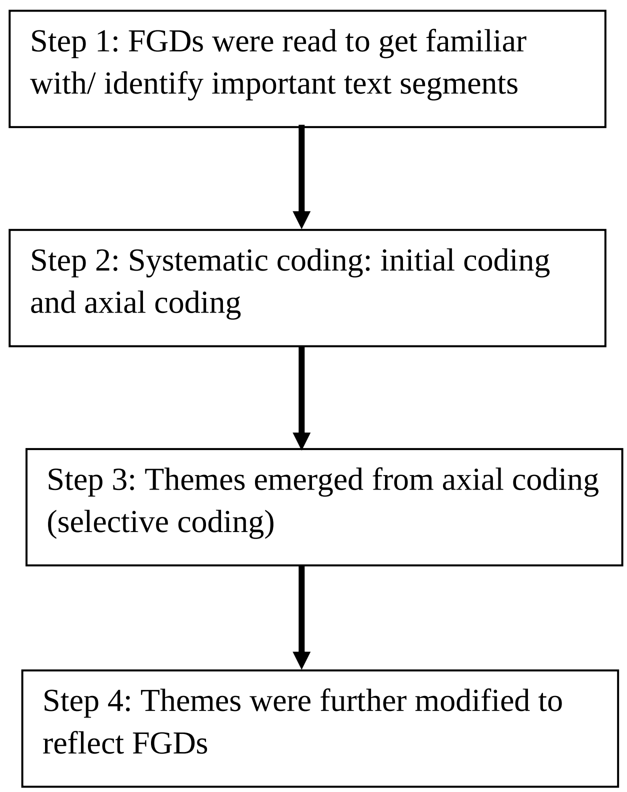

Figure 1: Steps used in coding FGDs

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CHAPTER 3. RESTORING SENSE OUT OF DISORDER: FARMERS' CHANGING SOCIAL PRACTICES UNDER BIG DATA AND ALGORITHMS

Abstract

Advances in precision agriculture (PA), such as big data technologies and machine learning algorithms, can transform agriculture by enhancing productivity, environmental gains and informing farming decisions rapidly and accurately. However, PA has implications for farmers' social practices and how farmers make sense of the social world. This study used social practice theory combined with social identity theory to explore how farmers' social practices are changing with the emergence of big data technologies. This paper used data from six focus group discussions and surveys with participants that represented different actors across the food system value chain. The study found that adopting big data technologies and algorithms necessitates farmers to learn and develop new competencies such as flying drones that collect farm information and interpret maps generated through PA. These new competencies are changing farmers' social identities. At the same time, many farmers are unable to change their identities to the new social expectations that PA presents because most farmers lack the required skills and knowledge to use PA.

1. Introduction

Precision agriculture (PA) technologies include a collection of hardware and software tools, such as unmanned aerial vehicles, global positioning systems, machine learning algorithms, and sensors mounted on farming equipment that enables agritech firms to collect site-specific information, analyze large amounts of farm data, and provide solutions to farmers, such as fertilizer recommendations, seeding plans, and grazing

schedule plans (Coble et al., 2018; Wolfert et al., 2017). Proponents of PA argue that through its expansive adoption on small and large-scale farms, crop yield can increase by 15 percent by 2030, and greenhouse gas emissions from agricultural activities can be reduced by at least 10 percent (World Economic Forum, 2019). While PA presents the potential to generate targeted on-farm and off-farm efficiencies, these technologies are changing the nature of work for a range of food system actors. For instance, PA is significantly changing farming from manual and experience-driven farm management to more reliance on data-driven recommendations (Butler & Holloway, 2016; Carolan, 2020b; Eastwood et al., 2017). Future farmers and farm workers will need to learn how to fly drones, collect farm data, and even operate most farm machinery remotely from their offices (Klerkx et al., 2019; Tsouvalis et al., 2000).

Digitalization in agriculture is rapidly changing social expectations of what a farmer does and what it means to be one (Klerkx et al., 2019; Klerkx & Rose, 2020). Social practices are activities that are "routinized ways in which bodies are moved, objectives are handled, subjects are treated, things are described, and the world is understood" (Reckwitz, 2002a, p. 250). Social practices are made up of three components; artifacts, competencies, and meanings (Shove et al., 2012). Meaning and social identities are similar as they constitute how people understand the world and make sense of who they are (Burke & Stets, 2012).

The introduction of new technology can change the everyday habitual performance and social expectations of individuals that adopt these technologies (Hinrichs, 2014; Shove, 2003; Shove et al., 2012). For instance, PA livestock tools such as automated body

condition scoring (ABCS) measures the health of farm animals and then provide recommendations to cattle farmers about appropriate quantities of animal feed required at different production stages such as lactation and pre-calving. The ABCS measurements can augment farmers' traditional methods of managing cattle health. However, farmers still need to learn new knowledge and skills for interacting with PA tools (Bewley et al., 2008). PA can change social expectations about farming and replace farmers' traditional roles of managing animals previously conducted through manually observing or physically examining animals to assess their overall health and body condition, with new roles and skills such as learning the ABCS system and managing farm data (Bell et al., 2018; Eastwood et al., 2019; Fraser, 2019; Klerkx, 2020).

Farmers have historically responded to changes in social expectations about farming by redefining their identity. Social identity is made up of different "sets of meanings that are tied to and sustain the individual" (Stets, 2006, p. 90). For example, in the last several decades, due to advancements in agricultural technologies and the production of commodity crops for export in the global food value chain, US farmers have begun to see themselves as suppliers of food to a food-insecure world (Brinkman, 2017). According to Jasanoff (2004, p.40), "…identities are important resources with which people restore sense out of disorder. When the world one knows is in disarray, redefining identities is a way of putting things back into familiar places." A digital revolution in agriculture may necessitate farmers to reconfigure their social identities to meet newer social expectations. A modern farmer performing digital agriculture *must* learn to collect large amounts of farm data, understand agronomic recommendations made by inscrutable machine learning algorithms, read maps, and make decisions using those maps (Rose &

Bruce, 2018; Rose & Chilvers, 2018). However, the formation of new social identities also exerts pressure, especially for farmers that have been historically marginalized by the process of industrialization. Indeed, a farmer's ability to learn new digital agriculture tools depends greatly on social characteristics, such as age, education, and access to broadband (Van der Wal, 2019). Extant scholarship suggests that many PA technologies are economically feasible for large-scale and conventional farming systems on which commodity crops are grown and for farmers who can financially afford expensive tools (Gardezi & Bronson, 2019). Moreover, the average age of farmers in the US is about 60 years, and many find the transition to digital technologies technically cumbersome. There is a risk that social differences based on income or farmers' knowledge and skills can become amplified as PA technologies become more commonplace in rural agrarian life. Emerging technologies can reproduce the digital divide between small and large farmers, between young and older farmers, and among farmers with varying levels of skills and expertise to use and interpret data and information (Bronson & Knezevic, 2019; Klerkx et al., 2019). Redefining social identities to meet goals of modernization is therefore limited to a certain group of farmers, those that already possess disproportionately higher social and economic status in agriculture.

Against this background, the question motivating this study is: *how are farmers' social practices (artifacts, skills, and social identities) changing through engagement with big data and machine learning algorithms?* The remainder of this paper is organized in the following manner: Section two presents a review of theoretical work on social practice and social identity theories. Section three detail the methods used in coding data for the study. The findings of this study are presented in section four by highlighting how social practices

are changing farm work and the ways by which some farmers come to redefine their social identities while others do not. Section five expands on these findings, which is followed by a brief conclusion in the final section of the article.

2. Literature review

2.1 *Theorizing social practice*

Social practice theory is situated within cultural theory. It explores the duality and interactions of social structures and individual agency by analyzing how certain practices are implemented by people through institutions and therefore routinized. It is by uncovering how different elements and patterns of daily routines emerge, continue, change, and disappear that one can begin to understand how to make sense of the social world (Shove et al., 2012). For example, conventional agriculture is primarily composed of farmers using different kinds of agrochemicals, such as herbicides and fertilizers. These practices have continued to emerge, change, and even disappear with, inter alia, rapid advancement in technologies and consumer preferences for organic food (Hargreaves, 2011; Jakku et al., 2019; McLaughlin & Mineau, 1995). Existing scholarship has examined an important question: how can new technologies redefine social practices and vice versa? Some researchers have approached this question by unpacking social practice as composed of three analytical categories: (a) materials, which is composed of technologies both hardware, software, and elements that form objects (b) competencies which include new skills, knowledge, and techniques (c) social identities which are made of symbolic representation, ideas, norms, and social expectation (Shove et al., 2012).

In the case of PA, materials encompass tools, such as hardware and software developed to assist farmers with agronomic or financial decision-making (Shove et al.,

2012; Shove et al., 2007), constitute the arrangement of PA. Historically, technological advancement in agriculture has evolved from horse-powered reapers and harvesters around the 18^{th} century to development in tractors and combine harvesters around the 20^{th} century (Acemoglu & Restrepo, 2018). As the world population is expected to rise 34% by 2050 (FAO, 2011), the dilemma arises for agriculture to match the growing population. Agriculture production will need to grow by 70% to keep up with the growth in population while reducing the ecological footprint from agriculture. At the dawn of the 21^{st} century, with advancements in technology, agriculture is witnessing a rapid influx of PA such as software, hardware, sensors, drones, artificial intelligence (AI), machine learning, autonomous robots, and big data applications capable of revolutionizing agriculture (Jakku et al., 2019; Klerkx et al., 2019; Rose & Chilvers, 2018; Sparrow & Howard, 2021). The development of big data technologies and machine learning algorithms has created new opportunities for data-intensive decision-making, enabling farmers to improve their productivity and support several agricultural domains and ecological preservation.

When farmers adopt PA, they require new knowledge and skills. Farmers have to learn how to operate automated milking technologies to milk cows, fly drones that have sensors attached to them to collect detailed topographic images of their farm, to name a few examples. These are new ways of 'know-how' for most farmers (Abdullahi et al., 2015; Bewley et al., 2008; Carolan, 2020a). Over time, practices become embodiments of skills, competencies, materials, and artifacts, and farmers can become carriers of these practices (Reckwitz, 2002b). At the same time, however, farmers may have to relinquish their traditional farming knowledge, such as manual milking practices or scouting for weed and pests by walking in the field, and instead embrace new knowledge by adopting PA

technologies (Eastwood et al., 2017). These changes in farming knowledge can take place through a devaluation or revaluation of traditional farmer knowledge. These can either augment farmers' work productivity or make their jobs redundant. Research on this aspect of PA is still not conclusive. However, what we know is that PA can rescript farmers and their farming practices by redefining expert knowledge (Tsouvalis et al., 2000). As a result, what it means to be a 'successful farmer' is now associated with a farmer who adopts PA technologies earlier than their neighbor or other farmers in their community (Jakku et al., 2019).

2.2 *Social identity*

In addition to material artifacts and competencies, social practices are also constructed and redefined through changes to farmers' social identities. Scholarship on social identity has its roots in symbolic interactionism and anchors itself in research conducted by Stryker (1980). Social identity is conceptualized as exploring how individuals think of themselves and ask the question of "who am I" and actively participate in this construction (Blumer, 1969; Stryker & Serpe, 1982). Therefore, the conception of social identity entails a person's knowledge of belonging to a social category or group. Individuals use social identity to view themselves as members of the same social category. Social identity is made up of several meanings that sustain an individual (Burke & Stets, 2012; Stryker & Burke, 2000). Social identities are socially constructed, resulting from social events, symbolic and reflexive, and in a state of change propelled by social structures (Burton, 2004; Burton et al., 2008; Butler, 1990; Korostelina, 2007). In research on farming systems, social identity theory has primarily been used to understand farmers' identity in relation to environmental sustainability (soil and water conservation) (Burton,

2004; McGuire, Morton, & Cast, 2013). McGuire et al. (2013) found that using performance-based environmental management processes such as having goals to track and measure ecological impacts from farming and watershed significantly influenced how farmers shift their identities from a profit-seeking entrepreneur to someone who is interested in adopting farming practices that improve and protect water quality for society too.

Yet, fewer studies have examined how farmers' social identities are changing in relation to PA. Existing research shows that PA is transforming work requirements from hands-on management to a more data-driven approach. Farmers who adopt emerging technologies are considered 'good farmers' compared to those who do not adopt these technologies (Gardezi & Bronson 2019; Gardezi and Stock 2021; Klerkx et al., 2019; Klerkx & Rose, 2020; Stock & Gardezi, 2021). For example, good farmers adopt and use up-to-date equipment (Gardezi & Stock, 2021). Farmers' adoption and transition to automated farming equipment such as robotic harvesters change the traditional nature of farming that requires physical labor to harvest crops. The observed changes in farm work because of digitalization are changing farmers' social expectations of their farming roles and their social identities (Groher et al., 2020; Klerkx et al., 2019; Shepherd et al., 2020). Farmers come to internalize these social expectations to redraw their social identity. For example, traditionally, farmers apply fertilizer onto the entire farm regardless of areas of need. They often used a physics-based model to enter their inputs and get recommendations based on how much yield they would like to achieve. This often led to greater environmental pollution from the excess use of nitrogen on the farm. Instead, with PA, farmers' roles are changing as they apply fertilizers using data or process-based models,

which are often developed using machine learning algorithms. The data and algorithms can allow farmers to maximize multiple objectives simultaneously (e.g., food security and environmental performance), but these technologies also change what it means to be a farmer. Farmers are now managing and monitoring variable-rate technologies to maximize crop production and environmental performance of their farms by identifying deficient areas on farms requiring small amounts of fertilizer while also contributing to mitigate agricultural footprints by lowering greenhouse gas emissions and water pollution (Clapp & Ruder, 2020). Farmers may now think of themselves as data scientists or observers of data and scouting the land on foot, only when needed to ground truth the results. Thus, it becomes essential to understand how new forms of social practices emerge through the introduction of big data and algorithms in agriculture. There is a possibility that farmers are making sense of these new technologies by re-ordering their social identities. Figure 2 visually represents social practice in relation to big data and machine learning algorithms in agriculture. It shows that materials, competencies, and social identity have an interrelation that influences who a successful and knowledgeable farmer is and what it means to be one.

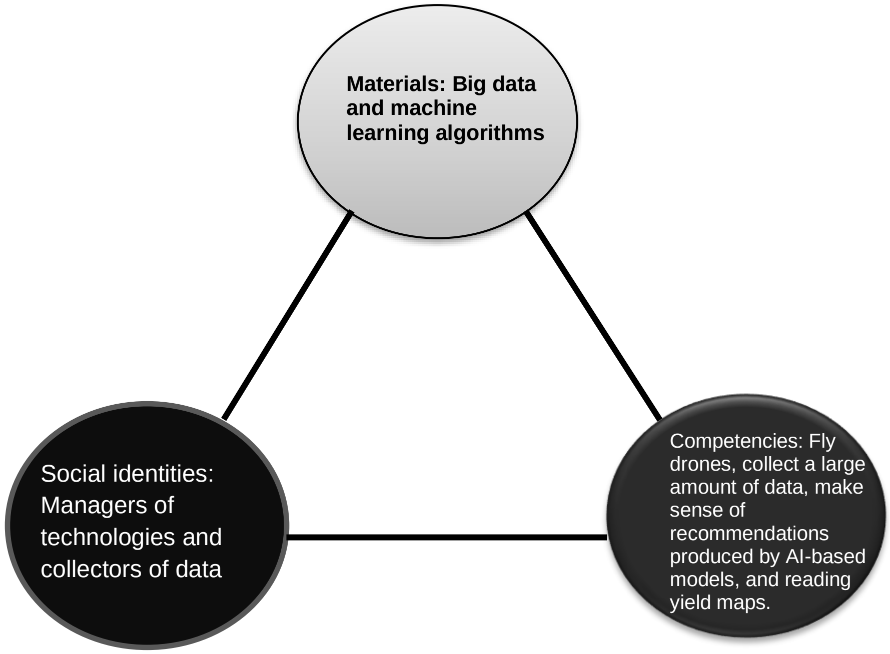

Figure 2: Elements of social practices related to farm management through big data and machine learning algorithms. It is through the existence and incorporation of all three elements in the moment of performance that a practice is achieved (visual modified from Shove et al., 2012).

3. Methods

This section outlines the data collection method, codebook development process, and the coding procedure for the FGD transcripts, and how the survey data was analyzed. Data for this study are from six FGDs held in the fall of 2019 in SD and VT with 52 participants that included farmers, academics, extension experts, NGO/government regulators, and technology developers. Participants discussed the risks and benefits of designing and adopting PA technologies by farmers in SD and VT. Participants also discussed questions relating to how PA influences the social practices and social identities of farmers. A follow-up survey complimented FGDs where participants answer questions on what it means to be a "good farmer." Farmers and non-farmers completed this survey on how PA might influence the social identities of farmers. Details about the study region,

population and sampling strategy, and the methods used in this chapter are explained in detail in chapter 2.

3.1 *Analytical approach*

This chapter used a qualitative interpretive method explained in chapter 2 to analyze FGDs, allowing the emergence of concepts based on theoretical perspectives guiding this study (social practices and social identity theories) and the existing literature on PA. This approach allowed for understanding, identifying, and exploring distinctive contributions and perceptions of stakeholders in the US food systems on the emergence of PA and its influence on farmers' social practices and social identity.

To code valuable pieces of the FGDs that can inform the understanding of the introduction and implication of PA in the US food production system, FGD transcripts were read several times to understand the narratives around changing social practices and social identities discussed by participants in SD and VT. During the process of reading, re-reading, and getting familiar with the data, notes were made on the side of FGD textual data that potentially answered the study research questions. To delve deeper into the FGD transcripts, codes were applied to textual information that reflected the implication of PA on social practices and social identities. Specifically, for instance, large texts such as "if you have fleets of drones and tools there could be some centralized place or can be stored on different people's land" or "We've had a ton of automation already, just like a continuation of the trend we have already seen in regard to, fewer manual labors, more machinery, those sorts of things" were coded into initial codes of *drone technologies or changing skill level and managing PA technologies.* These codes were further rearranged into axial codes such as PA automation, education, workforce development, and labor

displacement. These codes were further refined and reorganized into broader themes such as (knowledgeability and skills, managers of technologies, and data collectors) see appendix 1.

Before coding all six transcripts, a codebook was developed from one of the coded FGD transcripts following the procedure outline by MacQueen et al. (1998) and applied to the remaining five FGD transcripts. The codebook was developed by generating codes, a short description of what the codes mean, and specifying inclusion criteria for codes (see appendix 2 for codebook). NVivo QSR 12 software was used to manage the entire coding process. STATA was used to manage the survey data after survey responses were coded into excel. These coded responses were imported into STATA for further analysis.

In addition to analyzing qualitative data, survey data responses were coded into excel and imported into STATA software for further analysis. The study used both aggregated and disaggregated participants' responses to understand how PA is transforming the social identities of farmers and the perception of stakeholders on what it means to be a "good farmer." The main themes that emerged from FGD transcripts and survey data are expounded and explained in the next section.

4. Results

This section explores emerging themes discussed in the FGD transcripts regarding the question this study aims to elicit: *how are big data and machine learning algorithms changing farmers' social practices?* Two distinct results emerged from the qualitative interpretive analysis: First, how PA (mainly big data and algorithms) are imagined by various stakeholders to change farmers' social practices. Second, how *some* farmers are

unable to change their social practices and struggle to cope with big data and algorithms, each of these themes is articulated in the sub-sections below.

4.1 *Changing social practice in relation to materials, competencies, and social identities*

Given the potential benefits of increased productivity and efficiency that PA can potentially provide, farmers, particularly on large farmlands, are adopting these technologies more successfully (Clapp and Ruder, 2020). PA promises farmers that they can maximize two objectives simultaneously: crop productivity and environmental security. For instance, a farmer in SD expressed: "When you really look at precision agriculture, it's profitable to be a good environmental steward. When you precisely apply the herbicide, you need and don't have overlap, you've saved money and done good things for the environment. When you properly manage your watershed, your expensive fertilizer does not end up in the stream; it stays in the field, where you need it." Farmers are now thinking of their own identities as producers who can maximize profit and as stewards of the environment. All survey respondents (52 participants) perceived that it is either somewhat important or very important for a good farmer to be one who manages both for profitability and minimization of environmental impact.

The adoption of big data technologies and machine learning algorithms attached to drones has necessitated farmers to develop and learn new competencies that are reorganizing farming operations. Farmers have learned to fly drones equipped with sensors, flying over fields that produce maps, and learn to collect large amounts of data on soil health, water quality, soil moisture, soil carbon, and weather information on site-specific farms that provide monitoring capabilities. With these competencies to collect large farm

data, farmers have learned to make sense of recommendations produced by AI-based models and to read maps collected using drones (Higgins et al., 2017; Tsouvalis et al., 2000). For instance, one academic from Vermont asserts, “I see the robot system already having that database of seed or the hundred different varieties or whatever you select to choose from, and when you hit go, it says, where am I going?” These new social practices allow farmers to plan precisely and make necessary improvements in practices such as the application of fertilizers and the prevention of agricultural runoffs. The ability to read maps from big data transforms farmers from traditional cultivators to office managers. Participants in SD and VT responded to questions on what it means to be a good farmer. The aggregated response of stakeholders on the statement that “a good farmer is one who is willing to try new practices and approaches” shows that 100% of respondents agree that a good farmer is willing to try new practices and approaches. This finding is also consistent with the disaggregated analysis of farmers and other stakeholders. On the question of “A good farmer has the most up-to-date equipment,” responses have varied opinions as most respondents were inclined to have the most up-to-date equipment as not important in defining the identity of farmers. Other respondents suggested that farmers having an up-to-date equipment is important to identify a good farmer.

With big data technologies and machine learning algorithms, farmers precisely know GPS locations for every production process, rather than relying on intuition and labor-intensive data collection. An extension personal in VT asserts that highly skilled farmers are those that adapt and engage with big data application and machine learning algorithms for farming operations: “the best farmers are observational data collectors, every single minute of every single day. They may not perceive themselves as data

scientists, but information collectors." Indeed, farmers are passively becoming 'data gatherers' and less hands-on traditionally engaging with their field but through big data technologies and agronomic recommendations. The manual approach of farming by physically visiting the farm at intervals to observe and monitor crop health is replaced by aggregated data collected by farmers as they are performed in real-time without having to be physically present. These automated approaches provide farmers with accurate recommendations and more productive work time. The aggregated survey response of stakeholders on the statement that "a good farmer is one that scout before spraying for insect/weeds/disease" revealed that 100 percent of participants perceived that it is somewhat important, important, and very important that farmers scout before spraying which is still very significant for farmers identity. Therefore, despite this automated process, farmers still must go into the field to double-check the results from the algorithm.

4.2 *Misalignment in social practices under emerging big data technologies*

Farmers and farmworkers lack the high-level skills necessary to make sense of the recommendations they get from big data technologies. Without these technical skills, it becomes difficult to understand the recommendations produced by big data technologies. An extension personnel in SD assert that "there is little understanding of the agronomics back to the actual basic economics of saying we don't understand the agronomics, but of the black box"; therefore, many farmers collect lots of data but don't understand how these recommendations are made through the help of AI-based models. Farmers are feeling 'lost' about PA's 'black box' as farmers adopt these tools to produce and collect information and maps without having full knowledge about how this information is converted into farming recommendations. Therefore, the majority of farmers are not

knowledgeable about how to interpret and apply recommendations from these technologies.

Big data technologies and machine learning algorithms that have emerged still have barriers that hinder farmers from adopting these technologies. These barriers are closely linked to the high skills and cost of adopting PA (Kitchen et al., 2002). These barriers make it unsuccessful for social practices to emerge as material, competencies, and social identities. Therefore, social practices are not well aligned for many farmers and farm workers across the US food systems. For PA to be successful, it requires the alignment of materials, competencies, and social identities that co-evolve together to inform new social practices. Many of the farmers are having a difficult time using PA technologies which hinders the adoption of PA. Agronomic recommendations made by AI-based models are being questioned, as farmers lack the necessary knowledge to understand these recommendations. Although farmers are using big data technologies to collect farm data, farmers struggle to use the information as farmers lack the requisite skills, understanding, and competencies required to interpret information from field maps and big data that they collect from their fields. Interpreting these data requires high-level skills and training that most farmers lack (Tsouvalis et al., 2000). For instance, an industry expert from SD asserts that the most significant gap in the development of technologies right now involves a deficit in the interpretation of data from PA: “Absolutely. And that’s probably the biggest gap we have right now is in the interpretation of what the data is giving us to make agronomic recommendations.” Farmer’s lack of ability to interpret PA recommendations jeopardize the objectives of efficiency and increase productivity for farmers that PA seeks to offer.

With a lack of competencies to interpret agronomic recommendations emerging from big data technologies and machine learning, farmers are less trusting of these recommendations. For instance, a farmer in SD asserts, “I made a decision not based on data, not based on information, I went with my gut. And instead of planting our typical 11 to 13 thousand seed population, I went to 18. I mean, that is shooting the boot. And then, when it came time to put fertilizer on, I did not go by with the soil samples that my area should have for fertilizer for our targeted corn yield; I put on an extra 100 units. So, while all my neighbors are super excited because they have had the best corn harvest they have ever had, 120 to 130, I did 190.” Indeed, farmers are not trusting these technologies as they are not aware of how AI-based recommendations are made and which is in conflict with their experiential knowledge used on farming a particular plot of land. The lack of trust could partially be tied back to the lack of understanding of the technology and a lack of competencies necessary to use PA. These technologies are embedded in larger assemblages that go into the relations between farmers and agronomists. Farmers' interaction with agronomists is constitutive of their social identity. Their relationship with agronomists tends to allow farmers to trust them regardless (sometimes) of what the algorithm may be saying. Similarly, a technology developer in VT believed that farmers' social practices and identities had continuously evolved with the emergence of agriculture technologies: “before tractors existed, farmers weren’t mechanics, right? But I think one thing we need to recognize in that is that probably where the most inertia comes in is a cultural and identity and emotional issue in terms of switching jobs, acquiring new skills, whatever. You know, there’s a certain cachet and identity of being a farmer. You don’t think of yourself as a data scientist, that and I think there’s more of an identity barrier to making

that transition than there is a technical barrier, especially as the data science tools, as you know, so much easier and easier to apply and data gets easier to collect.” The continuous development of PA is indeed influencing how farmers see themselves through the superiority of knowledge that these technologies possess over the experiential knowledge of farmers.

Farmers' experiential knowledge is not considered in designing these big data technologies. For instance, a farmer in SD expressed that “so, trying to use the technology and the capabilities that we have at our fingertips, but then still using that intuition or gut hunch, you know? I mean, you get enough experience, and you make the right decisions off that gut hunch, and the more accurate, probably what you want to give them credit for.” There are trust issues that big data technologies and machine learning models can accurately give recommendations that are more superior to farmers' experimental knowledge. Hence farmers are doubtful if these technologies can make the right decision. There is a high risk as to the uncertainty of what big data technologies can achieve. For instance, an academic from SD asserts that “whenever we make farming decisions, we take limited information and use it to make decisions. We do not know the future either, the algorithm does not know the future, and it doesn’t know the weather, but we don’t know either. We are still making a decision based on what we know and what we expect. Is there any way that precision agriculture can take that same information and improve the decision-making process? And there is still going to be a chance that it will be wrong, right, because it still does not know the same things, we do not know, but is there any way that precision agriculture can improve that decision-making process?” The limitation of these

technologies is expressed as the future remains unknown; as a result, there are great chances that technologies may not generate the right recommendations.

Farmers are skeptical of big data technologies and agronomic recommendations as they lack the competencies and skills to ground-truth the information they receive from big data technologies. However, farmers are willing to adopt PA, deterred by the inability to ground-truth information that they collect from big data technologies. For instance, a farmer in SD believes: “I want more sensors, I want more technology, but we need to fill in those knowledge gaps of being able to how to use. I mean, we need to either have the human interaction to be able to – ground truth.” Therefore, many farmers and farmworkers lack the machine learning and data sorting skills required to operate PA technologies, creating a misalignment of social practices under big data technologies. An extension personnel in SD echoes the challenges associated with ground-truthing and validating agronomic recommendations: “there's still some ground-truthing that needs to be done, that I would assume that the data analysis and the AI is only as good as the data and the knowledge going in and so, I would suspect that continued agroeconomic research, leading into the precision agriculture tools will continue to be needed, as that ground-truthing.” Similarly, an academic in VT explained that “I think it’s a lot of that ground-truthing like the agronomist, based on what they see, algorithms that can do that. Still doing the research to figure out how to take the information and actually help the farmer use it to make a decision instead of using it to say I have this yield map, or I have this soil zone map of my field, but I need someone to take that and be able to use it and all that.” Therefore, the new social identity of a farmer as “data gatherers” could also translate into one who ground-truths recommendations produced by these algorithms.

For technologies such as big data applications to evolve into successful social practices, they need to be aligned to make it easier for farmers to adopt these new technologies. However, social practices in its three elements: material, competencies, and social identities have not worked for some farmers and farmworkers who are marginalized, specifically those with less access to capital, low-skilled laborers, and farmers operating small farmland. Most of the PA technologies are currently designed for conventional agriculture such as corn and soybean with little or no technologies that can support specialty crops cultivated on small farmlands. PA is further exacerbating the digital divide among farmers who engage in conventional and specialty crops. An NGO personal from VT expressed: “In the last six months, there has been a National Geographic and the New Yorker special on the millions of dollars they have spent to replace workers in the strawberry fields, but what about the rest of the specialty crop area which gets nothing and falls into disuse and declines? That’s what’s happening with our agriculture; we’re losing. That puts us at a competitive disadvantage with these specialty crops. If we could get climate change funded, we could learn a lot about how to grow them in a changing climate.” PA might reduce the demand for seasonal migrant workers to produce certain fruits such as strawberries at the expense of specialty crops. Therefore, the development of PA for certain types of farmers can be problematic in the future from an equity perspective. Due to these misalignments, farmers and farmworkers are unable to change their behavior and realign their identities to new forms of work under the emergence of big data applications and algorithms.

5. Discussion

Farming social practices are changing rapidly in response to the development of big data technologies and machine learning algorithms (Klerkx et al., 2019; Klerkx & Rose, 2020). For instance, some farmers who relied on experiential knowledge and general weather information, and soil health information from extension personnel can now deploy fly drones and mapping out site-specific information to improve their decision-making processes on how to grow food. The changes in farming practices as claimed by agritech are believed to increase efficiency on farms, reducing the ecological footprints. For technologies such as big data applications to evolve into successful social practices, there needs to be an alignment of elements of social practices to make it easier for farmers to adopt these new technologies. However, social practices in its three elements: material, competencies, and social identities of farmers have not worked for some farmers and farmworkers who are marginalized, specifically those that have less access to capital, low-skilled laborers, and farmers operating small farmland. Due to these misalignments, farmers and farmworkers are unable to change their behavior and realign their identities to new forms of work under the emergence of big data applications. Our finding points to the fact that although such framing is partially correct but have wide implication for farmers and farmworkers. We detail this implication of changing social practices on the future of work for farmers, the absence of policies for governing these technologies that potentially empower agritech, and the lack of confidence in recommendations that these technologies produce.

Although farm management has been in conjunction with farm advisors and farmers, big data applications and machine learning algorithms transform farmers' roles in the agrarian production process (Klerkx, 2020). Nascent technologies in agriculture lead to

new work platforms and services that will ultimately transform farmers' identities (Fielke et al., 2020; Klerkx et al., 2019). Farmers are increasingly seeking avenues to update their knowledge and skills to complement these technologies' rapid emergence. Farmers will need to update their knowledge and skills to remain relevant in the production systems based on the extensive data generated from farms requiring interpretations (Steinke et al., 2017; Tsouvalis et al., 2000). Indeed, automation in agriculture is shifting and replacing the traditional roles of farmers. The professional role of farmers is transformed into interpreting data collected from digital technologies for farm recommendations (Eastwood et al., 2019). This changing professional role can bring about new platforms and environmental systems in which farming operations are conducted. Advancements in precision technologies offer systems that potentially create new forms of advisory areas and services required by farmers (Klerkx, 2020). These changing roles place farmers' future of work on the pedestal of managers of these technologies and collectors of data as they use technologies to scout their farmlands.

While farming practices have constantly been changing, many farmers are becoming managers of decision support systems; they are reluctant to adopt PA as they collect a large amount of agriculture big data, capable of improving farm management decisions (Coble et al., 2018; Wolfert et al., 2017). Changes in farmers' social practices are altering agriculture with farming activities and farm management decisions transition into a more data-driven approach (Carolan, 2017; Wolfert et al., 2017). With a lack of clarity on how farm data is collected, collated, shared, and used to generate farming recommendations (Wiseman et al., 2019), farmers are reluctant to adopt the technology. The lack of a regulatory and legal framework to oversee how precision technologies and

agricultural data are managed by agritech firms largely contributes to the lack of adoption of these technologies. In addition to the lack of regulatory frameworks, farmers need to train and obtain clearance from the federal aviation administration (FAA) to operate technologies such as drones. Farmers will need to obtain certification and become certified drone pilots, learning all the rules to fly and operate drones safely. All drones will need to be recorded with the FAA (Murphy, 2020).

The site-specific information generated by using drones on the field to produce farm management recommendations makes farmers less trusting of farm recommendations derived from these technologies (Gardezi & Stock, 2021). Farmers collect this large amount of data and are unable to interpret most of the data they collect. The PA ‘black box’ creates an emotional strain for farmers as they are unable to understand the process that comes with using these PA technologies for recommendations. Farmers must have the ability and skills not only to collect farm data but must have the requisite skills needed to translate the data into meaningful management decisions and not rely only on agritech, which currently has the monopoly of knowledge on many aspects of the data collection and interpretation (Wolfert et al., 2017).

This discussion identifies that as technology advances, social practices (new technologies, new skills, and new social identities on how farmers view themselves emerge). This development in technologies has implications on making farm management and farming activities to be carried out efficiently. However, there is a need to ensure that farmers are equipped with the right skills and competencies required to operate these technologies for both data collection and interpretation of this site-specific information capable of addressing the grand challenges of the twenty-first century. Similarly, the

experiential knowledge of farmers needs to be embedded in how big data technologies are designed to ensure that marginalized farmers are not neglected in the process of transformation that comes with the introduction of big data technologies in agriculture.

6. Conclusion

This paper examines *how farmers' social practices (artifacts, skills, and social identities) change because of emerging big data, machine learning algorithms, and agronomic recommendations made by data-based models.* To answer this question, this study used a combination of social practice and social identity theories through a qualitative interpretive approach on FGDs and survey data in SD and VT. The study concludes that farmers' social practices are constantly shifting and emerging. For instance, farmers are learning to use big data technologies and machine learning algorithms; these technologies replace traditional reliance on extension personnel for recommendations or physically observing their field for agrochemical needs. Therefore, adopting big data and machine learning algorithms have significant implications for the future of work for farmers and farmworkers as their respective roles and farming practices are changing under the emergence of these technologies and agronomic recommendations that big data technologies generate. For farmers to adopt and correctly operate big data technologies, there needs to be an integration of farmers' experimental knowledge to develop these technologies. Training will be required for farmers who now collect a large amount of information through flying drones, as these technologies have replaced manually observing their farmlands.

This study found that despite the potential improvement in practices used to collect agronomic recommendations, farmers are still skeptical of adopting these technologies. The emergence of big data technologies and the evolution of social practices in three

elements: material, competencies, and social identities have not worked for some farmers and farmworkers who are marginalized, specifically those with less access to capital, low-skilled laborers, and farmers operating small farmland. The misalignment has made many farmers unable to change their daily practices and realign their social identities to the new forms of farm work under the emergence of big data technologies and algorithms.

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Appendix 1: Example of coding FGDs for changing social practices and social identities of farmers under the emergence of precision agriculture

Example text from FGD	Initial codes	Axial codes	Final codes
“we've had a ton of automation already, just like a continuation of the trend we have already seen. In regard to, fewer manual labors, more machinery, those sorts of things.”	Digitalization, Sensors, Robotic milk	Precision agriculture Automation	Automation of agriculture
“There is little understanding of the agronomics back to the actual basic economics of saying we don’t understand the agronomics, but of the black box.”	Lack of requisite skills, Training of farmers, Transition to new roles	Needed skills and capabilities	Knowledgeability and skills
“Sensors and data processing that ultimately to make precision agriculture successful we're going to need the best possible way to gather data in the best possible ways to process it.”	Collection of farm data Data collection through sensors Processing data	Data gathers	Data collectors
“In the last six months, there has been a National Geographic and the New Yorker special on the millions of dollars they have spent to replace workers in the strawberry fields, but what about the rest of the specialty crop area which gets nothing and falls into disuse and declines? That’s what’s happening with our agriculture, we’re losing. That puts us at a	Replacement of farmworkers	Labor	Labor is placement

competitive disadvantage with these specialty crops. If we could get climate change funded, we could learn a lot about how to grow them in a changing climate.”			

Appendix 2: Codebook for changing social practices of farmers under the emergence of precision agriculture

Code	Brief definitions	Inclusion criteria	Examples
Emerging PA technologies	Various PA technologies that are used to replace old and manual practices of farming	When there is a mention of new PA technologies	"Can install these soil sensors, or like sensors in the streams, and then use those to monitor the performance of these cropping practices that farmers are taking, or buffers, or other kinds of practices."
Reliance on PA recommendation	Farmers now make farm management decisions based on aggregated data and information collected from site-specific farmlands	When statements refer to farmers' reliance on technologies for management decisions such as fertilizer application.	"a lot of precision ag businesses in South Dakota make recommendations on products that they sell, and it's like that doesn't quite compute with a lot of farmers that I work with; "Yes, this company gave you this recommendation, but they also sell this product, so you should review it, right?"
Knowledgeability and skills	New forms of practices in the form of new knowledge.	Farmers learn new ways of carrying out farming activities using technologies	"A lot of education is needed for people to be trained into the implementation

			of those technologies.”
Managers of technologies	Farmers are becoming managers of a fleet of robots, sensors, and automated farming systems	Include when statement talks about including farmers making use of PA technologies	“If you have fleets of drones and tools there could be some centralized place or can be stored on different people's land”
Data collectors	Farmers now collect more enormous amount of data than previously known and available on site-specific farmlands	When statements make mention of data collected by farmers	“On our farm, we collect a lot of data that never sees the light of day.”
Social expectations of farmers to PA	What farmers are expected to do in response to advancements in PA	Include when discussion included what is expected of farmers because of advancements in PA	“I think the future of precision ag is coding”

CHAPTER 4. PRECISION AGRICULTURE AND THE FUTURE OF AGRARIAN LABOR IN THE US FOOD SYSTEM

Abstract

Precision Agriculture (PA) uses sensors, drones, and machine learning algorithms to provide site-specific information to farmers about targeted farm management decisions. However, PA raises critical social questions that have implications for farmers' autonomy and control over agrarian production systems. These technological systems can reconfigure farm labor, replacing or displacing agrarian workers, especially unskilled, seasonal, hired, and migrant labor. This study critically analyzes the social implications of PA through the theoretical lenses of accumulation by dispossession and the agrarian question of labor. The study used data from six focus group discussions that were conducted during Fall 2019 in heterogeneous production systems in South Dakota (SD) and Vermont (VT). The study asserts that agritech firms design PA technologies as accumulation strategies predicated on the dispossession of farmers' autonomy and control over agrarian production systems. As such, PA is fundamentally reconfiguring the future of agrarian labor in the US food system.

1. Introduction

Precision agriculture (PA) is a collection of technologies that support farmers in making informed farm management decisions (Bongiovanni & Lowenberg-Deboer, 2004; van der Burg et al., 2019). Farmers are adopting PA technologies such as tractors capable of automatically steering and navigating on a farm, farm equipment fitted with sensors, and various data collected through satellites, weather stations, and drones that operate through machine learning algorithms. PA technologies can purportedly provide 'precise' farming recommendations to farmers about when to sow seeds, graze farm animals, and harvest

crops (Coble et al., 2018; Wolfert et al., 2017). Proponents of PA in the private and public sectors, such as agriculture technology firms (henceforth *agritech*) such as John Deere, and state actors often frame PA as an innovative solution to address productivity gaps, resource depletion and ecological degradation in agri-food systems (van der Burg et al., 2019). For instance, a study conducted by the United States Department of Agriculture (USDA) revealed that many farmers who adopted PA increased their operating profits (Schimmelpfennig, 2016), though the economic costs of PA to smallholders and marginalized farmers within the increasingly globalized and concentrated agricultural sector remain understudied. Despite promising claims of economic and environmental benefits by agritech firms and the state, PA raises at least two critical social concerns: (1) Capital accumulation by agritech is enabled by the growing dispossession of farmers' data, agrarian production system, and autonomy in field-level decision-making, and (2) reconfiguration of agrarian labor, where agrarian labor is replaced or displaced. Dispossession and displacement are acutely perilous for workers who are unskilled, informally employed, and migrant workers (Bronson, 2018; Carbonell, 2016; Fraser, 2019; Rotz et al., 2019a; Stock and Gardezi, 2021).

Agritech firms (re)produce social exclusions in agriculture by designing and developing PA tools that are suitable for large holding and monoculture farming systems while excluding small and diverse farmers and farms (Bronson & Knezevic, 2019; Klerkx & Rose, 2020; Stock and Gardezi, 2021). For instance, wealthy and largeholding farmers disproportionately benefit from the use of PA because the high costs of many PA technologies are not a barrier to accessing the devices. On the contrary, many smallholder farmers lack sufficient capital to initially purchase and cover recurring fees and required

services that accompany PA technologies, and thus may be at a disadvantage (Bronson & Knezevic, 2019; Klerkx et al., 2019; Rotz et al., 2019b). For farmers who are willing and able to adopt PA, agritech firms have designed legal contracts that strictly protect their licensing agreements and intellectual property rights (Bronson & Knezevic, 2019; Carbonell, 2016). Through complex end-user license agreements, agritech firms dictate farmers' terms of engagement with proprietary data and machinery. Farmers who purchase equipment from agritech firms do not have control over the data that is passively collected by their equipment. Even when farmers have access to some of their data through agritech firm software (e.g., Climate FieldView) farmers are unable to switch software platforms if they want to move to another technology firm for data management (Carolan, 2018; Clapp & Ruder, 2020). This shifts the power of managing farming from the farmer to the agritech firms, who now not only sell their digital recommendations to the farmer about where and when to plant, seed, and spray but also recommend other products that they sell (Bronson & Knezevic, 2019; Gardezi & Stock, 2021). Agritech encourages farmers to adopt more PA tools and agricultural inputs through the process of 'nudging,' whereby private sector advisors recommend firm products and services based on personal and farm-level information collected by precision equipment (Rotz et al., 2019a).

Agritech's capital accumulation strategies have wider implications for agrarian production systems and farm labor. PA as a capital-intensive method of farming provides an alternative to more labor-intensive farming methods. For instance, robotic milking systems, one of the earliest precision livestock technologies, have inbuilt sensors that measure the amount of milk and monitor the health of animals, providing critical detailed information during feeding and milking (Allen 2017; Egan 2015; Charles 2018). These

technologies can increase profitability and may even reduce the ecological footprints of farms such as those driven by the leaching of phosphorus from dairy farms into streams and waterways. As is the case with other PA technologies, however, the adoption of these milking systems on farms are rescripting and reconfiguring agrarian labor with farmers becoming 'digital laborers' relying on automation and data-driven approaches, reducing the need for manual farm laborers and farmers' expertise (Eastwood et al., 2012; Klerkx et al., 2019). Robotic milking systems can reduce the need for agricultural labor in that sector by almost 50% (Allen 2017; Charles 2018; Egan 2015; Purdy 2016), yet the stratum of dairy labor is largely composed of migrant workers (Allen, 2017). PA farmers rely on recommendations from AI-based decision support systems such as drones and sensors to make insightful agronomic decisions on how much fertilizer to use/apply, or which breed of seed to use rather than relying on their experiential knowledge on planting, sowing, harvesting, and fertilizer or herbicide application on the entire field, and dictation of nitrogen and phosphorus levels in soils (Boursianis et al., 2020; Klerkx et al., 2019). Similarly, robots adopted by farmers can milk about 60 cows three times in 24 hours rather than the traditional two times carried out by farm laborers (Charles 2018; Purdy 2016). Machine facilitated efficiencies in production can increase the profit margins and improve time efficiencies unevenly throughout the agricultural labor force, with most benefits accruing to farm owners with enough financial capital, agricultural assets and inputs, sizeable landholdings or possessing a sufficient scale of production system. The widespread claim of economic and ecological benefits by agritech firms has generated large investments from the state, public, and private sectors. For instance, the global precision agriculture market in 2019 generated revenue worth $9.56 billion (USDA, 2019).

The global agricultural robot market is expected to reach $11.58 billion by 2025 (The Aspen Institute, 2019), a figure likely to rise as these technologies become more ubiquitous within production systems.

Agritech firms promote precision technologies that reconfigure agrarian labor, abstracting farmers from the relations of production through digital representations of the farm and farmer. In other words, under PA, farmers perform farming tasks that become encoded, enumerated, and algorithmically embedded into the PA technology while technology firms accumulate surplus value that emerges from farmers’ knowledge systems (Rotz et al., 2019a; Tsouvalis et al., 2000). While PA tools abstract farmers' knowledge into digital systems, manual methods become transformed into automated milking operations, scouting of fields for weeds, and pests become abstracted by drone imagery and sensors. Agritech firms then sell these algorithmically entangled digital representations of food production systems back to farmers who increasingly doubt their own expertise (Bronson & Knezevic, 2019; Gardezi and Stock, 2021).

As a corollary to changing representations of reality into virtuality, technological innovation in agriculture is transforming farmers into managers of precision technologies rather than laboring as producers. Although these new human-machine partnerships can make farm work more efficient and less time-consuming for more affluent farmers (Wolferet al., 2017), advancements in precision technologies aimed at increasing automation in farm tasks and efficiency may replace or displace different types of farm labor, which often involves a process of de-skilling or re-skilling farmworkers that produces inequality among other classes of farmers who are not digitally literate (Klerkx et al., 2019; Wolfert et al., 2017). This process can reduce demand for unskilled labor,

including migrant, hired, and seasonal labor (Carolan, 2020; Klerkx et al., 2019; Rotz et al., 2019). PA is swiftly bifurcating agrarian labor into two groups: one possessing high digital skills to manage agricultural technologies and another group having less technical skills and are subject to employers of labor (Rotz et al., 2019a).

These issues raise concerns for the future of agrarian labor in the US and motivates this study to ask the following research questions: (1) *In what ways is PA dispossessing farmers of their autonomy and production processes?* (2) *How might PA reconfigure future agrarian labor in the US food system?* This study draws from the literature on agrarian Marxism, specifically the *agrarian question of labor* and *accumulation by dispossession*, to interrogate the profitable process through which farmers are dispossessed of their autonomy and agrarian production systems, and ways in which PA can transform future US agrarian labor, with prospects of benefiting high-skilled rather than low-skilled agrarian workers. The agrarian question of labor offers a theoretical perspective to examine insights on agrarian transformation and politics associated with continuous innovation in the twenty-first century (Bernstein, 2004; Levien, Watts, & Yan, 2018). The remainder of this paper is presented as follows. The next section provides an overview of related literature on how PA is reconfiguring agrarian labor. The next subsection outlines the theoretical background of the agrarian question of labor and accumulation by dispossession. The methods section comes next, detailing the study site, data collection method, and the analytical approach for analyzing the focus group discussions (FGDs). The findings from the FGDs are presented in the next section. The findings presented are discussed, and the last session concludes the paper.

2. Literature review

This section addresses how PA technologies reconfigure relations of agrarian production with implications for farm labor by critically appraising existing literature on the subject matter. An overview of how PA is transforming the strata of farm labor and marginalizing certain labor groups is presented in the first part. The second part discusses two theoretical perspectives: accumulation by dispossession and the agrarian question of labor. These perspectives are used to anchor research on precision agriculture and the future of farm labor through Marxist analytical traditions.

2.1 Reconfiguration of farm labor and marginalization of labor groups

Capital investments in food production systems primarily focus on technological innovations that require new skill sets, thereby necessitating additional training of laborers for new tasks associated with the new suite of technologies (Acemoglu & Restrepo, 2018). For instance, in the twentieth century, the mechanization of agriculture in America coincided with a large increase in employment in new agricultural industries and factory jobs, including farm equipment manufacturers (Acemoglu & Restrepo, 2018). PA is currently transforming the technological apparatuses (hardware and software) used for farming through the integration of artificial intelligence and robotics, which are changing the skills required for labor in agriculture. On the one hand, agritech firms promise that automation in agriculture enhances farm work, creating efficiency and productivity, despite jettisoning unskilled and manual labor on farms. For instance, agricultural robots have already been developed to take over manual tasks, such as picking fruits and sorting them based on weight and nutritional value. Labor-technology partnerships may be enhanced by PA (Klerkx et al., 2019). For instance, farmers who adopt site-specific recommendations

can reduce their operation's environmental footprint by applying chemical fertilizers only where and when it is required (Bongiovanni & Lowenberg-Deboer, 2004). Similarly, farmers' adoption of automatic milking systems can monitor the health of animals in real-time, identifying diseased animals and providing health recommendations while reducing environmental pollution such as methane (Rotz et al., 2019b). PA farmers are now meant to interpret yield maps that are produced by farm data collected by overhead and ground-based sensors and analyzed using physics-based models or machine learning algorithms. This means that agriculture will require workers with more advanced skills to work alongside agricultural robots and interpret complex maps developed through PA tools (Lowenberg-DeBoer et al., 2020), nudging unskilled laborers further into economic precarity. Some scholars see the drawdown of unskilled labor as a solution, arguing that PA technologies and automation in agriculture solve problems of farm labor shortages, insofar as PA can replace the unpredictable and limited supply of hired, seasonal, and migrant workers in agriculture (Christiaensen et al., 2020). Social injustices against marginal laborers notwithstanding, automation combined with artificial intelligence can reduce the need for unskilled and manual labor and support high agricultural productivity and profits for agricultural capitalists and agritech firms (Auat Cheein & Carelli, 2013).

PA is replacing many low-wage seasonal, hired, and migrant workers from minority racial and ethnic groups (Rotz et al., 2019a). Despite augmenting higher skilled worker's productivity through technology, PA reinforces existing social, economic, and racial inequalities in agriculture (Bronson & Knezevic, 2016a, 2016b; Rotz et al., 2019a). This is problematic because the US has a history of systematic racial inequality in agriculture, such as the institution of chattel slavery for plantation agriculture and the USDA denying black

farmers loans for agricultural investments. For example, the Pigford v. Glickman 1999 lawsuit exposed racial discrimination against African American farmers who required support in the form of loans and financial assistance (Cowan and Feder, 2012). Therefore, PA technologies may perpetuate historic racial inequality and class relations by replacing migrant and marginalized farmworkers with AI technologies (Klerkx & Rose, 2020; Sparrow & Howard, 2020).

Capital investments in innovating the technological machinery that mediates the relations of food production have historically transformed and disrupted agrarian lives and livelihoods, (re)producing social inequalities and power asymmetries (McMichael, 2009; Miles, 2019). Likewise, PA technologies also reinforce the unequal mode of capitalist production and further marginalize specific labor groups (Klerkx & Rose, 2020; Nally, 2016; Miles, 2019). As currently utilized, PA innovations likely exacerbate existing power asymmetries between agritech and farmers, putting more power in the hand of a few agritech corporations or state actors (Fraser, 2019; Rotz et al., 2019). However, firms and farmers could responsibly innovate PA technologies, designing them to be sensitive and corrective of social inequalities, and wield them to support the growth of diverse communities of farmers and farmworkers, while creating more jobs in this process (Ivus & Boland, 2015). Yet the exigencies of capital accumulation within inequitable food production systems reinforce agritech's design and uneven deployment of PA. Agritech firms through PA technologies grab a large amount of farm data that is utilized to direct their innovations and investment opportunities, where the data is largely protected by intellectual property rights that impede farmers' access and control (Fraser, 2019; Rotz et al, 2019; Stock & Gardezi, 2001). The implications of PA with regards to social inequalities

remains gravely understudied, hence the impetus for this paper. Evaluating new strategies of agritech capital accumulation by dispossessing farmers, This study is situated within the context of accumulation by dispossession in the next subsection.

2.2 Theoretical perspective

2.2.1 Accumulation by dispossession

Marx theorized and described the evolution of capitalist social relations through *primitive accumulation*, which implies a series of events that contributed to producers' alienation from their means of production and subsistence; peasants become proletariats who have no choice but to sell their labor to the bourgeoisie. His classic analysis of primitive accumulation was grounded in the study of English enclosures where peasants were violently detached from their land and livelihoods (Wood, 2017). Marx contended that the process of dispossessing peasants from their land engendered the pre-conditions for capitalism. Dispossessed of land and without alternative livelihoods, peasants became a reserve army of labor whose surplus was needed for newly developed factories in the English cities. In this context, primitive accumulation emerged by separating producers from their means of production, which transformed farmers' livelihoods into capital and the workers into wage laborers (Marx, 1987). In this vein, capital is produced through detaching laborers from their property relations (Marx, 1983). Therefore, the process of primitive accumulation transformed varying types of relations (social and property) which promoted capital accumulation and created new relationships between capital and labor. As it relates to food production systems, primitive accumulation refers to historically specific and contingent processes that involve agrarian capitalists disrupting the social reproduction of producers vis-à-vis the coerced reconfiguration of farm labor and the

circulation of agricultural capital. For instance, the present innovation in PA is enabling greater control of farm data by agritech, allowing emerging stakeholders that are formally not agrarian and outside of the food production process to easily enter the agrarian space, and in doing so have an opportunity to harvest farmers' data (Fraser, 2019).

Harvey (2003) expanded upon Marx's concept of primitive accumulation arguing that dispossession is a process that continues rather than simply a pre-condition for capitalism as theorized by Marx, which he termed *accumulation by dispossession*. Harvey (2003) suggests that current processes of dispossession emerge from the economic sphere, specifically finance and credit systems. The capitalist's ceaseless pursuit of profit facilitates capitalist class to reproduce itself and its dominance over the laboring class. Therefore, "accumulation cannot be detached from class struggle" (Harvey, 1978, p.116). In this regard, capital accumulation depends on reconfiguring labor strata to create a surplus during the production process. This is often done by increasing the number of labor hours for increased productivity and introducing machinery and automating labor-intensive work processes (Harvey, 1978). Given the genealogy of exploitation of marginal laborers arising from capital investments in food production systems, the study asserts the importance of exploring the social ramifications of PA technologies. Next, the study explores the introduction of PA through the lens of the agrarian question of labor in the next subsection.

2.2.2. The agrarian question of labor

The so-called *agrarian question* emerged from Marx and Engels' work that focused on industrial capitalism. Marxist scholars such as Kautsky and Lenin, among others, began to apply Marx's labor theory of value in the industrial setting as a lens to understand the

emergence of capitalism and the politics inherent in agrarian societies (Akram-Lodhi & Kay, 2010; Bernstein, 2004, 2006; Levien et al., 2018). The concept of the agrarian question has acquired heterogeneous interpretations and applications over the past century, each revealing an essential aspect of contemporary Marxist discourse about the political economy of agrarian production (Byres, 1995; Moyo, Jha, & Yeros, 2013). Kautsky expanded Marx's (1990 [1887]), Engels' (1950 [1894]), and Lenin's (1964 [1899]) agricultural transition perspectives to explore ways in which capital infiltrates agriculture and creates new forms of production (Kautsky 1988 [1899]. p 46), defining the agrarian question as "whether, and how, capital is seizing hold of agriculture, revolutionizing it, making old forms of production and property untenable and creating the necessity for new ones" (Kautsky 1988, 12). The agrarian question is built on the premise that the "penetration of peasant agriculture by capital is a decisive moment in the development of capitalism" (Levien et al., 2018, p. 860). Kautsky (1988, p.297) asserts that "agricultural production has already been transformed into industrial production in many fields, and a large number of others can be expected to undergo this transformation in the immediate future. No field of agriculture is completely safe. Every advance in this direction must inevitably multiply the pressures of farmers, increase their dependence on industry and undermine their security."

Following the original contribution from Marx, Engels, and Lenin, which is now referred to as the classical agrarian question (Bernstein, 2004, 2006; Moyo, Jha, & Yeros, 2013), Byres (1995) framed the agrarian question as to the problematics of politics (originating from Engels), production (from the studies of Kautsky and Lenin) and accumulation (from Marx and Preobrazhensky writings). Likewise, Bernstein's (2006)

conception of the agrarian question focused on the economy (capital accumulation and production) and politics; capital provides a path for dispossessing peasants, all of which transform the agrarian mode of production and social interactions which agitate class tensions for peasants (Akram-Lodhi & Kay, 2010a, 2010b; Byres, 1977; Levien et al., 2018). Bernstein (2006) affirms that three interrelated aspects are visible from the classical agrarian question: capitalism seizes the agrarian mode of production and differentiates agrarian classes, how agriculture fosters industrialization emerges from the relations of production, and the political struggles it creates for agrarian classes (Levien et al., 2018). For instance, a key moment in the emergence of rural capitalism is connected to the appearance of rural wage labor, proletarianization as a consequence of the modalities by which agrarian capitalists dispossess peasantry from their landed property (Bernstein 2006).

While the agrarian question before neoliberalization focused on land distribution problems, with neoliberal capitalism accelerating globalization, Bernstein (2004) argues that the critical component of the agrarian question concerns labor "now detached from that of capital, and which generates a new politics of struggles over land (and its distribution)." The central message of the *agrarian question of labor* explores the consequences of the infiltration of capitalist relations into the countryside, leading to the commodification of labor and accumulation based on increased productivity. Indeed, agrarian Marxism concerns itself with the question of "what are the political consequences of capital transition in the countryside" (Byers 1996, p.27). The emergence of PA, for instance, serves as an important avenue to explore how the changing political economy of agriculture and its implications of capitalist penetration into the countryside fosters

capitalist development and undermines farmer livelihoods (Akram-Lodhi & Kay, 2010a). The labor problem emerges from how the agrarian questions of capital transform agriculture through expansion and intensification of capitalist farming relations, reconfiguring farming labor (Levien et al., 2018).

Disruptions in relations of production stemming from the nascent development of PA serve as an entry point to the classic agrarian question and the agrarian question of labor. The infiltration of PA requires that each case of dispossession be understood within the political, economic, and cultural context. Marx asserts that the process of dispossession plays out differently across geographies and social contexts (Marx, 1978). An illustration of historical dispossession in the US is conveyed by the violent alienation of Native Americans from their land (Greer, 2018; Murphy, 2018). However, dispossession in agriculture has taken new forms with the emergence of PA. Farmers who engage with PA technologies are now dispossessed through displacement or data enclosures, knowledgeability, and autonomy (Fraser, 2019; Gardezi & Stock, 2021; Rotz et al., 2019), driven mainly by market domination to increase productivity and reduce production costs by exploiting agrarian labor.

The agrarian question of labor offers a theoretical lens to examine the contention between capitalist farming and the fragmented classes of labor (Bernstein, 2006), consisting of landowners, agritech, farmers and unskilled laborers (e.g. hired, seasonal, migrant labor; Carolan, 2020; Klerkx et al., 2019; Rotz et al., 2019). Labor fragmentation occurs as traditional roles performed by farmers and wage laborers are taken over by automation. Some PA farmers now learn how to fly drones to know the right time to apply fertilizer to crops at specific locations, while hired, seasonal, and migrant workers are

dispossessed of their manual farming skills. The dynamics of innovation and accumulation are rescripting the demand for wage and unskilled labor. The changing nature of work further fragments the different groups of workers. The circulation of agrarian capital through PA technologies fragments labor classes "through insecure and oppressive and in many places increasingly scarce wage employment. Oppression and differentiation happen along the lines of gender, generation, caste, and ethnicity" (Bernstein, 2006). This study offers an essential step toward understanding the future of agrarian labor under capitalism. In particular, the agrarian question of labor allows us to interrogate how peasants thrive or even just survive, given the dispossessing forces and politics associated with capitalism. In essence, understanding the forms through which PA dispossesses farm laborers.

3. Methods

To examine how the introduction of PA is dispossessing farmers of their autonomy, production processes, and the future implications of agrarian labor, this section discusses the data collection procedure, the approach used in coding FGD transcripts, and the procedure used in creating the codebook for this study. Data for this chapter are from workshops held in SD and VT in October and December 2019. Six FGDs were conducted with various participants that included farmers, academics and extension experts, NGOs/government regulators, and technology developers. Participants were encouraged to discuss in-depth their perception of the main topics on which the study is situated. The overall focus on the FGDs was predicated on highlighting opportunities and risk PA technologies produce in both regions. The FGDs questions specifically addressing this study questions discussed during the workshop by participants are, for example, *how do you think automation will change farming? How might precision agriculture enable the*

automation of work? Will precision agriculture increase or decrease the overall labor requirement? What work will be lost to automation, and what jobs will be created? What areas on the farm has PA made the least impact and what the thought about rural communities being reshaped by PA? Chapter two of this dissertation gives a detail procedure on the data collection.

Analytical approach

FGDs transcripts recorded during workshops held in SD and VT were analyzed using an interpretive approach to qualitative analysis discussed in detailed in chapter 2. This approach was useful to allow themes to emerge from theory (accumulation by dispossession and the agrarian question of labor) and literature that guides this study. Drawing meaning from the FGD transcripts through a qualitative interpretive approach provided an understanding of the influence of PA on farmer's autonomy and future agrarian labor in the US food system. To code important segments of the FGDs transcripts, the textual data was read severally to gain insight into the main discussion about capital accumulation, dispossession, and agrarian labor. Textual data was coded when line codes reflected questions the study aimed at understanding. Some of the codes that emerged from the FGDs were labor, change in skills, training, labor shortage, data rights, and privacy which was categorized into themes to include *capital accumulation and dispossession of farmer autonomy*, *future labor dynamics*, and *skills and workforce development.* To code the remainder of the FGDs, a codebook (see codebook in table 1 appendix) was developed using insights from MacQueen et al. (1998) and applied to other FGDs transcripts. Emerging themes from the FGDs are detailed in the next section on how PA influences farmers' autonomy and future agrarian labor in the US food system. In the discussion, the

theoretical perspectives engaged in this study (i.e., accumulation by dispossession, agrarian question of labor) are used to draw implications for the study findings.

4. Results

This section expounds on emerging themes discussed in the FGD transcripts by participants to answer the following research questions: (1) *In what ways is PA dispossessing farmers of their autonomy and production processes?* (2) *How might PA reconfigure future agrarian labor in the US food system?* Using the qualitative interpretive analysis described in chapter two, three distinct themes emerged from FGDs: (1) Capital accumulation and dispossession of farmer autonomy; (2) future labor dynamics, and (3) skills and workforce development.

4.1 *Capital accumulation and dispossession of farmer autonomy*

Agritech firms claim that precision agriculture can increase the efficiency and productivity of farming processes, reducing the amount of pressure on natural resources while increasing farmers' revenue (Bayer, 2018). A technology developer from the Midwest described PA as: “using technologies for better agriculture production.” The influx of PA technology in SD and VT is considered to be a natural evolution of previous technological innovations in agriculture, such as genetically modified crops, that have ostensibly revolutionized agriculture. An extension personnel explained that “we have had a ton of automation already, just like a continuation of the trend we have already seen.” The adoption of these emerging technologies is beginning to change how farming is conducted in SD and VT, where manual farming practices (e.g., scouting, planting, fertilizer application) are replaced by PA technologies such as drones (figure 3), big data,

machine learning algorithm, and variable rate application technologies (figure 4), undermining or enhancing the expertise of the farmer. Automation in agriculture is promoted as eliminating the ‘drudgery work’ of agricultural production. According to one farmer in SD, automation is reorganizing “farmers' work-life balance,” thereby making it easier to have more productive work time. Efficiency gains notwithstanding, the reorganizing of farming through the adoption of PA has facilitated several forms of dispossession, mainly farmer autonomy and control of the production process.

Farmers in SD and VT are unevenly adopting PA, yet these technologies are closely related to components of the well-known industrial agricultural systems that erode farmers' autonomy and control over production systems (Clapp & Ruder, 2020). Farmers’ autonomy and control of production processes might be eroded, where farmers become collectors of farm data and information. As one industry expert from VT asserts, “We are right in the middle of precision agriculture; we are harvesting just an enormous amount of data every day on every milking.” Agritech firms have built an algorithmic ecosystem of data collection, a novel accumulation strategy that (re)produces asymmetric power relationships between farmers, vis-à-vis data ownership and transparency, which undermines farmers' autonomy and control of production processes. Data dispossession is sustained through contracts and end-user agreements that farmers are required to sign in order to utilize certain PA technologies. For instance, to increase crop yields, farmers sign contracts with companies (e.g., Climate Corporation) and their products (i.e., FieldView) to receive specific recommendations that promise to increase crop productivity. When farmers give up their rights in exchange for the perceived benefits of PA, they lose ownership and access to their farm data. In instances where their consent might be required,

they are not able to decide as to how their farm data will be utilized by agritech firms. In addition to data ownership, agritech places restrictions on farmers' rights to repair their PA-integrated farm machinery which is yet another modality of dispossession. The industry experts provide justification for creating these exclusions in the design of new technology, as identified by a technology developer in VT: "As you have to be a certified qualified tech to work on a robot, you cannot just, somethings you can touch but, in most cases, it requires, you know, a trade person to work on it." Even when these farmers have the technical 'know-how' to fix the PA tools that they operate, agritech contracts and end-user agreements prohibit farmers from modifying or repairing any part of their machinery. These contractual obligations shift power from farmers to corporations through farmers' inability to access data, thereby eroding the autonomy of farmers (Bronson, 2018; Carbonell, 2016; Fraser, 2019, 2020; Wolfert et al., 2017).

Figure 3: Drone *used by a farmer to spray and collect field information (Source: Pixabay: free for commercial use. No attribution required)*

Figure 4: Monitor showing control of other precision technologies and variable rate application *(Source: John Deere https://precisionagricultu.re/john-deere-and-the-birth-of-modern-precision-agriculture/)*

Agritech firms have a virtually unlimited ability to access and manipulate farm data collected. Agritech firms use this data to observe and predict farmers' behavior for the sole purpose of making profit (Stock and Gardezi, 2021). This process has the effect of dispossession farmers of their autonomy to function as producers in their own production systems. As farmers in SD and VT passively collect and give up their farm data, large agritech firms can extract information, 'adding value' to the aggregated data which is used in making recommendations on the kind of technology and agricultural inputs (e.g., chemicals, seeds) that farmers *need* to buy. Agritech's dispossession of farmers' autonomy through exclusive data access functions as a novel accumulation strategy that slowly erodes the farmers' ability to make insightful farming decisions. One academic from VT argues, "I see the robot system already having that database of seed or the hundred different varieties or whatever you select to choose from. When you hit 'go', it says: *Where am I going?* You tell it, and it looks up whatever data—historical yield data or whatever you put in for input—and it says: *I would recommend this, this, and this seed*. And you pick which

one." Farmers' reliance on the algorithmically derived recommendations of agritech firms not only reduces farmers' autonomy but also makes them question their own identity as producers. The identity of farmers is being negotiated through the emergence of PA technologies (Gardezi and Stock, 2021). Farmers are increasingly being perceived and perceiving themselves as 'data gatherers'. As one extension expert from VT puts it, "The best farmers are observational data collectors, every single minute of every single day. They may not perceive themselves as data scientists, but information collectors." Farmers' passiveness in collecting farm data is creating a major shift in roles performed by farmers and nontraditional actors, changing what it means to be a farmer (Klerkx & Rose, 2020; Rose et al., 2018; Gardezi and Stock, 2021). Farmers are abstracted from their traditional roles of cultivation because of data generated through PA sensors, drones, and decision support systems. For instance, a farmer in SD contends that PA technologies have the "ability to process data so much more quickly than we can as humans—and lots of data—and to be able to make a decision and change on that." The reliance on these technologies is changing the roles of farmers, agronomists, and extension personnel that offer agronomic advice to farmers before the adoption of PA technologies (Klerkx & Rose, 2020). These changes in roles are consistent with capitalist transformations of agriculture through the influx of capital and the intensification of machinery that transforms labor relationships between agritech and farmers (Levien et al., 2018; Thatcher et al., 2016; Harvey, 1978). These changing roles can compromise the autonomy of farmers, thrusting them into an uncertain future whereby agritech fundamentally reconfigures the strata of agrarian labor. A summary of insights from FGDs about the implication of PA as a strategy for capital

accumulation and dispossession of farmers' autonomy and control of the production process is detailed in table 2.

Table 2: An overview of insights from FGDs on PA as a strategy for capital accumulation, dispossession of farmers autonomy, and agrarian labor in the US food system

Capital accumulation and dispossession of farmers autonomy	*Agrarian labor dynamics*
• Farmers lose ownership and access to data protected by legal contracts • Manipulation of farm data • Extraction of valuable farm information to make profit • Farmers over-reliance on algorithm recommendations • Farmers become data gatherers • Famers lose rights to repair their PA integrated machinery	• Enhance efficiency and productivity • Reduce the amount of work on the farm • Address agrarian labor supply shortages • Displacement or replacement of manual laborers • Farmers become managers of a network of technology • (Re)producing inequalities among farmers and farmworkers.

4.2 *Future agrarian labor dynamics*

The evolution of sensors and decision support systems through PA is changing the future of agrarian labor dynamics. Agritech envisions the future of labor as enhancing efficiency and productivity. However, agritech's access to and control over data collected from production systems positions these firms as a formidable force in the political economy of agriculture. Proponents of PA envision the technologies as beneficial insofar as they can reduce the amount of work on farms and address the labor supply constraints of rural agriculture. Agritech's motive in creating these technologies is profit-driven. As one extension personnel from VT suggested, the majority of innovations existing in agriculture have been used in "optimizing monoculture, optimizing commodity production, optimizing larger and larger farmers."

Agritech's technological innovations in farming are threatening the expertise of manual laborers. The emergence of PA will force precariously employed and marginalized farm laborers to be displaced or replaced. For instance, the labor force of the dairy industry is largely composed of migrant workers—for example, roughly 1-2,000 undocumented migrant workers from Mexico are employed on VT dairy farms (Allen, 2017)—who will be displaced as tasks that these farmworkers engage in are now performed by machines. Drawing from a historical event in the manufacturing sector, one farmer envisions that the labor force in agriculture will be "replaced if the only thing you're doing is turning around at the ends and doing a little more monitoring. And you look at history and you look at manufacturing, and those jobs that are consistent and repetitive are the ones that technology has replaced." However, with the emergence of technologies, farmers envision managing a network of technologies that will be instrumental to agricultural efficiency and productivity. One farmer expressed, "I envision managing a fleet of robots or something along that line, where maybe I'm the tender truck driver that's moving them from field to field and managing ground-truth and doing that sort of thing." Techno-optimistic imaginaries of PA-mediated production systems enable agritech and agrarian capitalists to transform the relations of production in ways that render precarious farm laborers as surplus with reduced employment opportunities (Li, 2011). Farm owners and operators that utilize PA technologies increasingly become data harvesters.

Other participants suggested that PA technologies likely displace workers through the acquisition of technology. An academic in VT opined that "so like it used to be everybody sort of had their family farms, and then it's like fewer and fewer people, you know, fewer and fewer farmers on a much bigger farm need access to workers and then

now those workers may be getting sort of displaced.” Agritech restructures the relations of production by developing more machinery capable of automating the work process (Harvey, 1978). Ostensibly innovations of agriculture, PA technologies are accumulation strategies that transform agrarian lives and livelihoods, having the effect of (re)producing inequalities in the production system that disproportionately affects lower-skilled workers. As one industry expert in VT expressed, “If production is part of labor and capital, you increase the capital part and you reduce the labor part. So, you created inequality.” This process is evident in VT, as described by an extension personnel from VT: “When I look at a farm system, and particularly in VT, I love when a farmer shows up with his robots. Because it does those things you just mentioned, it changes the quality of life. People can actually live on the farm in a way that they haven’t lived on the farm before. But it displaces, if you want to take it to an extreme, if it displaces a migrant crew that is shipping their income back to Mexico, you know, we can’t be devoid of that. If we expect that, oh, we are going to have a lot of new technology on the farm.” Migrant and low-skilled workers are losing their livelihoods with the development of PA technologies that replaces their manual labor.

4.3 *Skills and workforce development*

The emergence of technology in society is in inseparably entangled with politics; their design is not value-free; hence they are not intrinsically good, bad, or neutral (Jasanoff, 2016). With the introduction of PA, the reconfiguration of agrarian labor is becoming inevitable, especially for farmers and farmworkers who are more likely to be displaced by technology and may require new skills to remain relevant to future work. A farmer from SD argued that they will need “one or two people on the operation [need] to

be really good at math and computers." Therefore, PA is redefining the roles of farmers from manual cultivators aided by machines to cultivators of big data that aid machines—digital laborers. However, another farmer from SD expressed that it is not only farmers who will have to upskill, but also those that will be assisting farmers with their decision-making and "the troubleshooting and the technical aspect of being able to keep some of these things running and working correctly." The commodification and exploitation of farmers' labor (manual-cum-digital) creates unemployment for low-skilled, migrant, and hired laborers (Carolan, 2020; Rotz et al., 2019; Li, 2010; 2011). The implication of farmers as digital laborers points to the evidence that farmers are not adequately rewarded for the farm data they generate and the service of passively harvesting data for agritech (Rotz et al., 2019). As such, the infiltration of agritech capital and technologies in production systems is further differentiating the labor classes of farming, positioning agritech and agricultural capitalists as 'winners' and unskilled laborers (e.g., migrant, hired, seasonal, undocumented) as 'losers.'

With end-user agreements protected by intellectual property rights, agritech ensures that agrarian production selects for specific skills, reconfigures identities, and rewires the knowledgeability of the farmers. Although farmers are contractually prohibited from fixing the PA technologies, PA requires farmers to learn more technically advanced skill sets, such as flying drones, that are now required to manage their farms. Acquiring new technical skill sets to utilize the PA technologies and spending production time managing the artificially intelligent machines eclipses manual tasks performed and the experiential knowledge possessed. In essence, PA alters the social identities of farmers. The social identities that are created under the emergence of PA are substituting the traditional

identities that farmers possessed such as “those that define a good farmer to be a productivist and profit-maximizing subject, with conservation identities that concurrently describe them as stewards of the environment” (Gardezi and Bronson 2020; Gardezi and Stock, 2021). For instance, a technology developer from VT explained that "before tractors existed, farmers were not mechanics, right? But I think we need to recognize that probably where the most inertia comes in is a cultural and identity and emotional issue in terms of switching jobs, acquiring new skills, whatever. You know, there’s a certain cachet and identity of being a farmer.” Agritech’s reconfiguration of farm labor by dispossessing farmers’ autonomy and control over the production system through PA technologies ultimately threatens the social identities of farmers as they are pressured to upskill in order to remain productively employed in farming and frantically strive for key performance indicators of efficiency and productivity in digital farming (Barrett & Rose, 2020; Schillings, Bennett, & Rose, 2021). In the next section, the implications of this study are discussed.

5. Discussion

PA technological interventions in production systems of SD and VT are leading to a consolidation of power for agritech and the further stratification of farm labor classes. Agritech firms’ design PA for large holding and monoculture agriculture systems and the majority of smallholding and marginal farmers are excluded. Similarly, legal contracts and licensing agreements backed by intellectual property rights prohibit farmers from owning their farm data. Agritech firms’ accumulation of capital is predicated on alienating farmers from the means of production; dispossessing farmers from their data, from farmers’ control

and autonomy within their production system, thereby capturing labor, land and data pertaining to labor and land (Li, 2011).

Three key implications emerge from this study's findings. First, PA introduces new perils to farmers' autonomy and control over production processes. Despite being discursively articulated as a solution to global food insecurities by agritech, production system stakeholders must consider the social implications of adopting PA. Yet such techno-optimistic discourses about PA's potential to circumvent famines in a climate-ravaged future entice farmers to adopt PA, irrespective of whether the social implications of these technologies are well understood (van der Burg et al., 2019). Hence, many scholars have legitimate concerns about PA's potential to deliver efficiency and productivity in light of unrelenting (albeit uneven) alienation of producers (Jakku et al.2019; van der Burg et al., 2019). The lack of transparency offers immense opportunities for agritech to use farm data that can be used to manipulate agricultural production systems to direct farmers to purchase certain forms of inputs and create recommendations that farmers require to improve production and efficiency. As a result of a lack of transparency, farmers lose their ownership, access, and control over data and their ability to make decisions. This has the effect of eroding farmers of their autonomy, undermining sustainable farming as agritech firms have more advantage over data collected by farmers. Information asymmetries could potentially impact how power is distributed and the reduction of farmers' autonomy in the food production system (Coble, 2018). For the future of farming to be sustainable, it is imperative to redesign how PA is currently formulated, where agritech has more benefits in data access and control to an open-source model, helping to ensure that data can be easily accessed and owned by farmers, which can ensure that farmers can have greater financial

freedom and autonomy (Rotz, et al., 2019a). Transparency in how farm data is collected and used by agritech can increase farmers' autonomy as more knowledge about the production process will better inform farmers' choices on recommendations (Van der Burg et al., 2019). Although farmers generate farm data, it does not guarantee that they have access and control as to how their data is to be used (Wiseman et al., 2019).

Second, the terms of engagement, contracts, and end-user agreements protected by intellectual property rights which dictate how agritech relates with farmers, avails no opportunity for farmers to negotiate the contracts and end-user agreements that guide their activities when adopting the PA technologies. When farmers do not agree to terms and contracts set by agritech firms, these technologies further lead to and contribute to the existing digital divide or exclusion of farmers who are not willing to engage because of a lack of skill sets or of understanding of the terms of engagement (Rotz et al. 2019a; Eastwood et al., 2019). The exclusion of some farmers may undermine the current and future sustainability objectives of agriculture. Further, farmers who adopt these technologies are eroded of their autonomy to fix their machinery. Although farmers can seek the help of approved technicians (Fraser, 2019; Jakku et al., 2019), the delay that comes with maintaining their equipment is creating a pool of tech savvy farmers who hack into computers to modify their farm machinery (Regan, 2019). To ensure that activities of hacking agricultural systems are limited, there is a need for regulating the activities around the collection and use of farm data to ensure that PA meets the objectives for food security and climate change interventions. The study proposes combining a governance framework that captures transparency in understanding the PA ‘black box’ associated with its operation and responsibly developing technologies that offer a potential solution that

allows farmers to be included in the design of technologies (Owen et al., 2012). This effort can promote data justice where farmers can be made "visible, represented, and treated as a result of their production of digital data" (Taylor, 2017).

Third, the introduction of PA is transforming agrarian labor in the US food system. PA can be unsettling for future and current agrarian labor in the US food systems (Erickson et al., 2018). PA is changing the labor dynamics as some labor tasks such as planting, and harvesting will be replaced by machines since machines now have the autonomy to make decisions and can now perform tasks previously performed by human labor. Similarly, there is evidence that PA can potentially alter the knowledgeability of end-users (Stock and Gardezi, 2021). PA can now perform routine tasks, which can be disruptive for the future of agrarian labor in the US food system. Farmers and farmworkers are becoming digital laborers due to displacements and the replacement of work done by farmers or farmworkers (Klerkx et al., 2019; Rotz et al., 2019), a novel accumulation strategy of agritech. Although farmer roles are changing, farmers are not compensated for collecting large amounts of data through the digital technologies they adopt (Stock and Gardezi, 2021). Farm data is refined for additional value because 'precise' recommendations are now crucial inputs and outputs—the 'new cash crop' (Fraser, 2018). PA is exacerbating agrarian labor hierarchies where classes of labor are created; one side is highly skilled and trained workers that can manage farms for productivity and efficiencies through PA, while other sets of farmers are lower-skilled laborers who do not possess the ability and skill to use PA (Rotz et al.,2019). Therefore, there is a potential risk that the majority of low-skilled farmers will be replaced and displaced. Agritech firms benefit the greatest from this newly constructed data ecosystem. For improved crop production and ecological benefits to be achieved through

PA, we suggest that governance mechanisms are established to oversee how technologies are developed and how data sharing among farmers and agritech can be carried out through an equity approach that can support the redistribution of power between agritech and farmers.

6. Conclusion

The introduction of PA has been described by agritech and the state as the future of agriculture, capable of improving farming efficiencies, crop production, and reducing the negative effects of climate change. However, the emergence of PA has far-reaching implications for farmers' autonomy and control over agrarian production systems. PA represents a suite of novel accumulation strategies by agritech firms that wield increasing power over the political economy of US agriculture. In this paper, we explored two important issues regarding the introduction of PA in the US food system: (1) *In what ways is PA dispossessing farmers of their autonomy and production processes,* and (2) *How might PA reconfigure future agrarian labor in the US food system?* To answer these research questions, we used data from focus group discussions and workshops in SD and VT. The study concludes that for PA to realize the proposed benefits for increased crop production against uncertain and extreme climate impacts, food system stakeholders must reconsider and redesign PA for considerations of equity and justice in data sharing to ameliorate the digital divide in farming that PA worsens. Current PA technologies provide agritech firms the power to control and manipulate farm data for their sole benefit. The lack of transparency that comes with adopting PA undermines the potential of farm data to be collected by farmers whose experiential knowledge can augment the technological applications towards efficiency and productivity in the production system. Ultimately, this

may jeopardize PA’s ostensible impetus of achieving a more sustainable practice of agriculture. As presently designed and implemented, the power asymmetries between agritech and farmers will continue through the dispossession of farmers' autonomy and control of production processes and the dispossession of farmers’ data. The future of farming is unsustainable if PA machines alienate the farmers that cultivate farm data.

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Appendix 1: Codebook- implications of PA on farmers autonomy and future agrarian labor

Code	Brief definitions	Inclusion criteria	Examples
The introduction on PA technology	Farmer's adoption PA	Where PA is used on farms	"We have had a ton of automation already, just like a continuation of the trend we have already seen."
Future agrarian Labor	What farmers are like to do in the future because of the introduction of PA	statements referring to farm work in the future	"I envision managing a fleet of robots or something along that line, where maybe I'm the tender truck driver that's moving them from field to field and managing ground truth and doing that sort of thing."
Data collection	Farmers are collecting large amounts of data	When there is a mention of data collected by farmers or through PA technologies	"We are right in the middle of precision agriculture; we are harvesting just an enormous amount of data every day on every milking."
Dispossession of farmers autonomy and data	How farmers lose control of their production process	Include when statement talks about farmers inability to control their production processes	"double-edged sword part. I mean, we get enough back now where you talked about it, I mean, it's beneficial to have the aggregated data for making decisions on the fly."
Skills and workforce development	Farmers now collect more enormous amount	When statements make mention of	that "the skill level of manual labor is going to drop, and

	of data than previously known and available on site-specific farmlands	data collected by farmers	one or two people on the operation is going to have to be really good at the math and computers.”

CHAPTER 5. PERCEPTIONS AND EXPECTATIONS OF FOOD SYSTEM ACTORS ABOUT DATA OWNERSHIP, PRIVACY, AND SECURITY

Abstract

Agricultural technology (agritech) firms, supported by inadequate regulatory frameworks, have increased capabilities to collect and analyze farm data. This has resulted in a new form of relationship between agritech and farmers: where farmers become data collectors. This new form of relation creates data and equipment ownership and privacy and security concerns such as transparency and trust issues in the US food system. Our study uses the responsible innovation framework to draw insight into the perceptions and expectations of food system actors in the US food system and elicit the importance of involving stakeholders at an early stage in the innovation process to anticipate future implications of technological innovations. This paper uses data from six focus group discussions (FGDs) with 52 agriculture stakeholders (farmers, government regulators, technology innovators, academia, and extension) in South Dakota (SD) and Vermont (VT). The study found that PA is a tool that can be used to understand and manipulate the world. However, to ensure fairness, transparency, and trust from big data in agriculture, there will need to be an early engagement of stakeholders.

1. Introduction

Precision agriculture (PA) is increasingly hailed as a promising approach to solve a variety of grand challenges in agriculture, such as food insecurity, low crop productivity, and damaging impacts of agricultural activities on people and the environment (Bongiovanni & Lowenberg-Deboer, 2004; Bronson & Knezevic, 2019; Eastwood et al., 2017; Kamilaris et al., 2017). PA constitutes an interconnected system characterized by computational modeling using machine learning algorithms, Internet of Things (IoT), cloud computing,

robotics, and sensors built into farming tools that are deployed in soil, water, machinery, and animals (Eastwood et al., 2017; Klerkx et al., 2019; Wolfert et al., 2017). PA allows farmers, universities, and agricultural technology (agritech) firms to collect large volumes of farm data such as climatic and weather measurements, water quality, and soil health. Such a large volume of high-velocity data is commonly referred to as 'Big Data' (Coble et al., 2018; Fraser, 2019; Sundmaeker et al., 2016; Wolfert et al., 2017). For instance, farmers can adopt various PA sensors that collect hundreds of variables and thousands of data points, such as livestock movements and animal body temperature, to enable 'smarter' robotic milking operations (Fraser, 2019; Jacobs & Siegford, 2012). Indeed, big data and the use of machine learning algorithms to process and analyze them can improve farmers' capacity to make better farming decisions (Coble et al., 2018; Klerkx et al., 2019; Wolfert et al., 2017). Agritech firms see the value in the proposition afforded by big data and PA to agricultural decision-making. For instance, in 2017, John Deere invested $305 million to acquire Blue River Technologies, which develops robotic tools appended to tractors capable of precision application of fertilizer and pesticides (Ryan, 2020).

Despite the benefits of these technologies to the farm economy and environment, concerns about data and equipment ownership, privacy, and security of farm and personal data have become universal to the broader PA endeavor (Ferrell, 2014; Sykuta, 2016; Wiseman et al., 2019). Corporations such as John Deere and Monsanto's Climate Corporation restrict farmers' ownership of machinery and data by establishing end-user license agreements (EULAs) protected by intellectual property (IP) rights. These agreements prohibit farmers from modifying, replacing, repairing, and editing any part of the PA equipment. Makers of technology are worried that without necessary IPs, farmers

could simply download the data themselves and transport their data to another equipment provider. Hence, agritech firms require farmers to seek permission from the agritech firm prior to using the data and take their equipment to an authorized agritech dealer (Fraser, 2019; Jakku et al., 2019). Existing EULA’s that restrict farmers' access to data and equipment can create a risk of power imbalance. It can shift power from farmers to corporations by deciding who has ownership and access to data and who does not (Boyd & Crawford, 2012; Bronson, 2018; Carbonell, 2016; Fraser, 2019, 2020; Jakku et al., 2019; Shepherd et al., 2018; Wolfert et al., 2017).

Farmers’ concerns about PA are not limited to data ownership. Issues regarding data privacy and security are at the front and center for many agricultural stakeholders (Coble et al., 2018; Ferri, 2019). These issues emanate from various reasons, including inadequate regulatory frameworks available to ensure data security for agricultural producers. For instance, current data privacy and security regulations present in the United States to protect data practices enforced by the Federal Trade Commission (FTC) are unable to protect farm data such as soil yield and nutrients as they are not considered personal data, and these frameworks cannot cover non-personalized agriculture data (Atik and Martens, 2020). Consequently, farmers have become reluctant to engage with PA, as suggested by a recent survey conducted by the American Farm Bureau Federation that showed that almost seventy percent of farmers are concerned about corporations and the government accessing their farm data and using it for regulatory or marketing purposes (American Farm Bureau, 2016).

Rural socio-technical transition to PA is a complex trajectory involving many different participants and institutions, such as farmers, agritech firms, and the state, and

touch upon socially and politically sensitive issues such as data ownership, privacy, and security (Asveld et al. 2015; Floridi 2019). Previous studies have examined issues of data ownership, privacy, and security from a farmers' interpretation of these risks (Bronson & Knezevic, 2016; Jakku et al., 2019; Sykuta, 2016; Wiseman et al., 2019). However, fewer studies have examined how various actors in the food system are interpreting these issues and ways in which they are dealing or coping with these limitations. This paper uses a responsible Innovation (RI) framework, which encourages inclusive engagement with a wide range of 'decision-makers' to identify potential problems associated with emerging technologies and find solutions that are more reflexive of social and economic contexts in which the technology is to be developed, used, and governed (Stilgoe et al., 2013; Von Schomberg, 2012). Against this background, the question motivating this study is: *What are the perceptions and expectations of various food system actors in the US towards farm data privacy and security in PA technologies?* For technological innovation in agriculture to meet societal values and needs, this study argues that the development of PA technologies needs to anticipate and account for the possible implications of PA innovation on society and farmers. As research and innovation around PA technologies further advances, there is a pertinent need to identify how various actors interpret concerns with data ownership, privacy, and security and how they envision attending to these concerns for sustainability.

This paper is structured in the following manner. The next section details the literature review, composed of two parts: first, a review of current initiatives on data privacy and security, and second, a review of the RI framework. The literature is followed by a method section detailing the data collection, sampling procedure, and analytical

approach. Section four presents the findings from the focus group discussions (FGDs). These findings are discussed in section five, and the last section concludes the study.

2. Literature review

The literature review is in two parts. The first part discusses current initiatives made by different actors involved in technological governance, including the government, private sector firms, and civil society, to safeguard data privacy and security for the user. The second part details the RI framework to anchor this study on understanding the societal norms and values with the ambition to increase the acceptance, desirability, and sustainability of innovations (von Schomberg, 2012). A review of how RI has been used in PA is documented.

2.1 *State of the art review on data privacy initiatives in PA*

Agritech firms have imposed restrictions on data ownership, as data constitute power— having access to data has power and capacity to create different services and products that allow agritech to make profits, benefiting from business insight that allows the provision of distinct market advantages (Wiseman et al. 2019). In efforts to address farmers' trust and trustworthiness in how farm data is collected, shared, and protected, agritech firms have come up with complex and lengthy EULAs and contracts protected by intellectual property rights. These EULAs dictate the terms of engagement between farmers and agritech (Wiseman et al., 2019). However, existing EULAs are not explicitly revealing of the scope of data collection, storage, and processes involved in transforming farm data at the point of acquiring these emerging PA technologies by farmers. Similarly, agritech EULAs are presently conceived as problematic as they leave no room for farmers to negotiate their rights on how their farm data should be utilized (Carbonell, 2016;

Ellixson & Griffin, 2017). Farmers many at times only find out that downloading or acquiring this technology automatically constitutes agreeing to the terms stipulated in the EULAs. In this sense, farmers are not aware whether they have been granted access to how their farm data is to be used (Wiseman et al., 2019). Agritech firms use EULAs to negotiate who controls data in the food system. Farmers often decide to give up their rights of exclusive data ownership in exchange for the supposed benefits of PA. However, farmers are not empowered to negotiate with agritech firms about how farm data is used. Hence, these contractual obligations create a risk of power imbalance and manipulation of farm data, as ownership and control are in the hands of the agritech firms (Bronson, 2018; Carbonell, 2016; Fraser, 2019; Wolfert et al., 2017).

In response to potential power asymmetries generated from concentrated ownership of data in the hands of a few agritech firms, public and private collaborations have begun attending to the challenges of farm data ownership, privacy, and security in the last decade. For instance, collaborations are beginning to emerge between farm organizations and agritech firms such as Ag Data Coalition in the United States (Ag Data Coalition, n.d.). This organization seeks to educate stakeholders on the value and best practices for transparency on how farm data ownership, control, and data sharing should occur. Big Data Coalition advocates for how data should be collected, who should own farm data, and what the role of third parties ought to be. Big Data Coalition believes that farmers own the information that is collected from their farms. Similarly, data privacy and security have been of concern to many companies under the flagship of a nonprofit organization called AgGateway (Wolfert et al., 2017). This collaboration aims for agritech firms to consider establishing policies, procedures, and agreements on using data instead of setting principles

and privacy norms (Wolfert et al., 2017). Although these suggestions have been offered, concerns over data ownership, privacy, and security in agriculture persist with the emergence of PA technologies.

At the global and national level, the European general data protection regulation (GPDR) and the federal trade commission (FTC's) are primarily legal frameworks employed by the European Union and the United States to protect consumers' personal data. The GPDR and FTCs serve the purpose of overseeing the prohibition of unfair or deceptive practices associated with data collection and use (Ferris, 2017). Because farm data such as soil yields and nutrients are not personal data, these frameworks are not designed to cover non-personalized agricultural data (Atik & Martens, 2020). Both in the EU and the United States, the GPDR and FTCs regulatory frameworks fail to address agricultural data privacy and security (Ferris, 2017). Current data privacy and security legislation in the United States are inadequate to support and protect data generated by precision technologies. Hence there needs to be federal and state legislation on how agricultural data should be governed.

There is an inadequate regulatory framework for non-personalized agricultural data (Atik and Martens, 2020). As a response to this regulatory vacuum, the private sector has initialized voluntary rules and principles, in which industry actors such as precision seed and machinery developers are co-developing codes and practices regarding consent, transparency, and disclosure to improve how data generated from farms through PA technologies ought to be collected and utilized. However, it is less clear whether these codes of practices are intended to complement future government regulation or to entirely avoid promulgation of regulation on-farm data (Sanderson et al., 2018; Sykuta, 2016).

Nevertheless, at present in the United States, an independent non-governmental organization consisting of farmers with the ambition to address privacy issues, since 2014 has implemented the American Farm Bureau's Privacy and Security Principles for Farm Data. There are similar ventures in other parts of the world, such as in New Zealand; the Farm Data Code of Practice intends to achieve similar results for improving farmers' trust in agritech firms. Codes of agriculture practices are naturally self-regulatory, which implies that they are not regulated by the government but rather designed, adopted, and implemented by social groups and organizations to create a path for good data governance and practices. Industry experts and non-governmental organizations primarily promote the creation of these codes and practices to improve PA adoption by farmers (Ferris, 2017). However, little is known whether these new forms of governance can successfully protect the interest of farmers.

There are examples of new and unique forms of governance of big data and algorithms in other sectors such as the healthcare sector. This provides an opportunity for the agritech firms and the state to understand how other social and economic sectors are addressing concerns regarding user data ownership and privacy. For instance, the United States healthcare sector is regulated through the Health Insurance Portability and Accountability Act (HIPAA), where personal information such as health status or payment for healthcare by an individual is covered by the privacy regulation (Tovino, 2017). HIPAA imposes strict regulations on data collection and disclosure of health data. Similarly, the Gramm-Leach-Bliley Act (GLBA) is a law that ensures financial institutions explain how they oversee how the personal information of customers in financial institutions is collected, shared, and safeguarded. GLBA restricts nonpublic personal information

disclosure (NPI) to a third party and informs customers when a breach of their data privacy occurs (Mamun et al., 2005). To protect internet-based application end-users, the US and the EU have policies that include the US Online privacy protection ACT and the EU Directive 2002/58/E.C., Directive on privacy and electronic communications (Baumer et al., 2004). These laws are enacted to regulate websites and online service providers. Although creating or enacting laws like the HIPAA or GLBA can potentially help farmers ensure that agritech firms do not exploit technology end-users for their sole benefit or allow third parties to possess the ability to manipulate farmers through aggregated farm data. Similar laws such as HIPAA or GLBA could be useful, but the greatest challenge remains as technology privacy can be considered different in diverse nations, or regions and as such, international legislation are different (Baumer et al., 2004). Firms and farmers can be resistant to any government regulation. Therefore, agritech firms will need to anticipate the future implications of PA innovations to responsibly designed agricultural innovations that may overcome data privacy issues.

2.2 Responsible innovation framework

When many social actors are involved in the development, use, and governance of new technologies, there are different expectations and perceptions regarding what technology can and cannot do, and for whom these will not work. The responsible innovation (RI) approach takes the notion of responsibility back to the developers of technology and policy to inquire about what it would take for them to respond responsibly and consciously to the demands made by society and the environment (Owen et al. 2012). RI is being positioned by its various proponents in academia and the government as an overarching guiding framework for science, research, and innovation policy. RI asks

technology developers and policymakers to integrate ethical, societal values and norms at an early stage of technology development. It highlights the importance of democratizing the process of innovation by emphasizing the correlation between higher levels of engagement with users and non-users of technology (Owen et al., 2012; Stilgoe et al., 2013). RI has been operationalized in previous work by enabling stakeholders from a wide range of interests and perspectives to anticipate the possible consequences (positives and negatives) of innovations. The European Commission (2015) defines RI as “societal actors (researchers, citizens, policymakers, business, third sector organizations) working together during the whole research and innovation process to align better the process and its outcomes with the values, needs, and expectations of society.” Thus, RI necessitates “taking care of the future through collective stewardship of science and innovation in the present. (Stilgoe et al. 2013, p.3)” Engaging stakeholders from the early stage of innovation development can help understand the collective responsibilities that ensure that innovation is ethical, acceptable, and socially and environmentally respectful (von Schomberg, 2012).

The essence of RI as a framework is not to hinder innovation but rather to ensure that the path of innovation is a more conscious one where concerns and responses to societal values and needs are taken note of in an innovation process (Asveld et al., 2015). Owen et al. (2012) described the RI framework to compose of four crucial dimensions: first, anticipation, which reflects on the essence to consider future risks and potential risks from a social, ethical, economic, and ecological standpoint. Second, reflexivity where assumptions and values of technology innovators might vary in relation to societal expectation; third, inclusion, which reflects involving key stakeholders that considers the diverse opinions, insights, and values to ensure legitimation and society-wide acceptance

of innovation; and fourth, responsiveness which recommends that actors, take meaningful action in response to insights that emerge during the RI process so that innovation processes align with needs expressed by other actors and values of society (Regan 2021; Stilgoe et al., 2013). Specifically, this study uses anticipatory and inclusive dimensions of the RI framework (Stilgoe et al., 2013) to elicit perceptions of various actors on privacy and security under precision agriculture in the US food system. Yet, less is known about how the RI framework can provide guidance for future development and governance of PA tools, such as big data and algorithms (Rose & Chilvers, 2018). The RI framework can potentially identify users' and non-users' concerns about data ownership, privacy, and security in relation to PA. Understanding stakeholder's concerns about PA is the first step toward the development of digital technologies and policies.

3. Methods

This section explains the procedure used in data collection and coding FGD transcripts from workshops held in SD and VT and creating a codebook. The study adopted the qualitative interpretative approach detailed in chapter two to understand the perception and expectation of US food system actors. This study used data from six FGDs held in SD and VT with a mix of US food system actors, which consisted of farmers, university academia and extension personal, PA technology developers, and NGO experts. These food system actors discussed the main issue that this study sought to understand on farmer's data privacy and security under the introduction of PA technologies. Participants discussed in-depth topics that related to the main subject matter that this study addresses. The FGDs discussion questions focused on issues of privacy and security; participants discussed questions such as: how do you feel about the potential of big data in general?

What issues does big data raise in agriculture? How will AI shift the market power and how decisions are made on the farm? Details of data collection are explained is detailed in chapter two of this dissertation.

3.1 *Analytical approach and coding process*

This chapter used the reflexive qualitative approach described in chapter 2 to code FGDs from workshops in SD and VT. The reflexive approach allowed themes to emerge through a flexible process where themes can be modified and combined to reflect the textual data. FGD transcripts were imported into Nvivo 12 QSR and read numerous times. In this process, codes were assigned to portions of the FGDs that reflected the perceptions and expectations of US food system stakeholders about ownership, privacy, and security of farm data. The coding process progressed by identifying initial codes from the entire FGDs. For instance, line coding such as "who owns it? who manages it? who gets access to it?" was coded as initial terms of data ownership and further categorized into themes such as ownership, manipulation that are reflective of the main subject of ownership, privacy, and security under PA (see, Appendix 1). After coding the first FGD, a codebook was created in accordance with the procedure laid out by MacQueen et al. (1998). The codebook guided the coding process for the remaining FGDs. The codebook provided a guide where the description of codes is provided, the criteria that ensure a code to be included, and an example of the textual codes from the FGD transcripts (see codebook in appendix 2).

4. Result

The current analysis aimed to understand perceptions and expectations of various US food system stakeholders on data and equipment ownership, data privacy and security

concerns and how these actors interpret these issues and ways in which they are dealing or coping with these challenges under the emergence of precision agriculture in the US food system. Stakeholder insights from the qualitative interpretive analysis were grouped into two key themes (1) *Concerns about data ownership, privacy, and security* (2) *Expectations about how big farm data can attend to social and ethical concerns*. These themes are further discussed in this section.

4.1 Concerns about data ownership, privacy, and security

Agritech firms aggregate farm data through sensors installed on proprietary equipment, such as tractors and applicators. Data are collected for variables such as farm yield, soil characteristics, and weather conditions. Agritech firms use this data and process it using algorithms to inform farmers about agronomic recommendations that can potentially improve farming efficiency, especially through the use of fewer input costs. However, the practice of collecting big data in agriculture is not value-neutral and can have implications for end-users and society (Boyd and Crawford, 2012). Agritech firms have designed the collection of big data and protected it through intellectual property rights in such a way that end users' data and equipment are owned, controlled, and managed by corporations, leading to concerns about asymmetrical power relations between farmers and agritech firms. For instance, one NGO personnel from SD questioned the issue of data ownership and access: "Who owns it [data]? Who manages it? who gets access to it?" These questions show that there is embedded value of big data to the agritech firms, and questions about winners and losers in this new innovation ecosystem are becoming more visibly concerning. Similarly, an extension personal from VT expressed: "I think for me, there is a fundamental starting point of who owns the data, and who benefits from the data

and how." These statements highlight that there are unanswered questions about ownership to and access of big data as it pertains to the development and use of PA.

EULAs that protect farm data introduced by agritech firms have embedded in them clauses prohibiting PA users from making repairs or maintaining any part of their farming equipment. By contractual agreement, only certified technicians are required to perform maintenance and repairs on these emerging technologies. Protecting and growing profits is an important reason for technology developers to erect intellectual property on PA. A technology developer from VT provided a useful explanation for why their firm aims to gain control over equipment and data produced using them: "Our model is similar that you have to be a certified qualified tech to work on a robot…and a lot of that goes back to safety and proprietary, you know, investment, things that we've done that are secure." While it may be a question of profitability and competition for the agritech firm, farmers, on the other hand, expressed frustration over their inability to repair and perform routine maintenance on their equipment or have access to farm data that they collect through PA. A farmer from VT expressed: "If I got to go back to the company that I just spent $300,000 on buying their equipment to get permission to learn about my hogs, that is like, *really?* Now, who wants to change a strut if I don't have to? But on the other hand, if changing the strut is going to enable me to work my system better, I can be more successful as a farmer." Other stakeholders argued that EULA imposes an additional cost of maintaining their equipment as it has always been customary for farmers to engage in repairing their farm machinery: "… and I should do that [repair equipment], and I don't like paying people to fix my stuff. I should do that." The inability of farmers to repair their equipment can cost

precious time and money as they often have to wait for an equipment dealer-technician to come out to the farm for carrying out repairs.

Agritech firms are imagining big agricultural data and algorithms as tools to gain control and dominate the agricultural production process. Extension personnel from VT gave an insight into how big data and equipment in agriculture is used to control the production process by the agritech firms: “I find it problematic that if I buy a John Deere piece of equipment and, I generate a boatload of data driving their field, by my field, my crops that I harvest, with my inputs with that I cover, that I don’t get that data without permission and access. And, then that defines the degree of success.” Although there are terms that ought to guide the collection and use of data, however, contracts allow farmers to relinquish their rights of ownership and how that data could be used, and for what purpose. Farmers seemed to have internalized new rules of engagement in PA systems. Sometimes this engagement is built on sentiments of fatalism; farmers are left with no choice but to accept these contract agreements because that is the first step toward using proprietary equipment. Two farmers from SD articulated concerns regarding EULAs: “You read the terms and conditions, don’t you [farmer 1]. Oh, every one of them all the way down to the end. There’s not much we can do about it. It’s going to happen. It scares me, but I don’t know what I can do [farmer 2].” Most of the time, PA users are left with no option but to agree to the terms of EULAs. There are fewer opportunities for farmers to negotiate their terms of engagement with equipment dealers.

Participants were concerned about data privacy and security breaches that could arise through the collection of agricultural big data. One common perception that emerged was that agritech firms can manage and monitor farm activities from planting to harvesting

and that these insights could be used to socially and economically disrupt their farm operations in the future. One farmer in SD perceived PA and big data as a form of surveillance: “Has anybody else read 1984? So, here’s the real difference between what actually happened the way it was projected in that book. In that book, the TV or the monitoring device that everyone had in their home, the government put it there. We buy our own and carry it with us. You know, how many times have you heard if power corrupts…then what about absolute power? And that’s what big data is.” This farmer imagines that while the decision to use big data and algorithms is seemingly a personal decision made by a farmer, however a secondary outcome of this decision is that it can possibly enhance the ability of agritech firms and government entities to encroach on private matters pertaining to the farm operations.

Participants expressed two potential negative outcomes through agricultural surveillance technologies. Firstly, stakeholders in the food systems expressed that monitoring of farmers could potentially be used to impose fines by the government on farmers who do not comply with environmental regulations. An industry expert expressed that “…a lot of farmers are thinking: Is this technology going to be used in the future to bring an enforcement action against me?” There is a potential concern among farmers that the government can monitor farmer’s personal or farm data and justify punishing them through more regulation or fines for not complying with sound environmental standards. Secondly, there was anxiety among participants regarding how big data can be used by the agritech firms to manipulate commodity and input markets. An NGO personnel in VT expressed: “the trust that farmers have in where their data is going to go because it also affects the markets, you know speculators get ahold of that data, and it changes what you’re

going to get when you go to market with your crop." For instance, analytical insights from big farm data can be used to sell farmers recommendations for buying agrochemical products. An NGO member from SD perceived ownership and controlled access to big data as a way for agritech firms to engage in information capitalism: "I mean, it is primarily used to sell your things since your phone is constantly tracking everything you're doing and then trying to sell you whatever you've been looking at. And so, is this data going to be used just to sell more products? Or, you know, you were saying about fungicides, maybe we are going to make these recommendations based on the need to sell more product versus what's actually good for the farmer and the farm.'' Indeed, social and ethical concerns pertaining to agritech's ability to monitor, manipulate and sell products are driving farmers' uncertainty about whether or not to trust these organizations and the products. Many stakeholders are not trusting of PA and big data. They perceive that the lack of transparency in how their information is collected is solely for the benefit of agritech, although they can benefit from the recommendation at a fee. An NGO personnel from SD expressed, "… Do you trust an organization that you think is trying to sell you something even if maybe it is in your best interest, but how do you feel about if the purpose is trying to sell you something?" Making recommendations through big data analytics can help to create efficiencies for farmers if the process of collecting, owning, and accessing big farm data is made more transparent and explainable. The same farmer from SD discussed the importance of transparency: "I think as long as there's some transparency and that like, hey, yeah, John Deere has my data, I got a discount on my annual subscription to whatever they're trying to sell you. I just need to be aware that they're going to try and hit me up for their crop insurance." The current non-transparent nature creates asymmetrical power

relations between agritech firms, the state, and users. Limited understanding about how data is managed and what it can be used for limits farmers' trust in these tools and impedes the adoption of PA technologies. Insights from stakeholder perceptions and expectations on the risk related to data ownership, privacy, and security under the emergence of PA are summarized in table 3.

Table 3: Summary of perception and expectations about data ownership, privacy, and security from FGDs

	Perception	Expectations
Data and equipment ownership	Monopoly of data and equipment through EULAs Domination of agriculture production system	Open data ecosystem Blockchain Need for policy regulation Need for small or independent technology companies to curtail the power of big technology
Data privacy and security	Monitoring for manipulating commodity markets Using data to sell products Trust and transparency Misuse of Information Extraction and exploitation of information	

4.2 *Expectations about how big farm data can attend to social and ethical concerns*

Focus group participants held various expectations about how data *ought to* be owned and accessed and how privacy and security can be managed under precision agriculture. A common expectation that emerged from these discussions was the promotion of open-source data and models that are capable of enhancing data privacy and security for farmers. A University extension agent from SD advocated for PA to be more open-source: "… I lean more towards like an open-source transparent, like people can know how data is being collected, processed, and presented to the public in a very open way, versus

companies being able to, like, collect data and sell it and like because it's just another way to exploit farmers, and then the people." The open-source model can potentially create transparency allowing data producers the opportunity to understand the type of data that is being collected, how it is processed and used rather than have a particular agritech monopolizing the process through complex contracts and agreements. While some stakeholders expected to see more equity in sharing agriculture big data through open-source data, others cautioned on how open-source model can also be used to exploit PA producers. One Academic from VT expressed: "… just because you make this data publicly available, I guess you were saying open science. Open science data can also be exploited by the private sector as well for their own goals, and because since they have more knowledge of exploitation, that would be different from the people and farmers who do not know." PA users are considered to need additional skills to be able to interpret the data that they generate and can be problematic for the majority of farmers who might not have the ability to gain the required knowledge to operate open sources models, allowing a dependence on technology companies for recommendation and interpretation of their data. There is a need for small or independent technology companies to curtail the power of big technology firms that monopolize data generated on farms.

Food system actors anticipated that policies and regulatory frameworks were required to guide data and equipment ownership and data privacy and security because of the introduction of PA. One extension personnel from VT expressed: "… policy tools are needed, I think, you know, in order for them to be trusted. I think that we need society to demonstrate to people who will be having data pulled from their enterprises that we have learned some of the lessons from some of these real abuses of power." Lack of regulation

will give agritech developers the power to always act in profit-maximizing interests without considering other social, environmental, and ethical values held by the community of users. There have been several examples in history of the consequences of innovation outpacing regulatory development. An academic in SD provided an example of the Cambridge Analytica scandal to highlight this concern: "the Cambridge Analytica example, let's not let that happen in this context. But that means a lot of upfront thinking and aggressive policy development." As most times regulations are unable to keep up with the fast pace of innovation, it can be particularly challenging to anticipate the intended and unintended consequences of new technologies, such as big data and algorithms in PA.

5. Discussion

Findings from the focus group discussion reveal relevant perceptions and expectations of US food system stakeholders on data and equipment ownership and privacy and security. The introduction of PA provides a path for agritech to monitor, manipulate, and sell tailored products to PA users. This process creates a lack of trust due to the non-transparent processes used for ownership, privacy, and security of farm data. The focus groups also provided insights into stakeholder perception of big data as not only useful for providing farming recommendations but also a tool for domination of agricultural process. Stakeholders believe that some sort of regulation will be needed to evaluate the processes involved in data collection to ensure that farm data are protected. I turn to the theoretical framework RI, for insight to inform the interpretation of US food system stakeholders' perceptions and expectations associated with big data and equipment ownership and data privacy and security concerns.

Two implications from the study findings are evident. First, PA has not been designed as transparently as possible, where both farmers and agritech firms fully understand how data and equipment ownership and privacy and security of farm data are protected. The gap has created a perfect opportunity for agritech firms to possess exploitative power by monitoring and manipulating users based on the data that is generated from farms. Agritech firms' access to farm data can propel commodification of data through behavioral prediction of farmers, which is the “new asset class” for the sole purpose of making a profit (Zuboff, 2019). Although some of these data are applied to product or service improvement, the rest are declared as a proprietary behavioral surplus, fed into advanced manufacturing processes known as “machine intelligence,” and fabricated into prediction products that anticipate what you will do now, soon, and later” (Zuboff, 2019). Therefore, technology is a tool through which the world can be understood and manipulated (Bowles, 2018, Gardezi and Stock, 2021).

The process of excluding end-users from negotiating the terms and condition to participate in PA automatically exclude farmers who may not agree to specific terms and conditions of the technology. For instance, a John Deere EULA requires farmers to accept the agreement, which will be ‘By clicking on the ‘I ACCEPT’ icon below, or by activating, accessing, or otherwise using the Software, you represent that you have read and understood this EULA, that you are legally authorized to enter into this EULA on behalf of Customer, and that Customer is bound by and shall perform faithfully all of the obligations of this EULA, including the warranty disclaimers, limitations of liability, and termination provisions contained herein. If a customer does not wish to be bound by the terms of this EULA, you must click the ‘I DO NOT ACCEPT’ icon below, and you will

be returned to the login screen." These contracts further create a digital divide for farmers hindering the progress towards efficient productivity and ecological sustainability as the majority of farmers are left out as they are not in agreement with certain terms associated with adopting these technologies. Agritech firms' contracts suggest that farmers data will not be given to third parties as claimed by agritech, for instance, a 2014 John Deere contract 'Deere shall not present Customer Data to third parties in any form or in any manner that would permit Customer's identity to be explicitly or implicitly revealed unless Deere receives Customer's prior written permission.' Yet, John Deere does not provide the steps to ensure that the data is not released to third-party companies.

Open-source models are considered one of the avenues to address data ownership, privacy, and security in food systems. These open-source models can give data producers rights over their data (Cabonell, 2016). The collection of data will need to be made open to ensure that it serves the benefit of the social good (Cabonell, 2016; Van der Burg et al., 2019). The ability of farmers to have access to their data in open platforms will create an opportunity to increase new economic activities (De Beer, 2016; Van der Burg et al., 2019). However, these open models have not been defined in terms of how they should foster fairness between farmers that produce this data and the public. There are challenges with the data been open as most farmers might not be well equipped to use the information on open-source platforms and require additional skills and knowledge to interpret the data from open-source models (Carolan, 2017). If not well defined, the open-source models could lead to further exploitation of farmers rather than resolving ownership, privacy, and security concerns as been open-source data is not a guarantee for transparency and fairness in data sharing. When data are free, it does not necessarily constitute fairness as this

information will be useful to some farmers and while others will not be able to use them, further creating a digital divide (Carolan, 2015; 2017). Therefore, there needs to be a critical reflection on how these digital technologies support or reinforcing digital divides.

There is no stand-alone procedure to handle issues of data and equipment ownership and privacy and security of data. In other sectors, such as the health sector, some form of regulation has been provided to minimize the threat to data as there are clear standards associated with collecting, processing, and transferring data. However, regulatory frameworks alone cannot protect data and equipment ownership, privacy, and security of farm data. Regulatory is only one aspect of solutions to promote data security and technological interoperability. The duties of protecting farm data cannot be relegated to only collection processing and sharing. The lack of a regulatory framework makes farmers vulnerable to inequality and marginalization by corporations (Bronson, 2018). For instance, farm data are highly susceptible to privacy threats, contributing to market asymmetries, where corporations and third-party agents can exploit farmers through market trading since no regulatory framework exists (Carbonell, 2016; Leone, 2017; Mark, 2019). Therefore, farmers are reluctant to use PA because of these challenges. Relying on regulatory frameworks alone is insufficient as it cannot keep pace with changing innovation to remain. The time lag effect is worsened by the complexity that comes with anticipating further technological advances, not capturing the social and ethical issues that should be addressed to make a difference.

For PA to achieve the goal of supporting current and future aspirations of food security and efficiency, it requires an early engagement of society in the creation and design of an innovation's visions, and the values needed to be embedded in the making of PA

(Bronson, 2019; Van de Poel et al., 2020). Including stakeholders in the design of technologies and the design of EULA's can potentially increase transparency and accountability, and fairness from the early step of development. PA users can negotiate conditions that will lead to fair outcomes on how their data will be collected, processed, and shared. Through RI, stakeholders can anticipate future consequences of innovation such as PA, which reflects on considering the future risk and potential consequences such as privacy and security issues that might emerge throughout the innovation process. Enabling a varied range of food system actors, not just powerful stakeholders, can create the inclusion of diverse set values essential to strengthen a responsible digital agricultural transformation (Bronson, 2019). Responsible innovation safeguards clear communication about privacy and security, which will undoubtedly build confidence in the process and trust in PA technologies.

6. Conclusion

PA is constantly presented as a technological fix capable of revolutionizing agriculture, such as providing farmers with precise management decisions for planting seeds, application of fertilizer and pesticide, and harvesting. PA can contribute to food security, reducing inefficiencies, increase productivity, and promote environmental sustainability (van der Burg et al. 2019; Wolfert et al. 2017). Despite the promising frontiers PA presents, farmers are reluctant to adopt PA as it raises social and ethical concerns (Bronson & Knezevic, 2019; Klerkx et al., 2019). This paper draws upon the RI framework to interrogate the perception and expectations of various food system actors in the US towards farm data privacy and security in PA technologies. To do this, we used a qualitative interpretive approach and thematic analysis. The study concludes that resolving

issues of data and equipment ownership and data and privacy is not a stand-alone process where regulation is used to address these concerns. For PA to be successfully implemented where concerns of society on data ownership, privacy, and security exist, the design and implementation will need to depend on and take into consideration the stakeholder dynamics with the food production systems on how emerging technologies are understood, adopted, and adapted in practices by farmers and other decision-makers. Specifically, there needs to be the inclusion of end-users in EULA formulation to negotiate the terms of engagement where their values and insights are incorporated to ensure transparency, accountability, and fairness throughout the process of data collection, processing, and sharing. The inclusion of stakeholders in the design process can build transparency and trust by including clear standards where future privacy and security concerns can be anticipated and incorporated to address these issues at an earlier stage and through each innovation stage. `

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Appendix 1: A sampling of coding structure on FGDs for perception and expectation of stakeholders

Sample text from FGDs	Initial codes	Axial codes	Final codes
"It is a reflection of regulatory requirements, and does it ease, ease the compliance, that could be a real benefit."	Regulatory requirements	Regulation	Need for regulations
: "the more I think about the future of, like, the use of sensors and data collection, the more I lean towards like an open-source model … because when we talk about farmers being worried about like data ownership and privacy if the idea was that all like that maybe the society invests in these sensors for a greater good and, and then, and so when farmers deploy them there."	Data ownership, Open-source model, Privacy Transparency	Data concerns	Data ownership concerns
"I mean, it is primarily used to sell your things since your phone is constantly tracking everything you're doing and then trying to sell you whatever you've been looking at. And so, is this data going to be used just to sell more products? Or, you know, you were saying about	Sell more products Recommendations Tracking activities	Monitoring Tracking	Monitoring and profit making

fungicides, maybe we are going to make these recommendations based on the need to sell more product versus what's actually good for the farmer and the farm.''			

Appendix 2: Codebook for perception and expectations of stakeholders under the emergence of precision agriculture

Code	Brief definitions	Inclusion criteria	Examples
Ownership	The ownership of PA technologies	When there is a mention of ownership of PA technologies	“Who owns it? Who manages it? who gets access to it?”
Manipulation	Farmer’s data used for manipulation purposes	If statement indicates some form of manipulation	“I mean, it is primarily used to sell your things since your phone is constantly tracking everything you’re doing and then trying to sell you whatever you’ve been looking at. And so, is this data going to be used just to sell more products? Or, you know, you were saying about fungicides, maybe we are going to make these recommendations based on the need to sell more product versus what’s actually good for the farmer and the farm.’’
Expectations of stakeholders	What stakeholders anticipate about privacy and security	Statement points in the direction of solutions to privacy and security in big data	: “the more I think about the future of, like, the use of sensors and data collection, the more I lean towards like an open-source model … because when we talk about farmers being worried about like data ownership and

			privacy if the idea was that all like that maybe the society invests in these sensors for a greater good and, and then, and so when farmers deploy them there.”
Agreements (contracts)	The end-user agreements firm us to own data and equipment	States that indicate Agritech contracts	“Our model is similar that you have to be a certified qualified tech to work on a robot…and a lot of that goes back to safety and proprietary, you know, investment, things that we’ve done that are secure.”

CHAPTER 6. DISCUSSION AND CONCLUSION

This dissertation highlights socio-ethical implications that come with the development and use of PA. The dissertation explored some of the challenges that PA technologies can produce when farmers adopt and employ these technologies in their crop and livestock production processes. The different chapters of this dissertation focused on specific aspects of the socio-ethical concerns that result from the design and adoption of PA, such as changes in social practices, social identities, data ownership, privacy and security, and agrarian labor concerns under PA in the US food systems.

Chapter 3 of this dissertation explored how the introduction of PA, such as big data technologies and machine learning algorithms, can affect farmers' farming-related social practices and how farmers respond to these changes. The study found that adopting big data technologies and machine learning algorithms has necessitated farmers to learn and develop new competencies such as learning to fly drones that collect various farm data and information. This has reorganized and redefined how farm is to be managed. Big data technologies and machine learning algorithms, together with new competencies that farmers are acquiring, is transforming farmers' social identities as farmers become subjects of these technologies and are now seen as data gathers and managers of technologies rather than performing their traditional farming practices of physically walking through the farm to scout for pests and diseases. However, this does not mean that farmers do one or the other, as some farmers were found to complement digital knowledge with ground-truthing information by physically walking through their farm field. Augmenting their local knowledge with data and information generated by drones and yield monitors is relatively easier for those farmers who have the financial resources and ability to acquire the

necessary knowledge and competencies to operate PA. Yet, challenges ahead remain for other farmers who encounter difficulty aligning themselves to PA's new social expectations. Most farmers and farmworkers who operate small farms cannot realign their social expectations under PA. This misalignment under the emergence of PA hinders progress towards increasing food productivity and achieving environmental sustainability. The government will need to ensure that misalignment in social practices and the current digital divide that PA exacerbates will need to be resolved by focusing not only on development of new technologies, but also systems of education and finance that can support the digital transition in agriculture.

In chapter 4, through a Marxist political economy lens of ‘accumulation by dispossession’, this dissertation sought to elicit how PA can drive farmers’ own alienation: loss of autonomy and control of crop and livestock production processes. This study found that PA can dispossess farmers through new data ecosystems designed by agritech firms to extract farmers' data and site-specific information that constitutes new accumulation strategies. These strategies can sustain asymmetric power relationships between farmers and agritech firms. For instance, agritech firms' carry an advantage over farmers when it comes to access to farm data. This accumulation of data can be used by agritech firms to predict and manipulate farmers' behavior by recommending them products for generating a profit. At the same time, farmers are detached from their traditional farming role that now requires them to collect farm data virtually through PA technologies such as drones and yield monitors. Agritech envisions the future of labor as enhancing efficiency and productivity. Contrary to this techno-optimistic vision held by the agritech firms, this study finds evidence that through the accumulation of data and dispossession of farmers’

decision-making powers, farmers and farmworkers can find it difficult to remain relevant in the food production systems. This is the time to reflect; farmers, farmworkers, agritech, and regulators who might be the cause or effect of these technologies must re-think PA's implications on future farm work and workforce.

In Chapter 5, I examined the perceptions and expectations of various food systems actors in the US towards farm data ownership, privacy, and security under PA. The study found that US food system actors perceived PA to prohibit farmers through EULAs from gaining control of their data and repairing their farming equipment. A perception among stakeholders is that farmers' privacy and security are threatened through data generated by agritech firms to monitor farmers' production process from planting seeds to harvesting crops. The study found that some stakeholders expected farm data and models to follow an open-source model to ensure transparency and reduce PA's privacy and security concerns. Food system actors further anticipated that some forms of policies and regulatory frameworks could guide and protect farm data and equipment are owned. In this study, I postulated that including PA end-users in technologies and EULAs can increase transparency, accountability, and fairness throughout data collection and storage processes. The goal of these participatory technology development approaches could be to anticipate future privacy and security threats that can be addressed at an early stage of PA development.

It is crucial to expand on similarities and differences that emerged from FGD transcripts in SD and VT based on heterogeneity in farm size and scale, differences in the type of crops, and livestock farming that is practiced in these states. Similarities are evident from the FGDs in SD and VT. Participants agree in SD and VT that PA can be instrumental

in resolving food insecurity and ecological footprints from agriculture. This is exemplified by farmers in both SD and VT adopting PA and acquiring skills to operate these technologies on their farms. However, participants worry that the adoption of PA by farmers is displacing labor in both SD and VT as most farm work such as planting, harvesting, or livestock feeding is now digitalized and automated. Another critical similarity in SD and VT discussed by participants is that as farmers adopt PA, large amounts of data are generated by farmers largely controlled by agritech through EULAs that abstract farmers of their autonomy and production process. Participants in SD and VT suggest that for PA to be adopted by farmers, there needs to be a structure that oversees the development of these technologies to ensure that farmers can own their data and control their production processes.

Divergent views exist among participants concerning the development of PA for farmers in SD and VT. Participants in SD suggest that the digitalization of agriculture currently favors monocropping and wealthy farmers who have the capital to adopt PA technologies to expand their soybean and corn farms. Famers in VT worry about the lack of diverse PA technologies used to grow specialty crops in VT. Farmers also expressed a lack of farming services for specialty crops. Agritech's concentration on the production of PA tools for monoculture and particular groups of farmers, exclude or farmers groups that grow different crops and livestock (re)produce existing divide digital between large and small farmers that have the capital to employ these technologies on their farms and those that lack the capital resources to adopt these technologies.

A synthesis of the results from various chapters suggests that the introduction of PA in the US food production systems serves as a way for alienating farmers and

farmworkers from their production systems. Emerging technologies that alienate farmers and farmworkers eliminate traditional and cultural farming methods in the US food production system. In other words, the claim of the potential benefit of PA by agritech to improve the quality of life for farmers and farmworkers might not lead to food security and reduction in environmental pollution with the emergence from agricultural activities. The proposed benefit of PA creates a new form of rationale where agritech turns farmers and farm workers subjects of capital accumulation. The advance in modern technology in agriculture is reflected in the social practices and identities that farmers create or are unable to meet up with the new social expectation of technologies. Furthermore, to challenge the new ecosystem created by agritech firms that abstracts farmers of their production processes, changes in social practices, and design that promotes privacy and security concerns of farmers' data appears to be the most irrational thing one can do. This is because the system embodies characteristics that promotes efficiency, productivity, and convenience. However, PA can exaggerate social inequalities among farmers and farmworkers who do not possess the resources to adopt PA technologies successfully. The digitalization and automation of every stage of agriculture are already leading to a weaker relationship between farmers and their natural environment and fewer interactions between farmers and farmworkers. PA is designed in a way where farmers will continue to rely on agritech firms, where farming operations and skills needed to carry out farming activities currently and, in the future, will be determined by agritech firms. Therefore, the kind of jobs or employment that is created is designed through the ideas of the capitalist nature of agritech firms.

Policy implications

From a policy perspective, the finding from this dissertation suggests that the socio-ethical challenges that emerge with the introduction of PA require a collaborative effort of stakeholders in the US food production systems in many areas. First, PA will need to be designed to include the experiential knowledge of farmers. The current design reflects a technocratic knowledge base where expert knowledge is seen as more superior in the design of these technologies. For small and large farmers to learn new practices and realign their social expectations under the emergence of PA, farmers' knowledge is required in PA development. Second, PA will need to be designed in a way that reduces the existing digital divide between different farmers groups, those who can adopt PA and those who are unable to adopt because of factors such as resources and the EULAs that are used to exclude farmers that do not agree to some terms and conditions that limits their ability to participate in PA. Third, although there are efforts aimed at ensuring that scientific sophistication of PA is achieved, agritech firms and nation-states on the need for adoption of PA, a greater emphasis to anticipate the socio-ethical implication of PA design is required, and these can be achieved by bringing together key stakeholders such as technology developers, policymakers, farmers, farm advisors, academia, and funding agencies to deliberate on concerns from these technologies. Fourth, there needs to standards on how PA should be developed to ensure that these technologies can improve equitable and sustainable environments.

Limitations of the study

Two critical limitations of this dissertation are discussed. First, data used in this dissertation was collected from two states in the US (SD and VT), which has left out other

regions where farmers produce different types of food crops and livestock in the US. Conducting a robust study that includes other states and regions of the US will elicit better the diverse socio-ethical implications that various farmers experience. Doing cross-national research can ensure that the design of PA can consider a wide variety of farmers. Secondly, the study was conducted with white farmers in SD and VT. However, the study has also left out framers from other races and ethnicities, and as a result, the study might not be generalized for all farmers.

Future research

For PA to meet future food demand and environment sustainability, further research into how PA affects different groups are required. A few directions for further research are provided. First, this dissertation considered white farmer and their experiences with PA. More investigation on marginalized farmers of other race such as black farmers will promote equity in how PA is designed for different farmers. Carrying out a study on historically marginalized farmers will provide an avenue to ensure that PA can move toward achieving food security and reduction in ecological footprint. Secondly, there is a need to understand further how the design of PA can be democratized where farmers are included in the formulation of the end-user license agreements and participate in anticipation of the socio-ethical implication of PA.