UK-RAS White papers

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UK-RAS NETWORK
ROBOTICS & AUTONOMOUS SYSTEMS

Training the UK Agri-food Sector to Employ Robotics and Autonomous Systems

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FOREWORD

Welcome to the UK-RAS White paper Series on Robotics and Autonomous Systems (RAS). This is one of the core activities of UK-RAS Network, funded by the Engineering and Physical Sciences Research Council (EPSRC). By Bringing together academic centres of excellence, industry, government funded bodies and charities, the Network provides academic leadership and expands collaboration with industry while integrating and coordinating activities across the UK.

This white paper explores the need for inclusive, multi-disciplinary digital education and skills provision across the agri-food technology sector. Robotics and autonomous systems (RAS) have demonstrated on numerous occasions their potential for real and transformative impact in productivity, efficiency and safety within agri-food environments. But how can these technologies become widespread in real operations within the UK? The technical aspects of how to operate and maintain these technologies are crucial skills that need to be developed within the community as well as general understanding of the potential of these technologies for new and exciting application domains. The UK needs trained workers with these skills and abilities. I hope this excellent white paper will identify the skills gaps and best training practices to ensure that agri-food, the UK's largest manufacturing sector, can fully benefit from the transformations in RAS over the next five years.

The UK-RAS white papers serve as a basis for discussing the future technological roadmaps, engaging the wider community and stakeholders, as well as policy makers in assessing the potential social, economic and ethical/legal impact of RAS. It is our plan to provide updates for these white papers so your feedback is essential - whether it be pointing out inadvertent omissions of specific areas of development that need to be covered, or major future trends that deserve further debate and in depth analysis.

Please direct all your feedback to:
info@ukras.org.uk
We look forward to hearing from you!

Prof. Robert Richardson
Chair, UK-RAS Network




Matthew Howard,
Department of Engineering,
King's College London, UK

Sam Wane,
Department of Engineering,
Harper Adams University, UK

Lyudmila Mihaylova,
Department of Automatic
Control and Systems Engineering,
University of Sheffield, UK

David Christian Rose,
Royal Agricultural University,
Cirencester, UK



Prabhakar Ray,
Department of Engineering,
King's College London, UK

Louise Manning,
Lincoln Institute for
Agri-food Technology,
University of Lincoln, UK

Elizabeth Sklar,
Lincoln Institute for
Agri-food Technology,
University of Lincoln, UK

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The paper is the product of STAR Working Group 3 (White Paper on Agri-tech Training), with members Dr Matthew Howard (lead), Mr Sam Wane, Prof Lyudmila Mihaylova, Prof David Christian Rose, Mr Prabhakar Ray, Prof Louise Manning and Prof Elizabeth Sklar.

EXECUTIVE SUMMARY

Robotics and Autonomous Systems (RAS) in agriculture has become an expanding area of interest for research and innovation, in both industry and academia. Robotic solutions have been demonstrated for a wide range of farming tasks, from planting and weed management to crop monitoring and harvesting—the concept of RAS in agriculture is no longer tomorrow's dream; it is today's reality. However, a number of factors have limited the uptake and deployment of RAS in the agri-food sector, including lack of access to robust digital connectivity, unfavourable cost-benefit relationships for many farms to purchase robotic solutions, often unmet requirements for reliable, trustworthy and user-friendly systems, and the need to upskill and lack of relevant training for the agri-food workforce, specifically for working farmers and growers.

Now more than ever, a range of digital literacy and skills are needed (e.g. computer programming and robotic engineering, telecommunications networking and cybersecurity, image processing and data analytics). With the use of collaborative robots, autosteer, Unmanned Aerial Vehicles (UAVs), Variable Rate Technology (VRT) and the plethora of associated information provided by Internet of Things (IoT)-based solutions, those in the agri-food sector need to be able to use cutting edge technologies to analyse new data, apply new knowledge, develop new skills and assess new opportunities to enhance their farm business performance.

Future RAS applications will require multi-disciplinary digital literacy and skills, not only on the part of developers but also on the part of those responsible for making purchasing and operational decisions. These skills include abilities to operate with new technologies at different levels of autonomy; to address safety, legal, ethical and information protection aspects; to embed project management and legislation aspects; and to cope with extreme conditions, such as severe weather (e.g. storms and floods), supply chain interruptions (e.g. lack of components to maintain or upgrade equipment) or infrastructure disruptions (e.g. rising energy costs or loss of access to reliable internet).

Competence and confidence across the workforce, from farm director to harvest manager to field worker, are critical to the successful application and full-scale roll-out of RAS in the agri-tech sector—but this will only come about with an upskilled workforce. This UK-RAS white paper aims to explore the RAS training needs of the agri-food sector within the UK and to identify potential routes to addressing these needs through provisions offered by academic, industry and professional organisations.

> "The progress made in the development of RAS in recent years provides indispensable tools for tackling the agrifood labour shortage— provided that the agri-food workforce can be made ready to fully exploit these opportunities."

CONTENTS

1. INTRODUCTION

Throughout its history, farming has seen a sustained evolution of agri-tech ever since humans first settled and planted crops—from the horse and plough to the tractor, from organic to chemical (to organic) fertilisers, and now to Artificial Intelligence (AI) applications and Robotics and Autonomous Systems (RAS). This evolution has driven those working in agriculture to develop and adapt new ways of working, adhering to updated government policies (e.g., on chemical fertilisers) and taking advantage of the latest technologies in order to reap the benefits of more efficient farming practices. In the UK, factors such as Brexit, Covid-19, the Ukraine conflict and various socio-economic trends, especially the increased living wage, have all contributed to a shrinking pool of available farm labour, making the need to accelerate adoption of innovative farming technologies particularly acute. Progress made in the development of robotics and AI in recent years provides a broad spectrum of indispensable tools for tackling the challenges arising from a diminishing farm labour workforce. However, without appropriate intervention, there may be low uptake of robotic technologies across farms, which may hinder the full exploitation of state-of-the-art RAS opportunities as well as negatively impact the role of agriculture in the UK economy.

The role of RAS in agriculture has become an expanding area of interest both academically and commercially, advancing rapidly over the last 5-10 years. Many start-up organisations have emerged within the agri-tech industry offering robotic solutions for a wide range of tasks such as weed management, crop monitoring, planting and harvesting, changing the status of RAS in agriculture from a concept of the future to a product on the market today. However, a range of factors means that the uptake and deployment of RAS in the agri-food sector remains relatively low compared to other industries (Gil et al. 2023), despite the substantial potential for RAS approaches to alleviate both long-standing and newly-arising issues in the sector (Duckett et al. 2018).

There are two major issues that agriculture faces today: (i) shortage of available farm labour and (ii) environmental sustainability. This white paper primarily responds to the first issue—labour shortages. The European Union (EU) agri-food sector has an ageing workforce (Eurostat 2018; DG AGRI 2021), a lack of succession in family businesses (Lobley, Baker, and Whitehead 2010) and considerable reliance on dwindling migrant labour (Kalantaryan et al. 2020). Large-scale automation in previous decades has provided one solution, allowing a reduced workforce to manage the same area of land. However, the use of heavy machinery has led to negative environmental impacts (e.g., soil compaction) that, in turn, have had adverse effects on farm yield and production costs (Mousazadeh 2013).

In response to this, recent years have seen a shift towards agri-tech strategies and tools that enable farmers to improve sustainability and increase productivity with more targeted interventions (White et al. 2021), e.g., through precision agriculture (Blackmore 1999). Examples of state-of-the-art technologies currently in use in UK farming include robotic milking in dairy farming (Lundström and Lindblom 2021; Koning 2011) and Global Positioning System (GPS) for spatial accuracy with in-field navigation (Shalal et al. 2013; Blackmore et al. 2009). Such technologies have integrated well with traditional farming methods, enabling improved efficiency using off-the-shelf solutions and leading to economic benefits, without damaging the environment or other critical assets such as livestock and soil. Emerging technologies that have penetrated other sectors and are entering the agri-food sector include IoT (Xu, Gu, and Tian 2022; Thilakarathne et al. 2021; Shalimov 2023a), autonomous vehicles (e.g., UAVs (Rejeb et al. 2022; Shalimov 2023b; Kim et al. 2019; Qu et al. 2022) and Unmanned Ground-based Vehicles (UGVs) (Gonzalez-De-Santos et al. 2020)), multiple collaborative robots (Ju et al. 2022) and Machine Learning (ML) approaches to plant recognition for autonomous weeding (Salazar-Gomez et al. 2022).

Generally, the successful adoption of innovative technologies is more common in large-scale agri-food operations with the revenue and scale to support the initial investment. For instance, looking at the uptake of robotic milking, studies in Norway (Vik et al. 2019) and France (Veysset et al. 2001) suggest that farms with automated milking systems have larger herds and are larger than the national average, while another study in the Netherlands (Bijl, Kooistra, and Hogeveen 2007) evaluated a range of economic factors for farms investing in robotic milking, identifying a reduction in labour costs when such systems were implemented.

Small-scale family farms and agri-food businesses may lack the revenue, connectivity and/or technical competency to take advantage of innovative RAS solutions (Castle, Lubben, and Luck 2016). But smaller farms are less resilient when it comes to fluctuations in the workforce, implying they stand to benefit even more from RAS solutions. This points to the critical need to upskill and re-skill the agri-food workforce in order to keep up with technology advances.

This white paper identifies and discusses various factors that highlight the need for inclusive, multi-disciplinary digital education and skills provision in order to support wide-scale innovation and adoption across the agrifood technology sector. The paper is organised as follows. First, Section 2 describes the need, reviewing the range of technologies presently available for deployment in agricultural settings, as well as emerging systems anticipated over the next 3-5 years. Second, Section 3 discusses the digital skills gap in UK agriculture, looking abroad to recognise similar skills gaps and identify best practice responses for addressing the gaps. Third, Section 4 suggests modes for delivering training to UK workers in the agri-robotics sector. Finally, Section 5 provides conclusions and highlights the recommendations for future training.

2. THE NEED

2.1 CURRENT TECHNOLOGIES IN AUTOMATED FARMING

On farms, Robotics and Autonomous Systems (RAS) have to operate in complex and dynamic environments and need to follow the same safety standards as current farming machinery. The variability of tasks and operating conditions requires robots to be adaptable. The complexity of tasks and operating environments means that robots must be able to work alongside humans, sharing with human co-workers tasks that stateof-the-art robots cannot perform on their own. Robotic farming systems must be integrated with the farmer, in sync with farming practices and have the ability to supply relevant and timely information.

A wide range of practical, real-world factors, such as weather variability and energy reliance, means that laboratory-tested or indoor RAS solutions may be stretched when deployed in rural outdoor settings. The ability of farm workers to understand how to install, calibrate, debug and troubleshoot RAS could save on downtime and reduce need for calls to manufacturers or third-party service providers for maintenance.

A distinct set of engineering and information technologies underpin state-of-the-art RAS. Key technologies that form the foundations of products on the market today are described below: robotic hardware, covering the mechanical, electronic and computing platforms that enable physical interaction with the farm environment and workers; network connectivity, so that RAS can talk to each other and to human users; database systems, so that data collected on-farm and externally (e.g., market information) can be stored securely and accessed when needed; sensor devices, to collect data on the farm, in fields, glass houses, barns, etc; autonomous navigation, where farm vehicles such as tractors or specialised robots can operate safely and without human drivers; and artificial intelligence, to build data-backed models that can inform driverless vehicles and decision-making by farm managers.

Robotic hardware. The physical hardware elements that comprise robots include mechanical and electronic components to perform actuation and sensing and computational components to handle data processing, basic system control and AI functionalities. To support on-farm agriculture practices, there are generally three types of approaches to hardware platforms: (i) attachments (implements) are developed to be mounted on existing farm vehicles (e.g., tractors); (ii) bespoke robotic vehicles and/or manipulators are developed to perform specific single functions (e.g., harvesting strawberries); or (iii) multi-function platforms are developed that can perform several different types of functionalities. The first option is the most economical, but typically does not offer fully autonomous operation (i.e., because most tractors are designed for human driving). The second option tends to support activities that occur only at specific times of year and is more likely to be provided through service contracts (e.g., Robotics as a Service (RaaS)) rather than farms investing in bespoke equipment (similar to how many farms access combine harvesters). The third option is typically more expensive to build, purchase and maintain because multi-function platforms are more complex.

There are many different types and varieties of robotic sensors, covering a broad spectrum of physical and ambient properties. Common sensor devices used on farms and farm robots are described below. Robotic actuation hardware includes locomotion mechanisms (e.g., wheels, treads, rotors, etc) and manipulators, including arms with prismatic and/or rotational joints, offering multiple degrees of freedom, and grippers, where recent advances are exploring soft materials for handling delicate fruits and vegetables (see Section 2.2). Not only Unmanned Ground-based Vehicle (UGV) platforms, but also Unmanned Aerial Vehicle (UAV) platforms have uses on farms. The latter requires pilot licensing (as mentioned in Section 3.1). Computing devices for on-board robot processing are also broad and varied, ranging from small micro-processor boards (e.g., Arduino[1]) to small-footprint high-speed Graphics Processing Units (GPUs) (e.g., NVIDIA Jetson[2]).

Network connectivity. Wireless (telecommunication) networks, such as rural cellular (mobile), Zigbee radio and LoRaWAN, are necessary for transmitting and receiving data amongst on-farm devices, as well as communicating with cloud (off-farm, internet-based) services. In order to be useful, networks must be easy to connect to and provide secure and reliable (continuous) access. Connectivity includes all components that are linked using a wired or wireless network to share information, either locally via Local Area Network (LAN), across a wide area of the farm (e.g., Long Range Wide Area Network (LoRaWAN)) or globally via the internet. The rural environment has historically been poorly served by commercial telecommunications connectivity, and alternatives to the mobile phone system has led to on-farm adoption of low-power local network

[1] https://www.arduino.cc/
[2] https://developer.nvidia.com/embedded-computing

technologies (e.g., Zigbee, LoRaWAN), as well as the use of satellite communications. In future, the roll-out of 5G (fifth generation) telecommunication networks could be an enabler of farm-edge processing (using private 5G systems (Gomez et al. 2021)) or cloud processing (which could use either private or public networks), allowing the hardware in the field to be simpler and more robust.

RAS infrastructure requires access to robust networks that connect UAVs and ground robots with each other and with human operators, even when connectivity may be sporadic. Networks operating on farms need to follow approved standards, not only to ease connectivity and provide compatability, but also to ensure secure access to data. Cybersecurity threats, including hacktivism, can bring about significant risk, both to commercial business and population health (where food data is manipulated).

Cybersecurity is an important aspect since a significant amount of data and information is transferred via networks and stored remotely e.g., on cloud computers, so users must be aware of threats, vulnerabilities and how to prevent them (Baker et al. 2020). Different types of cyber threats exist and there are a number of initiatives to raise awareness in the agri-food sector and educate farmers on how they can introduce safeguards into their business. Some solutions include timely identification of the types of threats, such as extortion, phishing, malware or hacktivism, and for each threat, how to choose and implement potential mitigation strategies.

Database systems and data analytics. Data is the new currency on farms, as sensor systems are widely installed to gather vast amounts of data, monitoring everything from weather conditions and soil moisture to animal mobility and market trends. Managing different farming conditions and a multiplicity of crop varieties in conjunction with weather, consumer/market drivers, and fluctuations in labour availability and capability, requires the ability to interpret data trends that inform decisions and to manage people and agrifood production accordingly. Traceability of food, from seed to shelf, is a market expectation as consumers are becoming better informed about factors such as food miles, fertiliser and crop protection product use and problems with labour conditions (e.g., factories closing due to workers with Covid-19 (Halliday 2020)). The whole process, from the management of raw materials to the transportation of the final products to consumers, requires comprehensive databases of workforce, product, process and time management. Whatever technologies are adopted on farms need to be applied correctly, with an awareness of the levels of accuracy that are achievable and agreements on data ownership and availability.

Timely provision of and access to data is key to the productivity of agri-food activities, for both crop and animal farming. Data can arrive through a range of different wireless network channels and sources can include on-farm IoT sensors (measuring properties such as air temperature, humidity, wind speed, animal weight and carbon dioxide), on-vehicle cameras (such as optical, infrared and hyper-spectral), and thirdparty cloud services. Some of these, such as weather sensors, already have a long history of use in more intensive food production systems.

Sensor devices. There are many sensing products on the market today that allow farmers to collect data on their crops and fields. These include weather stations that report on air temperature and humidity, gas meters that report on carbon dioxide levels, moisture sensors that measure degree of soil wetness and digital cameras that observe plant growth. A range of different types of cameras can be mounted in static positions to monitor changes in one location over time or placed on mobile vehicles to gather data across the farm. These include visible spectrum RGB (Red-Green-Blue) cameras, RGB-D cameras that include a depth (D) channel in order to gauge distance from camera to sensed object, stereo cameras that offer enhanced depth information, infrared cameras to estimate surface temperature of objects, multispectral cameras that capture images using a discrete set of wavelengths and hyperspectral cameras that capture images across a continuous range of wavelengths. These last three types of cameras in particular are useful for imaging plants at various stages of growth and are common for plant phenotyping tasks (Li, Zhang, and Huang 2014), analysing physical traits associated with particular genotypes and plant varieties.

Sensors are used on farms not only for monitoring plants and cropping environments, but also for monitoring farm animals. Animal welfare and the ethical treatment of animals used in food production are issues of societal importance, and assessment of animal welfare can be improved with the use of sensor technology (Kooij and Rutter 2020). The design and integration of technology within animal production can improve access to timely information and can provide signals for the early indication of a potential welfare issue. Examples include the high degree of automation and sensing in environmental monitoring and control in buildings on poultry farms with real-time feedback in the event of an issue, using camera systems to monitor the movement of housed broiler chickens to detect problems with feeding systems or disease. Leg-mounted accelerometers (wearables) can enable the detection of the early stages of lameness in dairy cows and automated systems can detect mastitis in dairy cattle (Voort and Hogeveen 2022).

Autonomous Navigation. Controlled Traffic Farming (CTF), now widely available, enables the practise of driving a farm vehicle only over specifically allocated sections of land (rather than randomly over the field), causing less damage to soil sub-structure and delivering higher crop yield. A ten-year study at Harper Adams University showed results from the 2017–18 season revealing that CTF delivered 8% higher crop yield of winter field bean (Kaczorowska–Dolowy et al. 2019).

Autonomous navigation systems integrate mapping and path-planning algorithms that calculate optimal routes for planting, spraying, weeding, addition of nutrients and/or harvesting—minimising the traffic across the land and allowing accurate and efficient turns to ensure the crop gets the maximum use from the field. This practice reduces soil damage by limiting the number of passes by a heavy vehicle, as well as reducing cost and environmental impact of fertilisers, herbicides, pesticides and fungicides.

Sensors used in navigation (e.g., magnetometers, GPS, LiDAR and IMU) can estimate the position of a robot and/or a crop and autosteer can guide a tractor to follow pre-defined rows, making more efficient use of the field and reducing cognitive load on a human driver. Information from multiple sensors can be fused (merged) to improve prediction accuracy, often through probabilistic techniques such as Kalman filters (Kim and Bang 2019).

Public access and safety are key challenges for autonomous farm vehicles, due to the open nature of rural environments. RAS must be able to identify differences between static and dynamic objects, discern different types of objects, and mitigate collisions between the public, livestock, other vehicles and utility objects. Competition events help developers test their methods in controlled settings, for example the Hands Free Farm Hackathon (Harper Adams University, UK)[3] (Franklin et al. 2021), Pitch Your Robot (Wageningen University, Netherlands)[4] and the 2023 International Field Robot Event (University of Maribor, Slovenia)[5].

Artificial Intelligence and Machine Learning. AI technologies enable farmers and farm systems to make data-backed decisions, where knowledge is gained though the analysis of data acquired from sensors interconnected throughout the farm landscape and processes. These on-farm data sources could be linked to off-farm input streams, such as cloud services that provide live metrics on weather and markets. Plant recognition and early indication of invasive species can be sensed using ML techniques which require onboard recognition systems, sometimes working in tandem with cloud computers. Whilst intelligent systems can learn to spot trends, these still rely on human experts to train the ML systems, by providing off-line annotation of sensor data (e.g., identifying bounding boxes of plants and weeds on camera images) or on-line “teaching” of robotic behaviors (e.g., Learning from Demonstration (LfD) (Argall et al. 2009)).

[3] https://agri-epicentre.com/wp-content/uploads/2022/03/Hackathon-whitepaper.pdf
[4] https://www.wur.nl/en/activity/pitch-your-robot.htm
[5] https://fieldrobot.nl/event/index.php/2023/01/24/3445/

2.2 AREAS OF EMERGING TRAINING DEMAND

The rise of innovative agri-tech offers many benefits and is gradually converting the traditional field of agriculture into a technology-intensive sector (Barrett and Rose 2020; Klerkx, Jakku, and Labarthe 2019). There are several areas where RAS technologies are entering, or are poised to enter, the UK agri-food sector.

Collaborative robots, or Co-bots. The rise of collaborative robots—robots designed to work safely in close proximity with people—is making it more common for people to be able to interact with robots even if they have little or no technical background. These systems reduce the requirement for conventional computer programming skills for robot operation through the use of simplified programming interfaces, making deployment faster and more flexible. These systems show particular promise in the protected crop sectors, where they can be deployed for horticultural production tasks such as grading, collation, propagation of plant materials (Sena, Michael, and Howard 2019) and harvesting (Velasquez-Lopez et al. 2022).

Soft robotics. Advances in soft robotics are enabling an unprecedented ability to handle and manipulate delicate, irregularly-shaped materials, such soft fruits and berries (Navas et al. 2021; Kondoyanni et al. 2022). For example, special soft grippers have been designed to perform delicate tasks like harvesting blackberries (Gunderman et al. 2022) and strawberries (Sugathakumary et al. 2022).

ML-guided applications. An expanding set of applications guided by state-of-the-art ML methodologies are improving the ways in which robots can perform crop care and harvesting tasks and intelligent systems can monitor farm animals. For example, new ML approaches are leading to advanced visual manipulation of complex produce, such as tangled herbs and baby-leaf salads (Ray and Howard 2020). ML-based guidance has also been tested for identifying the "picking point" for strawberry harvesting (Huang, Wane, and Parsons 2017). Various precision livestock technologies such as AI-enabled cameras allow continuous monitoring of livestock, and the ability to automate management actions are approaching commercial readiness at scale (Schillings et al. 2021).

Precision localisation. Advances in highly accurate spatial technology (e.g., GPS combined with RealTime Kinematics (RTK), allowing position resolution of around 2cm) are enabling new autonomous driving technologies for crop care at the level of individual plants because the exact location of each plant can be recorded. When paired with Deep Learning (DL) (Smitt et al. 2022), these technologies can be used to pinpoint, track, treat and harvest individual plants rather than an entire field—the goal of precision agriculture.

Robot fleets. Groups of robots working together, also referred to as robot teams or robot fleets, are the subject of a number of new approaches to farm automation. These include intelligent, dynamic coordination of human-robot teams for on-farm efficiency. For example, robots can provide on-farm transportation for produce picked by human workers (Harman and Sklar 2022), reducing the time that skilled workers spend carrying things (e.g., freshly picked strawberries) around a soft fruit farm (e.g., from field to packing station). Robot swarms can perform crop care tasks such as sowing seeds (Kondoyanni et al. 2022). Vehicle routing paired with market mechanisms can ensure that shared resources (e.g., implements) are distributed fairly across cooperatives (Lujak, Sklar, and Semet 2021).

3. THE GAP

It is useful to employ a readiness assessment instrument to determine whether conditions are suitable for the uptake of robotic technologies at scale. Vik et al. (2021) argue that technologies can only be widely deployed in agriculture if and when: (i) the technology is ready (working and reliable); (ii) the market is ready (supporting conditions for scaling); (iii) the organisations are ready (tech companies and the agri-food industry can support scaling); (iv) the regulations are ready (laws and regulations encourage the responsible use of robotic technologies); and (v) the user is ready and able to accept (with good connectivity, ability to invest and adapt, and with the necessary skills). This last point is critical: without a workforce equipped with the necessary skills and knowledge to use RAS technology, RAS adoption i n the agri-food sector will remain low.

Here, we review the skills gap in the UK (section 3.1) and describe the international landscape (section 3.2), highlighting needs and best practice in other countries, and also review the range of associated non-technical skills that are necessary for upskilling alongside technical skills (section 3.4).

3.1 THE DIGITAL SKILLS GAP IN THE UK AGRICULTURE SECTOR

Robotics and Autonomous Systems promise many economic, social and cultural benefits to the agri-food sector (Rose et al. 2021). Economically, there is a potential to reduce labour and other input costs (LowenbergDeBoer et al. 2019). Socially and culturally, RAS technologies may improve the well-being and lifestyle of those working in the agri-food industry, freeing up time to spend with family, or innovate further with the products they provide (Sparrow and Howard 2020). Moreover, gains arising from increased RAS use can protect consumers from unnecessary cost rises, increase choice, enhance the quality of food products and provide assurance as to the ethical, welfare and environmental standards of what they consume (Duong et al. 2020). However, a wide range of barriers are hampering effective adoption of RAS technologies, including: high cost of investment capital (da Silveira et al. 2023), reliance on external organisations for repairs and upgrades (da Silveira et al. 2023), lack of technological infrastructure in agriculture (Adriant, Simatupang, and Handayati 2023), loss of experiential knowledge (da Silveira et al. 2023), technology fatigue introduced by complex technology (Hörner et al. 2021), staff redundancies, lack of reliable, scalable and trustworthy autonomous systems (Sparrow, Howard, and Degeling 2021).

At present, the UK suffers from gaps in the training landscape, meaning that the digital skills necessary for RAS adoption are lacking and, if in place, are not at the levels required. Higher-level training (i.e., undergraduate degree level and beyond) are well catered for through general (robotics or mechatronics) and specialist (agricultural engineering) programmes at higher education institutions. For example, a recent search of programmes that mention robotics on UCAS[6] returns over 300 programmes in the UK.

However, vocational and apprenticeship level training in RAS lacks standardisation, and the Continuing Professional Development (CPD) offering that covers smart RAS technologies remains limited. There is no UK-wide recognised qualification in RAS operation that can be regarded as equivalent to other professional operators' licences (e.g., heavy goods vehicle driving, fork lift operation), except drone piloting, which technically is not 'autonomous' because a human operator must maintain line-of-sight control at all times. In part, this reflects the challenge in designing training approaches for these systems: unlike traditional machinery, RAS exhibit complex, adaptive behaviour, suggesting efforts to improve training provision should go hand-in-hand with further research into the best means to deploy and maintain RAS. Lack of industry standards also means that any training which does exist is delivered by system manufacturer, customised to the specific hardware and software they are selling.

As pointed out in (Pearson 2022), there is an active demand from the horticultural sector to adopt RAS technologies that are well proven and also to explore emerging agri-robotic innovations.

[6] https://www.ucas.com/explore/search/all?query=robotics

3.2 THE INTERNATIONAL LANDSCAPE

A recent report from the UN Food and Agriculture Organization (FAO 2022) summarises the challenges in agricultural automation, considering key business case studies, socio-economic impacts and policy options. The UK is not alone in facing challenges due to lack of labour, increasing automation, market globalisation, digital disruption and climate change. These challenges are transforming industry and labour markets globally, with a growing impact in the agri-food sector (Fetsi, Bardak, and (eds) 2021). Understanding how international competitors are preparing to support their workers to address labour market changes can help in choosing appropriate training provision and policies in order to be able to adapt RAS widely across the UK agri-food sector.

Despite availability and advancements, the benefits of RAS remain largely untapped. For example, the adoption of robotic milking varies substantially across countries: it is employed on 30% of dairy farms in Iceland and Sweden, 20-25% in Denmark, The Netherlands, Norway, Belgium, and Switzerland, and less than 10% in Canada, the UK, and the USA (Eastwood and Renwick 2020). Lack of digital skills has been identified as a significant barrier to uptake. However, fostering the right skill set is not straightforward, including finding an appropriate balance of hardware-oriented versus software-oriented skills. Developing the right skill set involves understanding how learning happens in the agri-food sector and requires planning and foresight to consider all components of the agri-food workforce, such as farmers, farmworkers and farm advisors, as well as seasonal factors in order to account for what skills are most needed at what times of year and when different members of the workforce would be available to train on and test new skills. Being successful in future farming, businesses will require a complex balance between digital literacy, digital skills, management, communication, collaboration, attitude and open-mindedness (Krzysztofowicz et al. 2020).

A review of the skills strategy adopted in 11 countries presented by the Organisation for Economic Cooperation and Development (OECD 2019) underlines the requirement for future farmers to be more skilled and innovative. Data from the European Training Foundation (ETF) (Fetsi, Bardak, and (eds) 2021) and countries such as Albania, Armenia, Bosnia and Herzegovina, Egypt, Georgia, Lebanon, Kosovo1, Moldova, Montenegro, Morocco, North Macedonia, Serbia and Turkey indicate that jobs in manufacturing, construction, and agriculture are mainly at risk due to automation and digitalisation, suggesting insufficient provision of training opportunities for workers in these countries. Meanwhile, in the EU, at least 20% of workers are overqualified with respect to their technical skills for jobs in the agri-food sector (Fetsi, Bardak, and (eds) 2021). This highlights the need for providing re-qualification and training at the right level for this sector.

In an evolving labour market, workers need more transversal skills and multi-disciplinary competencies (Fetsi, Bardak, and (eds) 2021). A strong lifelong learning system is desirable, as well as closer ties between vocational (specialised) training and companies. Israel provides a good example where RAS technologies are quickly adopted and new agri-tech has been successfully applied, including use of big data and AI. Examples are advanced irrigation and biotechnology (Fetsi, Bardak, and (eds) 2021). This has been enabled through cooperation between public and private sectors, with attention to technical, digital and soft skills, and stronger investment in lifelong learning with a focus on young people and women. Through these investments, productivity in the agri-tech sector has been enhanced.

Overall, the lessons from the international landscape confirm the need for investment in training, tailored to the right level for the sector. These will need to be customised for UK-specific needs, especially linked with the seasonal demands of crop harvesting and care, livestock production, climate aspects and the changing patterns of seasonal labour.

3.3 NON-TECHNICAL SKILLS GAP

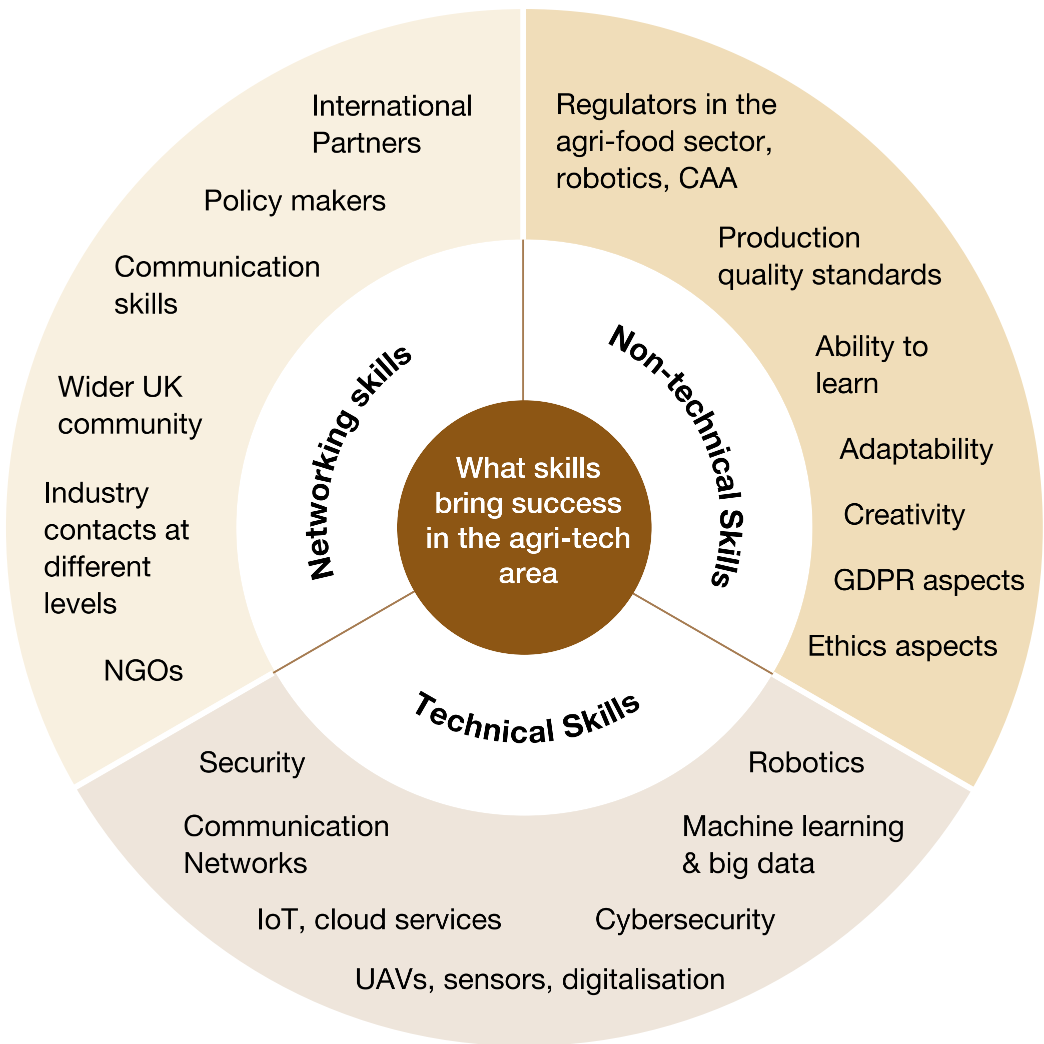
To make the most of RAS technologies, training should not only cover the general operation and use of the RAS in question, but also must be tailored to the specific socio-economic challenges within the sector. When working with farms, it is paramount to emphasize that technology is not here to replace, but rather to give opportunities to remain productive with access to a smaller workforce and to allow the existing workforce to develop new skills. With an efficient mutual understanding between farmers and tech-enablers, farmers can develop new skills and tech-enablers can better understand crop and farm animal practices. For example, for using a robot milker, the tech-enabler must understand the behaviour of the cow.

It is imperative that appropriate training supports existing skill sets and helps to minimise errors, avoiding any losses on farms, especially livestock (which is typically higher-value per inventory item than plants). For the well-being of farm animals, it is necessary for tech-enablers (e.g., inventors, engineers, robot handlers etc) to follow animal welfare and ethical protocols. Farmers and tech-enablers need to be in agreement as to the complementarity and suitability of livestock rearing tasks within a farm's wider livestock production system. RAS working in close proximity to livestock will require strict controls to avoid any loss of or injury to livestock. This means incorporating animal behaviour and animal welfare aspects into training protocols for technology developers. Engaging farmers in the design stages for new technology development and training for RAS workers should prevent them having misapprehension regarding the adoption of the new systems.

Training around the use of AI technologies require data handling skills from the viewpoint of explainability and intepretability (Manning et al. 2022), with clear relevance to farm decisions (e.g., the RAS could present an ordering of alerts and risk levels in decisions made from data: from high (resulting in death), to medium (losing a contract), to low (minimal cost-saving). Farmers need to understand and interpret the data not just as a number but as a number with clear relevance to farm decisions. They also have to adjust to how the use of the technology redefines their self-identify as the farmer.
Several key skills that are outside the ordinary scope of a typical agri-food business may also need to be introduced in order to comply with legal, ethical, security and safety issues and other regulatory requirements. For instance, increased RAS use will likely require those in the sector to take on new skills in handling data, to ensure appropriate data collection, transmission, compression and storage, in compliance with General Data Protection Regulations (GDPR) (ICO 2021). Moreover, the use of RAS may also require those in the agri-food sector to understand and adhere to previously unfamiliar safety standards, for instance, UAV use requires compliance with UK Civil Aviation Authority (CAA) regulations.

3.4 SKILLS GAP SUMMARY

The gaps in the skill set for workers within the agri-tech sector can be broadly classified as technical and non-technical. Technical knowledge gaps include: (i) Ability to use RAS technology (e.g., UGVs, UAVs, sensors, networks, etc); (ii) Ability to maintain RAS hardware and software; (iii) Understanding of computer hardware (from micro-controllers to embedded processors) and networks, including setup, continued connectivity and security; (iv) Data use and cybersecurity awareness, from collection to storage, adhering to ethics principles, the requirements of GDPR and understanding of data sharing agreements; and (v) Periodic re-qualification of skills aligned with the latest emergent technologies. Non-technical knowledge gaps include: (i) Understanding of agricultural practices (cropping and livestock) by technology developers and enablers; (ii) Understanding of farm management practices (e.g., financial and crop planning, labour recruitment and management); and (iii) Awareness of government regulations and legal requirements. Transferable and multi-disciplinary skills require a system that offers re-training from one area to another, inclusively and diversity and diversity of training.



4 RECOMMENDATIONS

4.1 NEW SKILLS FOR A NEW AGE OF AGRICULTURE

Historically, farmers have been able to operate more efficiently when they have control over their own equipment, including basic maintenance and being able to fix small issues as they arise. Just as the switch from horsepower to mechanical power in the 1900's required re-skilling of farmers (with the need to drive and maintain machines), the move towards RAS deployment requires acquisition of new skills. This reskilling has already begun to occur in many agri-food sectors, where a range of new technologies are in use for poultry and pig farming (e.g., welfare monitoring), dairies (e.g., robotic milking), indoor horticulture (e.g., automated seeding) and outdoor broad acre fields (e.g., CTF).

Skills training needs go both ways—from farmer to technologist and vice versa. Individuals working on farms need to be aware of and understand their robotic hardware and software, while those designing and supporting agricultural RAS technologies need to understand how farms operate. If a farm robot breaks, RAS customer service might not be available quickly and every day lost to broken equipment negatively impacts farm productivity. But when it is available, RAS service providers (as well as sales forces) need to be familiar with on-farm practices (e.g., when to clean shoes, what to touch and not touch, etc), just as farmers need to possess basic digital skills and understand the core working principles behind their technology.

The variety of RAS technologies available increases daily, and farmers may want easy access to new opportunities. Many farming robots will most likely operate, at least initially, following pay-per-service models (e.g., RaaS), as opposed to a farmer's outright purchase of specialist equipment (hardware) and/or accompanying or stand-alone software tools. With an RaaS model, the farmer is offered a service contract and/or a license agreement to use the technology for a particular farming operation. The use of contractors for specific operations on farm is well established, especially where they provide performance of tasks or access to large or expensive equipment that would only routinely be undertaken on farm a few days per year. The integration of RaaS means that farmers can reduce their risk of financial commitment to new equipment while still benefiting from the advantages new technologies have to offer.

The machinery itself requires proprioception, a form of self-awareness that underpins the ability to report errors, request maintenance, continue operation even if not fully functional or stop if minimum operation is no longer possible. This 'graceful degradation' is standard in modern vehicles and space robotics, enabling the technology to be useful despite minor malfunctions, and is a crucial feature in the design of agri-robots.

Meanwhile, the optimal use of on-farm technology will continue to need all the traditional skills of a farmer or grower, agronomist and other members of the farming team, with their intimate knowledge of how to use their land to its best advantage, as well as the economics and management of an agri-food business. There is a widely held hypothesis that the utilisation of technology in farming can attract a younger, more diverse workforce into the sector, as currently there is an expanding issue of young people eschewing farming for technology-related roles. In 2016, a third of farm holders in the UK were over 65 years of age, with only 3% of farm holders being under 35 (DEFRA 2022). However, the 'farm holder' is the person that is the designated owner of the farm, while the total UK agriculture sector workforce of around 480,000 is not reflected in that statistic; there are around 200,000 holdings, so the average age of the workforce is not 65—it is the average age of the person designated as the owner. What this means for digital skills training is that the sector population is changing and skills training provision must reflect and cater to the diversity of the farming workforce.

Farms that make money, as with any business, are those that not only know the relevant numbers (e.g., crop yield, cattle productivity, etc), but also are able to predict—as accurately as possible—their revenue, productivity and risks going forward. This requires forward planning of labour, time, and consumables to maximise benefit. In horticulture, for example, due to the short shelf-life of most farm products, the consumer-driven nature of supermarkets, weather extremes and labour availability, an agile Just-In-Time approach will need to be embraced. Entrepreneurial skills are needed to take advantage of the opportunities that agri-tech provides, using the data as feedback to continuously inform and adjust farm practises. Due to tight profit margins and increasing demands of retailers and food service, the traceability of goods to source and the efficient use of agronomic data will be required as a condition of supply. The agricultural economist farmer will need a global perspective as the demand for variety, organics, and nutrition increases.

It is helpful to consider skills categorised in line with an OECD typology of types: cognitive skills, social and emotional skills, job- and occupation-specific skills, and digital skills for all-round upskilling of the agri-food workforce to embrace the agricultural revolution 4.0 (OECD 2019). The imagined 'Farmer 4.0' needs to be innovative, highly-skilled, diverse and data-driven, being motivated to develop their skills constantly and to see the value in collecting, interpreting, and making precise decisions based on data (Barrett and Rose 2020). (Krzysztofowicz et al. 2020) propose twelve different farmer profiles based on their chosen style of farming. Specifically, they highlight the importance of being curious, open, resourceful and having a problem-solving mindset in making a farmer more adaptive. Understanding how to conduct digital marketing and engage with people across the supply chain, including consumers will become increasingly more important (Roche et al. 2020) , as well as managing diversely skilled teams, understanding the health and safety and legislative requirements of robotic technologies, and generating business plans to identify opportunities to incorporate robotics.

4.2 DELIVERING RAS TRAINING TO THE SECTOR

With the diverse range of RAS technologies entering the agri-food sector, it is apparent that a higher-skilled agri-tech workforce will be a pre-requisite for sustainable and economical farming in the future (Klerkx and Rose 2020; Rose and Chilvers 2018). Moreover, considering the diversity of requirements, filling the skills gap will necessarily require the involvement of multiple stakeholders, bringing together the knowledge and experience of farmers, growers, agri-food business leaders, technology providers, advisors and academics, across the domains highlighted in this white paper. Training may be delivered to those that need it through several channels, including further education, higher education and CPD.

Due to the nature of the business, training whilst working and apprenticeships will be an essential offering to the busy, profit-focused farmer. Technical colleges involved in rural and land-based skills provision, with a vocational educational offering can help facilitate or initiate this among new entrants into the sector. In the UK, professional bodies such as the Institution of Agricultural Engineers (IAgrE), the Institution of Mechanical Engineers (IMechE), the Institution of Engineering and Technology (IET), the British Computer Society (BCS) and the Institute for Agriculture and Horticulture (TIAH) are well-placed to provide CPD to their members, enabling them to keep their technical knowledge updated. Mechanisms such as chartership, peer-to-peer learning and formal courses are available. These bodies are also active in setting standards and formalising ethical and regulatory requirements. Specialised undergraduate and postgraduate degree courses in agri-tech are also available across several higher-education institutions in the UK. At the grass roots level, the offer of short specialised courses, virtual conferences and presentations, and interest groups providing an immediate tangible benefit will be necessary. The advent of agri-living labs which act as a practical technology demonstrator would allow the farmer to see the benefits of technology in action. This has the added benefit of raising awareness of emerging RAS technologies, providing farmers with a degree of future-proofing in their RAS investment-related decision making.

Across these modes of delivery, a key requirement is to promote a culture of lifelong learning. This is especially important considering that the development of RAS is continuous and fast-paced, meaning the skills required to make use of it must constantly be updated as other skills become out-dated and eventually obsolete. This also requires each of the bodies delivering training to be in constant conversation with academics and industry technology providers, to ensure their training offer is kept up-to-date with emerging RAS trends. In turn, as new technology becomes increasingly smart, adaptive and capable, it will be crucial to invest in research that provides a sound evidence base for the effectiveness of approaches to upskill the UK workforce.

Agri-robotics is a cross-disciplinary area. It is important not only to provide training for farmers and plant scientists to understand the technologies behind RAS, but also to consider professional training in the other direction, i.e., RAS professionals who seek to gain some background in agriculture. A range of schemes exist, including BASIS training[7] and Nuffield scholarships[8].

[7] https://basis-reg.co.uk/scheme-facts and https://basis-reg.co.uk/schemes
[8] https://www.nuffieldscholar.org/

5 CONCLUSIONS

This UK-RAS white paper has explored the needs of the UK agri-food, agri-tech and RAS sectors to upskill and re-skill the workforce in order to enable successful exploitation of current and emerging RAS technologies. In the global agri-food sector, it is apparent that there is a growing gap between the increasing level of automation and the readiness of the workforce to adopt and exploit it: part of the so-called digital skills gap. In the UK, filling this gap is particularly important due to socio-economic issues facing the agrifood industry, including factors such as Brexit, Covid-19, the Ukraine conflict, rising energy costs, other inflationary pressures and the increasing living wage. These have all contributed to a shrinking pool of available farm labour, making the need for innovative farming technology particularly acute. The progress made in the development of RAS in recent years provides indispensable tools for tackling these challenges— provided that the agri-food workforce can be made ready to fully exploit these opportunities.

To achieve this, a coordinated effort among many stakeholders will be required. In particular, this white paper has identified seven key recommendations relating to addressing the skills gap, in order to improve the readiness of the agri-food, agri-tech and RAS sectors for full-scale roll-out of RAS technologies:

1. Provide technical RAS training that is tailored to the specific needs of the agri-food industry and spans a broad range of topics, from robotic hardware and software to data management and security to AI and data analytics;
2. Provide training that goes beyond the technical operation of RAS technology to include ethical, legal and regulatory issues;
3. Invest in research into best practice for RAS training to provide a sound evidence-base for design and delivery of courses;
4. Ensure that training providers (e.g., professional bodies, further and higher educational institutions) are appraised of the most up-to-date information on emerging RAS trends, uses within agri-tech and best practice RAS training;
5. Ensure that technology developers are able to access professional training that introduces them to farm practices, covering cropping as well as livestock;
6. Raise awareness in both technical and agricultural communities about the opportunities, benefits and challenges that the introduction of RAS can bring to the agri-food sector; and
7. Strengthen collaborative work between end users, farmers, industry, technology providers, agricultural advisors and academics in order to lower barriers to entry and integration through user-friendly interfaces and machinery that adheres to standards (where they exist).

All of these recommendations must be considered in-line with standard Equality, Diversity and Inclusion (EDI) policies and practices. In return, the extensive deployment and adoption of RAS technologies offers a golden opportunity to drive resilience in the UK agri-food sector, improve productivity and working conditions, while also promoting environmental sustainability and biodiversity.

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ACRONYMS

AI Artificial Intelligence. 3, 4, 7, 9, 10, 13

BCS British Computer Society. 12

CAA Civil Aviation Authority. 10

CPD Continuing Professional Development. 9, 12

CTF Controlled Traffic Farming. 6, 11

DL Deep Learning. 7

EDI Equality, Diversity and Inclusion. 13

ETF European Training Foundation. 9

EU European Union. 3, 9

FAO UN Food and Agriculture Organization. 9

GDPR General Data Protection Regulations. 10

GPS Global Positioning System. 3, 6, 7

GPUs Graphics Processing Units. 5

IAgrE Institution of Agricultural Engineers. 12

IET Institution of Engineering and Technology. 12

IMechE Institution of Mechanical Engineers. 12

IMU Inertial Measurement Unit. 6

IoT Internet of Things. 1, 3, 6

LAN Local Area Network. 5

LfD Learning from Demonstration. 7

LiDAR Light Detection And Ranging. 6

LoRaWAN Long Range Wide Area Network. 5

ML Machine Learning. 3, 7

RaaS Robotics as a Service. 4, 11

RAS Robotics and Autonomous Systems. 1, 3–13

RTK Real-Time Kinematics. 7

TIAH Institute for Agriculture and Horticulture. 12

UAV Unmanned Aerial Vehicle. 5, 10

UAVs Unmanned Aerial Vehicles. 1, 3, 5, 10

UGV Unmanned Ground-based Vehicle. 5

UGVs Unmanned Ground-based Vehicles. 3, 10

VRT Variable Rate Technology. 1

"With the diverse range of RAS technologies entering the agri-food sector, it is apparent that a higher-skilled agri-tech workforce will be a pre-requisite for sustainable and economical farming in the future."

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