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# What are the implications of digitalisation for agricultural knowledge?

**Julie Ingram\* and Damian Maye**

Countryside and Community Research Institute, University of Gloucestershire, UK

## **Correspondence:**

Corresponding Author

Email: [jingram@glos.ac.uk](mailto:jingram@glos.ac.uk)

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## **Abstract**

In this perspective paper we consider the implications of a digital transformation for agricultural knowledge, a subject which hitherto has received limited attention. We raise critical questions about how digital agriculture will intersect with established modes of knowing and decision-making. We also consider the implications for the wider Agricultural Knowledge and Innovation System (AKIS), specifically the roles and capabilities of those who provide advice to farmers, as well as those responsible for data analytics, and the organisations and institutions that link and support them. We conclude that new data driven processes on farm, as well as the changing AKIS dynamic under digital agriculture, bring new demands, relations and tensions to agricultural decision-making, but also create opportunities to foster new learning by harnessing synergies in the AKIS.

## 1 Introduction

It is generally agreed that digital agriculture<sup>1</sup> will deliver a step change in efficiency, productivity and sustainability at the farm level and across the value chain (Aubert et al., 2012; Wolfert et al., 2017). Sensing systems and associated analytics can provide producers with better information to make more timely decisions with more predictable outcomes, while automating tasks using sensing technologies and machine learning can increase reliability. Rapid developments in the Internet of Things (IoT), cloud

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<sup>1</sup> Digital agriculture typically involves both the collection and analysis of data to improve both on-farm and off-farm decision (Leonard et al., 2017), although here we refer to different forms of digitalisation in agricultural production systems.

computing, robotics and Artificial Intelligence are accelerating the transition to smart farming and the promotion of big data and precision agriculture to improve agri-food sustainability. The expectation is that smart farming approaches will ultimately improve knowledge about an individual enterprise, or via efficient sharing and learning from data from multiple enterprises (Robertson et al., 2018).

However, although this 'fourth agricultural revolution' brings the promise of multiple gains, it also brings with it technical, social, economic, ethical and practical questions, with significant implications for how commercial agriculture is structured, practiced and governed. Research to date is only just exploring the full ramifications of this so called 'disruptive innovation' in relation to these aspects (Bronson and Knezevic, 2016; Jakkuet al., 2016; Carolan, 2018; Klerkx et al., 2019; Rotz et al., 2019). One question that is not being fully addressed, however, is: what are the implications of digitalisation for agricultural knowledge?

Digital applications and platforms have the potential to dramatically change the way knowledge is processed, communicated, accessed and utilised. For farmers, digital applications will provide decision-making capabilities that were previously not possible, potentially leading to radical changes in farm management (Sonka, 2014; Wolfert *et al.*, 2017). As smart machines and sensor networks increase on farms and farm data grow in quantity and scope, farming processes will become increasingly data driven and data-enabled (Wolfert et al., 2017). This raises critical questions about how digital agriculture will require new capabilities, support decision making and interact with, and potentially disrupt, established modes of knowledge processing.

There are significant implications for the whole Agricultural Knowledge and Innovation System (AKIS)<sup>2</sup>, specifically the roles and capabilities of farmers, those who provide advice to farmers, as well as those responsible for data analytics, and the organisations and institutions that link and support them.

These considerations are important if we are to enable digital agriculture to be effectively implemented.

## 2 Digital agriculture and knowledge processes

Our understanding of knowledge in agriculture has evolved from regarding it as a transferable commodity to something more diffuse emerging out of technical and social interactions. This understanding underpins the AKIS concept and the multiple knowledge generation, exchange and utilisation processes operating interactively between the heterogenous actors involved ((Klerkx *et al.*,

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<sup>2</sup> The AKIS concept refers to complex arrangements and interactions between actors, knowledge organizations (agricultural research, extension, and education organisations) as well as the informal networks of heterogeneous actors (supply chains, policy makers etc).

2012). Analysis of the potential impact of digital agriculture on the AKIS to date has tended to follow a supply-orientated narrative, examining, for example: digital services in extension (Steinke *et al.*, 2020), social media usage, digital literacy and access (Bronson and Knezevic, 2016); and adoption of technologies (Pierpaoli *et al.*, 2013; Barnes *et al.*, 2019; Lowenberg-DeBoer and Erickson, 2019). Whilst these perspectives are insightful, we argue that digital agriculture requires us to fundamentally rethink these knowledge processes and to reflect on the consequences of a shift towards data-driven processes.

This perspective piece refers especially to conventional agricultural systems and draws on research primarily from developed countries. In this brief discussion inevitably we have to use shorthand terms for the different AKIS actors: farmers, advisers, researchers, etc. We acknowledge that these groups are not homogeneous and we know that farmers' interactions with, and access to, digital agriculture differs significantly depending on multiple farm, farmer and wider enabling factors (Barnes *et al.*, 2019; Vecchio *et al.*, 2020).

### 3 Digital agriculture, farmer knowledge and decision making

#### *3.1 Decision support - analytical capabilities*

Digital agriculture offers the ability to utilise technology to convert precise data into actionable knowledge to drive and support complex decision-making on-farm and along the value chain. The promise is that, whilst past sources of knowledge were based on general knowledge often derived from research experiments, smart technologies may be able to offer on-farm, local-specific information to farmers (Poppe *et al.*, 2015). As such, digital agriculture reflects a shift from generalised management of farm resources towards highly optimised, individualised, real-time, hyper-connected and data driven management (Van Es and Woodard, 2017).

Of the three pillars of digital agriculture: robotics, sensors, and Big Data analytics platforms, the latter is critical. The large amounts of data being currently generated on farms by, for example, yield monitors, are of little value unless they can be turned into useful decision support tools for farmers (Weersink *et al.*, 2018; Janssen *et al.* 2017).

However, some scholars suggest that our capacity to collect large amounts of data outstrips our ability to convert it into usable information. Data analytics<sup>3</sup> and decision support are fundamental for fully-enabled digital agriculture, but to date the interpretation and use of data from smart technologies is

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<sup>3</sup> Analytics is the capability available to analyse data (Shepherd *et al.*, 2018)

not matching expectations (Leonard *et al.*, 2017; Weersink *et al.*, 2018) and the capability to effectively analyse these data to achieve promised improvements is limited.

Whilst there is evidence of uptake of GPS technologies that simplify the work (e.g., auto-steer systems) or passively collect data (e.g., yield monitors) (Lowenberg-DeBoer and Erickson, 2019), they signify 'embodied-knowledge technologies' (Griffin *et al.*, 2017) that require no additional skills to capture their value; in other words, they rely on the knowledge that farmers already possess regarding how to operate their machinery. This is distinct from the information-intensive technologies which use data collected from the farm as input into a decision support system that generates a prescription for the variable inputs. This distinction, some argue, explains the low uptake of variable-rate (VR) technologies which require new skills and decision-making models compared to the widespread adoption of GPS automated steering systems, yield monitors, and grid soil sampling (Weersink *et al.* 2018). Barnes *et al.* (2019) for example in a recent European survey noted this distinction in adoption patterns. Capalbo *et al.* (2017) point to the many cases where VR application of nutrients continues to be based on simple rule-of-thumb or empirical approaches.

Overall, it is felt that the difficulty of constructing, maintaining, analysing, and sharing such data limits the opportunity to derive effective decision rules with high information value to producers (Weersink *et al.* (2018). Given this, there is still a heavy reliance on the user to interpret the data. Studies have also found an increased learning load for farmers from using digital agriculture tools and the need to invest in human capital (Van Es and Woodard, 2017; Eastwood *et al.*, 2019).

Apart from the difficulty of providing decision support, farmers, advisers and researchers are finding it hard to manage, interpret, or make use of their data as a result of their volume and complexity (Van Es and Woodard, 2017). Typically farmers do not need high frequency and precise data for every decision (Robertson *et al.* 2018) and have limited capacity to deal with data complexity (Lioutas *et al.* 2019).

Despite these challenges, there are multiple examples of technologies available, from farm management software solutions (e.g. AGERmetrix and FieldView™ in USA and Agrivi in UK) to decision support tools (e.g. FieldNET Advisor™ in the USA) (Kamilaris *et al.*, 2017; Saiz-Rubio and Rovira-Más, 2020), that show how analytic capabilities are advancing.

However, limited decision support continues to reduce farmers' ability to meet the new demands of digital agriculture and can present significant adoption hurdles (Pierpaoli *et al.*, 2013; Knierim *et al.*, 2018). Whilst we cannot characterise the complex implementation problems of digital agriculture as solely due to limited capabilities in analytics and data use (Lowenberg-DeBoer and Erickson, 2019), it

is evident that the optimism for digital agriculture is not yet matched by analytic capability within the AKIS.

### *3.2 Disruptions to farmer knowledge and decision making*

Although there is a suggestion that skilled agricultural workers have the highest estimated probability of automation compared to other workers (Nedelkoska and Quintini, 2018), the extent to which this will support or replace decisions in farming depends on the technology. Sensors provide raw data (e.g. weather data), and smart devices (robotic vehicles, drone mounted cameras) will allow sophisticated farm management advice (Walter et al., 2017), while smart systems have the capability to execute autonomous actions (Budaev et al., 2019). For the former, human interpretive skills for decision making are still important, but for the latter the role of humans in analysis and planning is increasingly assisted by machines.

The nature and extent to which the human role shifts in the 'sense–analyse–act' cycle in achieving actionable knowledge is debated. Whilst many agree that farmers' knowledge is not about to be replaced by algorithms, it is suggested that their involvement will be at a much higher intelligence level, leaving most operational activities to machines (Wolfert et al., 2017). This distinction between strategic and tactical action releases the farmer from mundane day-to-day monitoring although it also removes the opportunity for observational knowledge which contributes to experiential learning.

There is a perceived risk of increasing reliance on technical experts and the technology resulting in a loss of tacit knowledge if the cognitive processing of information is delegated to machines or algorithms (Jago et al., 2013; Shepherd et al., 2018). Arguably the farmers' experiential knowledge acquired over the years is at risk (Moschitz and Stolze, 2018). However, the opportunity for farmers to acquire a better knowledge of their production sites and thus gain greater certainty when making decisions increases (Rösch and Dusseldorp, 2007). The use of digital technologies, such as sensors for monitoring animal behaviour, can arguably also replace the lost knowledge of older generations (Moschitz and Stolze, 2018). Furthermore, new systems are expected to support handling a higher complexity as well as an increased local adaptation which may be beyond individual experiential knowledge (Aubert et al., 2012).

More fundamentally, decision making and experiential processing commonly applied on farm have been supported in the past with descriptive and diagnostic tools and models explaining what and why things have happened. Digital agriculture heralds an era where these learning opportunities will be potentially diminished, in which the 'what is known' is prioritised over the 'capacity to know'.

With respect to decision making, new sources of data are seen to create the opportunity to inform and drive a change in decision making from one that is typically characterised as being highly intuitive

to one that is data driven and processed in real-time (Xin and Zazueta, 2016). This, many argue, requires a change in the mode of working for many farmers, transitioning from experiential decision-making to data-driven processes (Eastwood and Kenny, 2009; Nuthall and Old, 2018). However, in reality many farmers have been transitioning towards more data-driven decision making processes for some time, integrating different information sources and drawing on different levels of analysis, using, for example, precision agriculture and DSS.

Insights from studies of DSS, reveal that they largely support, rather than replace, the decision maker; that farmers use DSS, not in a deterministic way to provide specific answers, but as learning tools (McCown, 2001; Baars, 2011; Lindblom *et al.*, 2017). Experience with participatory design of DSS suggests that, a better appreciation of how farmers build tacit knowledge, the mind's store of decision rules and background information through repeated experience, may improve decision support for digital agriculture. In particular, understanding how this experiential processing can combine with analytical processing, where information is obtained through statistical description (Marx *et al.*, 2007); Hansen *et al.* (2019), can help to overcome difficulties at the interface between data and decision making. Working with farmers in developing technologies can also address the limited opportunities product developers have to ground truth information (Kamilaris *et al.*, 2017). Although there are few examples yet of co-created digital technologies there is acknowledgement that farm management and information systems require a user-centric approach (Fountas *et al.*, 2015; Van Es and Woodard, 2017).

#### 4 The changing AKIS dynamic under digital agriculture

Farmers draw on multiple sources of knowledge and innovation support services in the AKIS (regulators, supply chain actors, conservation experts, NGOs, policy makers), however, for many, farmer networks and farm advisers remain key. Evidence to date of the impacts of digital agriculture suggest potential shifts in these knowledge relationships.

##### *4.1 Enabling or disrupting farmers' knowledge networks*

Informal networks, between farmers and often including other actors, are one of the main knowledge exchange mechanisms in farming communities which lead to learning and innovation (Leeuwis and Aarts, 2011; Ingram, 2015). The extent to which digital agriculture will disrupt or enable these network processes is an important consideration. Proposed smart systems, which promise to take and learn the best practices from advanced precise farmers, formalise and transfer their knowledge and support to other farmers in everyday decision making (Budaev *et al.*, 2019) could arguably replace interpersonal networks. However, the potential for digital technologies to support collaborative knowledge creation has also been identified (Eastwood *et al.*, 2012). ICT enables farmers to exchange information, benchmark their production against others, establish cooperation and peer review, and

maybe even develop informal information systems that can complement more formal information systems (Wolfert *et al.*, 2017). Many farmers have started to mobilise and organise themselves (e.g. in cooperatives, online communities) to create and share know-how, technologies and experiences, and big data understanding (Kamilaris *et al.*, 2017; Carolan, 2018). Distributed sensing systems can form the basis for knowledge platforms for social learning (Robertson *et al.*, 2018).

#### *4.2 Innovation support services*

With respect to support services, farm advisers have always been important as interpreters of data and information. The digitalisation of expert knowledge into decision support tools or via artificial intelligence has the potential to disrupt advisory services and change the adviser's role (Wolfert *et al.*, 2017). Digital agriculture tools can provide farmers with analytical power and access to information previously unavailable (Ayre *et al.*, 2019). This may mean advisers need to reassess their capabilities, practices, services and skills as they respond to new demands (Eastwood *et al.*, 2017; Rijswijk *et al.*, 2018). They may also need to create new networks with technology providers and R & D (Lundström and Lindblom, 2018). Although there is a potential role for technology suppliers to take on greater advisory support for farmers and act as knowledge 'translators', they can often lack the farm systems expertise or knowledge networks to adequately support on-farm use (Eastwood *et al.*, 2016). To address this problem, researchers propose a co-development approach for building the capability to use digital agriculture tools (Eastwood *et al.*, 2019).

#### *4.3 New entrants and changing roles*

The emergence of new suppliers of equipment, software and services, business models and networks creates a new dynamic within the incumbent AKIS. The public and private sector generally operate together to establish a wide variety of data, knowledge and institutional arrangements that together constitute "a decision making infrastructure" that supports management in agriculture (Capalbo *et al.*, 2017). This is evolving under digital agriculture with new disruptive entrants (e.g. digital technology companies) and various models of development and investment appearing, including new business models that challenge incumbent forms (Phillips *et al.*, 2019). The changing roles of old and new software suppliers and the emerging landscape of data-driven initiatives (Lesser, 2014), with the prominent role of big tech and data companies and research universities has been observed (Keogh and Henry, 2016; Van Es and Woodard, 2017; Wolfert *et al.*, 2017). The dynamic between the new and established players is often framed by discussions of private-public data accessibility, ownership and governance (Bronson and Knezevic, 2016; Jakku *et al.*, 2016); however, issues of knowledge are also key, and are redefining AKIS boundaries. The tensions and synergies between these new entrants and those in public bodies and universities are of particular interest. The former have limited understanding of agronomic principles but excellent market access, while the latter have the expertise



and institutional learning which has provided the foundations for understanding the processes driving agricultural systems, through decades of experimental research and sophisticated modelling (enabling diagnostic understanding).

The opportunities for combining their different analytics are highlighted by Antle *et al.* (2017 p258) who point to synergies between the modelling community, which is strong on analytical capability, and the developers of user-related farm-level products. Harnessing big data and the analytical powers of models can also lead to what Capalbo *et al.* (2017) referred to as a virtuous circle which builds on both and will allow a new generation of models and decision support.

At a more fundamental level the arrival of new analytics raises the questions about knowledge and data-driven processes. Established R&D institutions applied analytical techniques associated with descriptive and diagnostic analytics which led to the effective application of what Sonka (2014) calls 'Small Data'. An important question for Sonka is: "how can the best aspects of the Small Data system be linked to the application of Big Data technologies?" Whilst he acknowledges that "knowing, at increasing levels of precision, "what" happened in the field or in animal facilities does have value, he argues that knowing "why" is also key to agricultural applications.

This shift in analytics also has the potential to significantly impact the AKIS in other ways, moving us from 'hindsight' to 'foresight' (Shepherd *et al.*, 2018). Digitising agriculture will take these systems to predictive (what will happen) and prescriptive (how can we make it happen) analytics, which are future focused. This development again raises questions about where our understanding of the mechanisms underpinning these predictions and prescriptions lies.

## 5 Conclusion

New data-driven processes on farm as well as the changing AKIS dynamic under digital agriculture brings new demands, relations and tensions. However, there is also great potential to both build on established ways of knowing and to foster new learning by harnessing synergies.

Morakanyane *et al.* (2017 p437) defined digital transformation "as an evolutionary process that leverages digital capabilities and technologies to create value". We would argue that these capabilities are crucial and extend beyond the digital domain per se to the knowledge capabilities of all actors in the AKIS. Enhancing capabilities at every level, from the farm and adviser level, to new technology and software providers and established researchers, will be important if digital technologies are to achieve their full value. Equally facilitating opportunities for combining different analytic approaches and capabilities should be supported. Fostering co-learning and collaboration in implementing new technologies should be an important strand for future development and research.

## 6. Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Author Contributions

J Ingram prepared the main draft and D Maye contributed material and ideas and edited the text.

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