

RESEARCH PROJECTS

Use of AI in the UK Food System

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Abbreviations

AI	Artificial Intelligence
FSA	Food Standards Agency
REA	Rapid Evidence Assessment
TIAB	Title Abstract
UK	United Kingdom of Great Britain and Northern Ireland
US	United States of America

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Executive Summary

In recent years, advancements in Artificial Intelligence (AI) – or the use of machines to undertake tasks that would otherwise require human intelligence to perform (Future Risks of Frontier AI, 2023) – have seen multiple sectors increasingly incorporating AI into their work. This includes the food sector, which is using technologies like deep learning, robotics, and natural language processing to sort and classify foods, predict yields, and control for food safety, among many other functions (Di Vaio et al., 2020). AI has the potential to have large impacts on both daily work within the food sector, and to be a potential solution to longer term and more existential challenges, like the rising global population or climate crisis (Di Vaio et al., 2020; Marvin et al., 2022; Mavani et al., 2022; Short et al., 2022; Strauss et al., 2023). However, the field of AI is a very broad and

an uncertain one, which is both changing rapidly, and largely represented by private companies with a vested interest in preserving confidentiality (Future Risks of Frontier AI, 2023).

Given the increasing trends of AI use in the food sector both within the UK and globally, it is important to stay abreast of the ways in which AI is being utilised, where technology can be further optimised and what barriers and challenges may be encountered or may emerge as a result of using AI. There are already many concerns around current use of AI in the sector, including potential failures in transparency around the algorithms in use, in how they make decisions (also known as the AI 'black box'), and around data access and use infringing privacy or exposing trade secrets (Jouanjean, 2019). This lack of transparency adds to the significant levels of uncertainty which exist around the progress and capabilities of any kind of AI.

This research sets out to establish an initial understanding of the current use of AI in the UK food system, where research is concentrated, and where activity may be likely to occur in the near future. To do this, it combines a rapid evidence assessment of academic and grey literature into the use of AI, with a scientometric analysis of global academic publication and patent data. This more historical data is supplemented by a high level horizon scan of emergent topics of discussion in the food sector based on scraping of major websites, blogs, journals and news outlets.

Key findings

Levels of research globally into AI have been consistently high over the last six years. Scientometric analysis found that, globally, over the last six years there have been high levels of academic knowledge generation in the areas of AI and food systems, and the UK has remained one of the top five countries publishing in this field.

Research within the UK has focused less on translation and implementation. The number of patents published within the UK is significantly fewer than the number registered by the global leaders, the USA. Research within the UK appears to be concentrated at the beginning stages of research, concentrating on testing theory or developing new ideas, rather than on developing products for immediate application in industry, or researching the impact of the implementation of new tools. While it is important to acknowledge that these findings rely on first author and country of applicant data, which may underrepresent international consortiums of researchers or multi-national companies which include the UK, these findings are echoed in the academic and grey literature searches

Industry and academic interest is focussed on future and emerging trends in AI. We identified very few use cases of AI within the UK studied in an academic context, although did find far greater evidence of prospective tools being developed with input from UK researchers: that is tools that are not yet, or may never be, used outside of a research context. Grey literature searches, on the other hand, unearthed multiple references to use cases of AI within the UK food industry. This may suggest a lack of systematic implementation of AI within the UK. Similarly, horizon scanning demonstrated This indicates that academic and industry interest is on synthesising general trends in AI use and predicting applications, with primarily industry leading discussions of actual use. although discussions of actual use were again limited to industry.

The challenges of AI use discussed are primarily around the labour market and algorithmic bias. Horizon scanning also revealed a limited interest in exploring the challenges of the use of AI in the food system, although did represent more engagement with these topics than found in the academic literature. Emerging conversations focussed primarily on the impact of AI on the labour market, or on concerns about algorithmic bias.

Thematic assessment revealed a large focus on food production, supply and waste. Other emerging trends included a focus in articles about the use of AI in agriculture to manage the supply or production of food, and on the potential of AI to mitigate climate change, with a particular focus on reducing food waste. The majority of research, including all systematic reviews found, were concentrated either at the beginning (food supply and production) or end (food waste) of the food system.

AI use cases within the UK were present across the food system. Use cases of AI were found within grey and academic literature at each of the six stages of the food system: supply, production, processing, distribution, consumption and waste. The potential for scaling tools was identified at the food waste and food supply stages in particular. However, tools at the supply stage were most likely to be hampered by concerns around data organisation and sharing, and while the UK has a lot of the infrastructure required to scale the AI tools used at the food waste stage, coordinating different proprietary tools may be a barrier to widespread adoption. Tools at the production stage were more likely to involve complex and likely expensive specialised robotics, although some examples of AI-enabled apps and platforms were found at the intersection of production, consumption and distribution, with smaller companies using AI to enable distributors to manage inventory. Otherwise, there was more limited evidence of use within the areas of food processing, distribution, and consumption, although, evidence from the grey literature searching and horizon scanning suggests there is growing interest in tools for individual consumers.

Recommendations and next steps

Our study revealed some key areas for future research as well as wider recommendations which are applicable to multiple stakeholders operating across the varied facets of the food and agriculture ecosystem. Recommendations:

1. Government institutions may consider proposing guidelines or codes of conduct, akin to the US executive order, to generate more transparency in the use of AI and underpinning algorithms in the food industry.
2. There is a need for more planning and investment in capacity building to support adoption of AI tools and technologies across the food supply chain.
3. More cross-disciplinary efforts are needed to assess AI utility where food systems interact with other areas.
4. More efforts demonstrating economic and social benefits of technology adoption are needed to engage with the public, and the food industry at large to drive technology acceptability underpinned by robust evidence outlining both risks and benefits.

Areas for further research

1. More systematic research into the use of AI in the UK food system is needed.
2. More research on industry practices and challenges on AI use and scalability is needed.
3. Gap analysis and stakeholder engagement could identify opportunities for tool development.
4. Global capabilities assessment could identify opportunities for the UK.
5. Developing rules of engagement for the use of AI tools in the food system could create transparency in the use of AI in the food sector.

1. Introduction

1.1. Context

In recent years, AI has gained increasing prominence and utilisation in multiple sectors, ranging from improved diagnostics and rapid drug development in healthcare to weather forecasting, modelling, and agricultural optimisation (Cook & O'Neill, 2020). Broadly defined, AI involves training and using computers and machines through employing machine and deep learning algorithms, among others, to execute intelligent behaviours autonomously, such as learning, judgment, decision-making, self-monitoring, interpretation, diagnosis, and analysis (Ahmed et al., 2022; Javaid et al., 2023; Zhang & Lu, 2021). Branches of AI are broad, including Machine Learning, Natural Language Processing, Computer Vision Robotics, Artificial Neural Networks, and Expert Systems (Kutyauripo et al., 2023). Consequently, AI technologies exist in many applied forms and outlets, including but not limited to: robots, imaging, laser scanning, apps and wearables, virtual reality, and voice activated devices (Javaid et al., 2023; Ma et al., 2023). Use of different types of AI is variable across societal and industrial sector, and advancements at the cutting edge of AI contain more uncertainty around the risks and opportunities that could materialise as a result of their use (Future Risks of Frontier AI, 2023). As a primarily informally regulated technology, with the EU AI Act the only formal oversight mechanism in place, the risks and challenges of engaging and scaling AI is an area of active research and debate globally.

Nonetheless AI utilisation in the food sector is on an upward trajectory, not unlike the healthcare sector. Among the AI tools that are promising to revolutionise the food sector, the most prevalent appear to be: machine learning utilising deep learning; AI-powered software robots; and natural language processing (Di Vaio et al., 2020). These types of AI offer many benefits and opportunities for the food system. They have the potential to increase the efficiency and effectiveness of tasks across the food system stages (e.g., food quality determination and quality control; food sorting and classification; prediction of yields; food safety; developing new food products in the food processing industry), and provide economic, social and sustainability benefits (Di Vaio et al., 2020; Marvin et al., 2022; Mavani et al., 2022; Short et al., 2022; Strauss et al., 2023). They also offer solutions to current challenges like the rising demand for food necessitated by the growing world population (Mavani et al., 2022); climate change (Di Vaio et al., 2020); chronic labour shortage issues that have arisen in recent years in the food system in the UK and other economic pressures (Strauss et al., 2023).

Demand and utilisation of AI in the food system is only intensifying, with expectations that it will become a fundamental driver for transforming the future of the food system (Strauss et al., 2023).

Globally, the application of AI in food systems has culminated in: use of AI powered drones for precision agriculture in China, use of AI analytics to predict yields and reduce food waste in the US, use of AI in health analytics for livestock to reduce antimicrobial use in the US and EU and use of AI in food distribution and logistics in the UK and the US (Shang, 2023; L. Wang et al., 2022).

It is therefore important to stay abreast of what gaps AI is filling, where technology can be further optimised and what barriers and challenges may be encountered or may emerge as a result of using AI. There are already many concerns around current use of AI in the sector, including potential failures in transparency around the algorithms in use, in how they make decisions (also known as the AI 'black box'), and around data access and use infringing privacy or exposing trade secrets (Jouanjean, 2019). This lack of transparency adds to the significant levels of uncertainty which exist around the progress and capabilities of any kind of AI. Predicting what AI technology is capable of next can be challenging even for the developers of a tool; if outside evaluations cannot understand the inner workings of many models then making judgements, or synthesising understandings, of the current or future status of AI challenging (Future Risks of Frontier AI, 2023). Therefore, research in this field is needed to provide a more rounded view of the promises and risks that accompany the application of AI in the food sector.

1.2. Study objectives and scope

This research on the 'Use of Artificial Intelligence in the UK (United Kingdom of Great Britain and Northern Ireland) Food System' was commissioned by the Food Standards Agency (FSA), the food regulator for England, Wales and Northern Ireland concerned with ensuring that food is safe, that food is what it says it is, and that food is healthier and more sustainable (FSA, 2022). The purpose of this research is for the FSA to better understand the current and potential future uses of AI in the UK food system. More specifically, the research is intended to support the FSA's understanding of how the food system may operate in the future; what risks and challenges it may present in terms of food safety; what steps the FSA could take to ensure that it supports and stays abreast of innovation in the food system; and for the FSA to understand where further research is warranted. As such the key research questions for the study are:

1. What is the current focus of research on AI in the food system?

2. In what areas and for what purposes is AI likely to have the greatest applicability in the future (next 10 years) in the food system?
3. Where AI tools are currently being used within the food system:
 - a. Who is using them?
 - b. What are they using them for?
 - c. What form of tools are being used?
 - d. What are the benefits of these tools for the user and wider community?
 - e. What risks and challenges have been identified in these areas linked to use of these tools?

This research is timely given the recent developments in AI and the level of interest that it has generated across public and private sectors. To date, an assessment of how AI use cases and how AI might evolve and impact the food system in the UK has not been undertaken, and this research intends to provide preliminary novel insight into this area.

1.3. The 'food system'

The 'food system' is a very broad term and covers the whole 'farm-to-fork' process (Meybeck & Gitz, 2017; Miller et al., 2023; Queenan et al., 2022). These various processes include, but are not limited to, the main stages of food production, processing, distribution, retail and consumption (Andress et al., 2020; Carrad et al., 2022; Harris et al., 2022; Meybeck & Gitz, 2017; Miller et al., 2023; Nishi, 2022). Some definitions also extend 'system' to include food waste management (Miller et al., 2023). There also appear to be multiple lenses applied to the 'food system', including sustainable food systems, circular food systems and global food systems.

For the purposes of this research, we sought to define the 'food system' through:

1. Consultation with the FSA, with reference to the model they use to define the scope of the food system (see [Figure 1](#)).
2. Preliminary searching of academic material to see how the 'food system' is defined (see [Box 1](#)).
3. Definitions included within systematic reviews which emerged from our Rapid Evidence Assessment (REA)

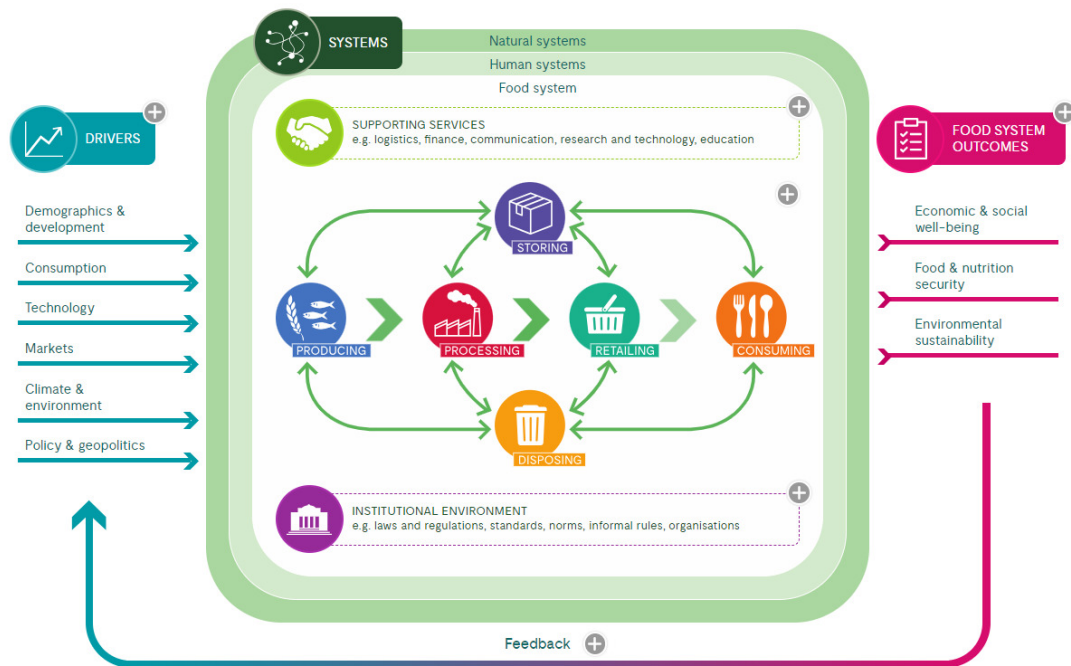


Figure 1. The food system as conceptualised by Foresight4Food and the FSA

Source: Foresight4Food (*Food Systems Model*, 2022)

The FSA and multiple systematic reviews all conceptualise the food system as broken down into distinct components which include: production, processing and retailing. However, there are some differences: Yadav et al. (2022) and the FSA consider 'consumption' as a separate category where Sharma et al. (2020) do not; Sharma et al. and Yadav et al. both understand 'food distribution' as spanning what the FSA defines as 'storing' food as well as 'retailing'. Finally, Sharma et al. also include a category of 'pre-production', which covers activity before food is edible and refers to the upstream food supply. Sharma et al. reference Borodin et al. (2016) in their conceptualisation of food supply chains, who rely on the simplest model of all, with only four stages: production, processing, distribution and consumption.

Based on these models and definitions, we propose the following discrete but interlinked components which map to FSA's view of the food system:

1. **Food supply:** the growth of food, including preparing environments for growth, identifying optimal conditions, and predicting yields to best manage resources ahead of production.
2. **Food production:** the process of converting raw materials into food, by, for example, picking, harvesting, butchering or milking.
3. **Food processing:** the process of changing or manipulating food (e.g. preserving, packaging, chopping, juicing, or cooking food).

4. **Distribution (inclusive of FSA 'storing' and 'retailing')**: the transport, storage, and retail of food.
5. **Consumption**: the eating of food, or purchase of food to eat.
6. **Food waste/disposal**: the loss or re-purposing of otherwise unwanted foods.

Like Borodin et al. (2016) we are collapsing retailing and storing into one category of 'distribution'. We are also adding Sharma et al.'s (2020) concept of pre-production, which we are calling 'supply'. We are using the terminology of 'supply' rather than pre-production because preliminary searches into academic literature found that this was more commonly used as a term. Like the FSA, we are also including food waste (or 'disposing') as its own category. This is because waste management was mentioned in the scope of our definitions as a part of the food system, and surplus food, and what happens to it, is a key output of the food system.

Box 1. Definitions of the ‘food system’ following preliminary investigations

The food system is “dynamic, enormous in scope, increasingly complex, and intimately tied to public health and the environment”. It operates at multiple scales influencing food production, supply and prices, dietary habits, environmental sustainability, and population health (Freedman et al., 2022)

‘The current food system...encompasses food production, processing, distribution, retail, consumption and waste disposal’ (Nishi, 2022).

‘[The] food system...is defined as the activities, outcomes, and actors involved in the “farm-to-fork” process, and the associated economic, social, political, environmental, and health drivers’ (Queenan et al., 2022).

‘A popular version of the U.S. aspirational food system starts with food experts and advocates that have problematized the notion that average citizens lack a model that envisions food as part of a supply chain starting with production and ending with consumption’ (Andress et al., 2020).

The food system can be defined as ‘[t]he web of actors, processes and interactions involved in growing, processing, distributing, consuming and disposing of foods...’ (International Panel of Experts on Sustainable Food Systems (IPES-Food), 2015).

‘The food system is a complex web of activities and influences that revolve around the sequence of events in a food supply chain; primary production of food commodities, processing, distribution, access, marketing, consumption, and waste management’ (Miller et al., 2023).

‘A food system gathers all the elements (environment, people, inputs, processes, infrastructures, institutions, etc.) and activities that relate to the production, processing, distribution, preparation and consumption of food, and the outputs of these activities, including socio-economic and environmental outcomes’ (Meybeck & Gitz, 2017).

2. Methodology

2.1. Rapid evidence assessment

A REA methodology was utilised to identify and analyse literature associated with AI in the UK food system. An REA is a form of literature review and evidence synthesis that is quicker than a systematic review, but more rigorous than an ad hoc searching approach (Varker et al., 2015). Within the REA, academic literature searches and grey literature searches were conducted, as detailed below, and focussed on providing a few exemplar use cases of AI being applied in the UK food system.

2.1.1. Academic literature

We used both PubMed and Web of Science as the databases for our academic literature searches.

Our primary aim was to find academic articles that explored the use of an AI tool within the UK food system, to create a list of potential case studies for further exploration (i.e. a 'use case'). We also hoped to discover systematic reviews that could provide a picture of the general landscape of research into AI in food and activity in industry environments.

Details around how we designed our search strategy and generated search strings, including concepts and terms searched for, are described in full in Annex A.

Searches were conducted in three waves:

Wave 1: we searched PubMed for terms relating to: AI; components of the food system; the UK; FSA strategic priorities ([Box 2](#)). This was filtered to publications since 2019 and generated 15 results at the time of searching.

Box 2. Search String 1 in aggregated form

(Machine learning OR artificial intelligence OR self-learning systems OR neural networks OR computational algorithms OR deep learning) AND ("food supply" OR "food production" OR "food processing" OR "food waste") AND ("food safety" OR "food authenticity" OR "consumer interest" OR "consumer behaviour" OR "sustainability" OR "circular food economy") AND ("United Kingdom" OR Britain OR England OR "Northern Ireland" OR "Scotland" OR "Wales")

Wave 2: we repeated this search on PubMed but without reference to FSA strategic priorities, as our search results from Wave 1 were small ([Box 3](#)). We title abstract (TIAB) screened the results (see Table A 3 in Annex A for inclusion and exclusion criteria). We then removed all the duplicates generated by the two searches to produce a list of 20 results for full-text review.

Box 3. Search String 2 in aggregated form

(Machine learning OR artificial intelligence OR self-learning systems OR neural networks OR computational algorithms OR deep learning) AND ("food supply" OR "food production" OR "food processing" OR "food waste") AND ("United Kingdom" OR UK OR England OR Scotland OR Wales OR "Northern Ireland" OR Britain)

After conducting a full-text extraction on these 20 studies, we found that none of the outputs pointed to the UK-based use case. Instead, results were either primary research focusing on developing and testing the efficacy of a new tool that had not yet been used outside of a research context (n=5), which we will describe from this point on as ‘prospective tools’ or were reviews of trends relying on secondary data collection

Wave 3: we searched the same search string ([Box 3](#)) on Web of Science to expand the data source. This returned 171 results, and 167 results after removing any duplicate results between this search and the initial searches. We then TIAB screened the 167 results according to the criteria described in Table A 3 (see Annex A).

From this third search, as laid out in the flow diagram in Figure A 1, we identified:

- 18 prospective tools (to form a total of 24 prospective tools when combined with the results of our PubMed searches).
- 2 UK-based use cases of AI.
- 6 relevant systematic reviews.

Relevant information was extracted from these outputs. Further references made in the systematic reviews to UK-based activity was also followed up on to produce:

1. An additional 4 UK-based use cases of AI (two in grey literature, two academic).

2.1.2. Grey literature

We piloted the same search strings ([Box 2](#), [Box 3](#)) used for searching PubMed and Web of Science into Google Scholar. However, results were unmanageably large and beyond the scope of the study parameters.

We streamlined our approach and conducted three Google searches for terms relating to AI and the UK food system (see [Table 1](#)). We scanned through the top 20 results of each search (40 outputs after de-duplication) for references to UK use cases. Companies that were described as using AI tools in either no explicit country or in countries that were not the UK were not considered. Similarly, tools that were described but not attributed to any specific company were also eliminated.

Table 1. Grey literature searches

Search term	Date	Time	Number of results
AI in UK food system	13 th February 2024	17:09	279,000,000
AI in UK food	14 th February 2024	09:27	524,000,000

Search term	Date	Time	Number of results
Artificial intelligence UK food	14 th February 2024	09:48	94,100,00

Source: Rand Europe

We found 13 different use cases across 12 articles (see Figure A 1) which fit this definition and sorted these according to their position in the food system: supply (n=2), production (n=4), processing (n=2), consumption (n=5).

2.1.3. Case study selection from grey literature and academic literature

Case studies were purposively chosen from both the grey literature and academic literature searches, with studies that had been found through academic literature results prioritised.

The following criteria were considered in determining the final case study selection from both grey and academic literature:

1. **Location within the food system.** The primary consideration in determining case studies was to ensure that each point of the food system was discussed, so that we had even coverage across the stages.
2. **Relationship to an FSA strategic priority.** Where possible, we attempted to map case studies against the FSA strategic priorities, searching for instances where AI was used to: determine food safety and authenticity; predict consumer behaviour; and aid sustainability.
3. **Frequency and amount of information.** Finally, remaining cases which were referenced through multiple sources, i.e., grey literature, academic literature and horizon scan (see below), were prioritised.

Details of the rationale for our final selection is shown in Appendix A (Table A 4).

2.2. Horizon scan

On 23rd January 2024 we used Feedly, a web scraping software, to begin scraping major websites, blogs, journals, and news outlets for articles using the search terms in [Box 4](#). This search ran until 5th March 2024, and generated 297 results in total, of which 155 were found to be relevant and scanned.

Box 4. Search string 3

"Artificial intelligence" AND "food system" OR "food supply" OR
 "food production" OR "food processing OR "food waste"

Articles were clustered under four broad categories:

1. Descriptions of emerging trends and arguments for the potential of AI.
2. Investment or business news.
3. Descriptions of new technology use cases.
4. Warnings of challenges to, or the risks of, adopting AI within parts of the food system.

Articles were then further tagged with one or more themes (as laid out in [Table 4](#): Horizon scanning themes) which emerged inductively from reading, through reference to stages of the food system, and in accordance with the FSA strategic priorities. Articles which covered multiple themes were coded multiple times, and articles which did not discuss themes deemed relevant (for example, news about awards won) were not coded.

2.3. Scientometrics

We conducted a high-level publication and patent data analysis using Search String 2 ([Box 3](#)). For publication data, OpenAlex was used to extract papers published between January 1st 2018 and December 31st 2023 which matched the search strings in the title, abstract, or text. The same approach was taken for searching for patents in Espacenet, a worldwide patent registry.

Descriptive statistics were obtained about papers and patents, looking at the number of papers per country over time and the most frequently publishing countries (with the national affiliation of the first-listed author, inventor, or grant agency as our proxy for this) over time.

However, there were a range of limitations to this approach. For data collection, we were limited by the coverage of the given source where OpenAlex and Espacenet, while comprehensive, may not cover the entirety of the corpus of publications and patents that exist globally.

Additionally, in the case of OpenAlex, we faced a decision over whether to search for our search terms in the title, abstract, or full text where this was available. Whilst we decided to search for our terms in the title, abstract and full text in order to comprehensively capture outputs, this

could have included papers considered out of scope. This was reflected in the results of the topic model, which provided a better overview of areas of application of AI when run on this larger dataset. However, it also produced more irrelevant topics.

Furthermore, our identification of papers with specific countries based on the institutional affiliation of the first author is a limiting factor. This is because, due to international scientific collaboration, many papers are published by researchers from multiple countries and are based on multi-national research programs.

2.4. Limitations of the methodology

While the REA was structured and thorough according to the parameters determined at the beginning of the project, it is not a systematic review. Therefore, there has been selection bias in our approach as well as limitation in scope. In the academic literature review, we were unable to review all of the publications within the last five years that related to 'food' and AI in the UK due to the number of results available, and so we may have missed both prospective tools or in-depth use cases. Moreover, we largely relied on the systematic reviews our search generated to provide a picture of global research and activity trends in AI and food. However, these reviews were not limited to the UK and often either focused on other countries or failed to note the country in which research or activity was happening. While we attempted to pursue references that seemed to describe a use case that might be based in the UK, it is possible that we missed some. Equally, we discarded any review that emerged from the academic literature that was not systematic, as our focus was on finding use cases and primary research. Non-systematic reviews that talked about processing for example, were not read but may well exist in large numbers. While the systematic reviews we found were largely focused on agricultural technology or food waste, the lack of systematic reviews about food processing, consumption or distribution and AI may not be a symptom of a lack of wider research, but one of less organised attention, and so we may be missing part of the picture around where research is concentrated.

Given the complexity and interconnectivity of the food system with broader sectors such as environment, climate, and health, there are aspects of AI use that could be used in the food system but are not apparent, for instance the use of AI to detect antimicrobial resistance in livestock for the purpose of mitigating the impacts of antimicrobial resistance. However, this use case is also relevant to the food system itself. These interconnected use cases have not surfaced in our methodology which is a significant limitation.

Similarly, due to the limited nature of the project and the huge number of search results generated, we decided to focus on specific aspects of the food system, rather than including anything related to food per se. This meant that we may not have captured research that is happening at, for example, the production stage, but which was referred to with different terminology within research articles. We may also have missed activity happening at different points of the food system not covered by our search terms (for example: consumption, where the results were very large in volume but of which many seemed irrelevant).

The academic results largely focused on prospective tools or discussed use cases in other countries. It is therefore challenging to draw conclusions about likely implementation, or of how the UK context specifically may encourage or discourage use of specific tools. We attempted to supplement this gap in our knowledge with grey literature searching and horizon scanning but were largely reliant on producing case studies of specific tools and extrapolating possible directions in AI use from how their performance has so far been recorded.

The grey literature itself was utilised within a limited scope due to the small scale of the study which means the industry activity and perspective is largely underrepresented in this study. Moreover, it is very possible that a lot of AI activity within industry has not been reported on at a large scale or in a transparent manner due to commercial sensitivities. This is both a finding of this report, and a limitation of it. Without a more systematic or objective investigations into AI use, we are reliant on records that are not always rigorous; which may conceal commercially-sensitive but perhaps critical information; or are made by parties with a vested commercial interest in the success of the tool. We have attempted to draw neutral conclusions, but largely have to point to a need for more research, particularly research which engages with industry.

3. Landscape of AI use in the food system

3.1. Research outputs of AI use in food systems

Global knowledge generation in AI and food systems has been consistently high over the last six years

Globally, levels of research into the use of AI within the food system have been relatively consistent over the last six years; as seen in [Figure 2](#), more than 1200 publications on the topic have been published every year but 2020. The COVID-19 pandemic saw a divergence of research attention towards COVID-related scientific study, and away from other areas of scientific exploration, so it is likely that a large portion of this drop may be

ascribed to the pandemic (Riccaboni & Verginer, 2022). While activity has yet to reach pre-2020 levels, there is a clear trend of rising publications again since 2021, which suggests that the importance of studying AI in food continues to be of academic interest.

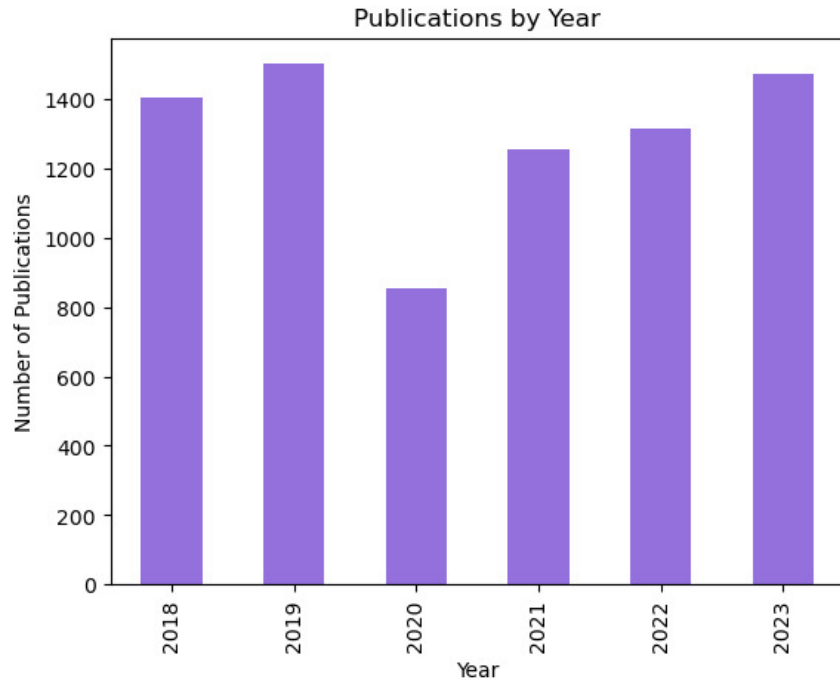


Figure 2. Number of publications about using AI in the food system

Source: RAND Europe analysis 2024

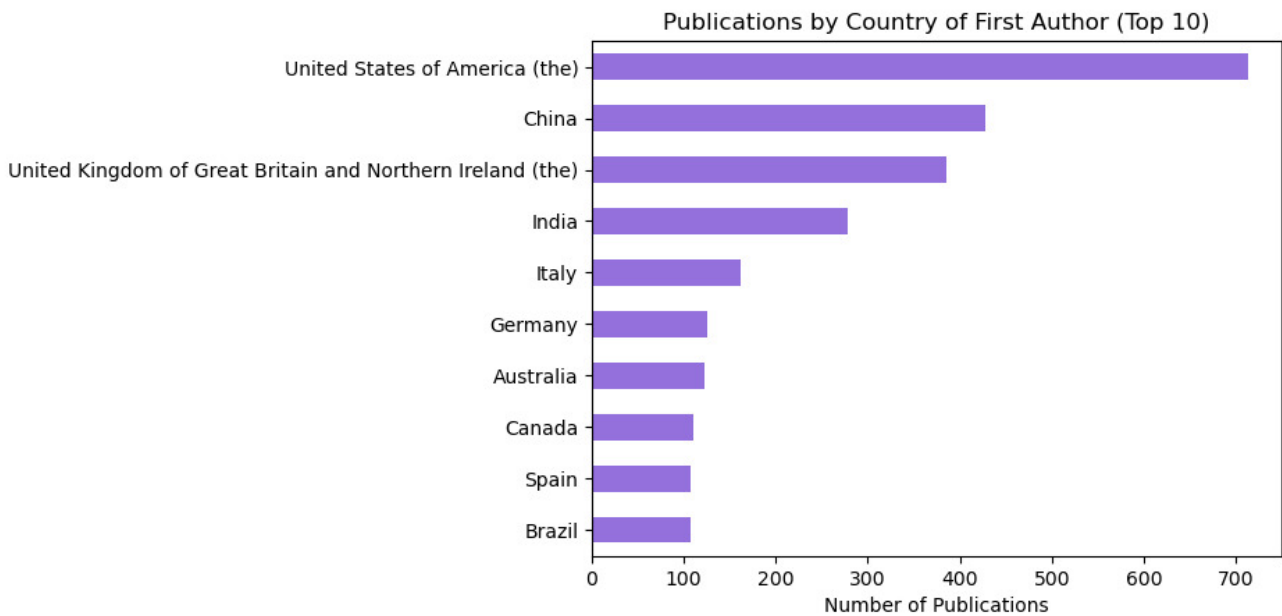


Figure 3. Number of AI in food publications by country of first author

Source: RAND Europe analysis 2024

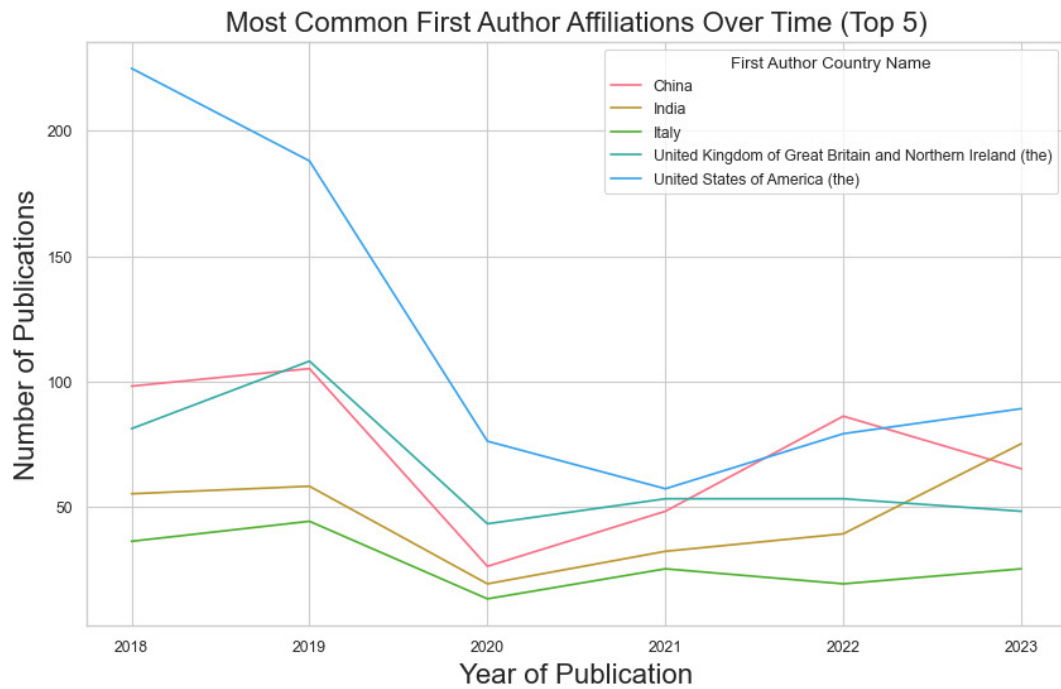


Figure 4. Most common author country affiliations in research into AI in food over time

Source: RAND Europe analysis 2024

AI use cases within the UK food system are limited with less focus on translation and implementation

The global landscape of translation and commercialisation activity, which is predicated on patent analysis as a proxy, highlights a steady rise in activity over the last five years which is a positive indicator of AI utilisation in the food system ([Figure 5](#)). While research into AI in food has been relatively high within the UK, this appears to be concentrated relatively upstream of translation. [Figure 6](#) shows the number of patents registered between 2018 and 2023, and the country of the first named inventor. While this shares the same methodological weaknesses as analysing publications by first author, there is a significant difference in the UK's relative global positioning. While the UK is once again third in the world for patents, as it was for number of publications published, the gap between the UK and the leading country, the USA, is much greater. The UK registered fewer than 500 patents between 2018 and 2023, while the US registered almost 4000. In contrast, the difference between the number of patents registered by the UK and other nations further down the global positioning is much slimmer, with Japan, Canada and Germany registering similar numbers of patents to the UK. This suggests that research within the UK is less likely to be focusing on product development for practical application but is instead more upstream at the discovery stage of research, focussed on testing and conceptualisation. We propose this insight with heavy caveats

given the limited methodology. Moreover, it could be that multinational companies are applying for patents from other jurisdictions which could be underrepresenting the UK market.

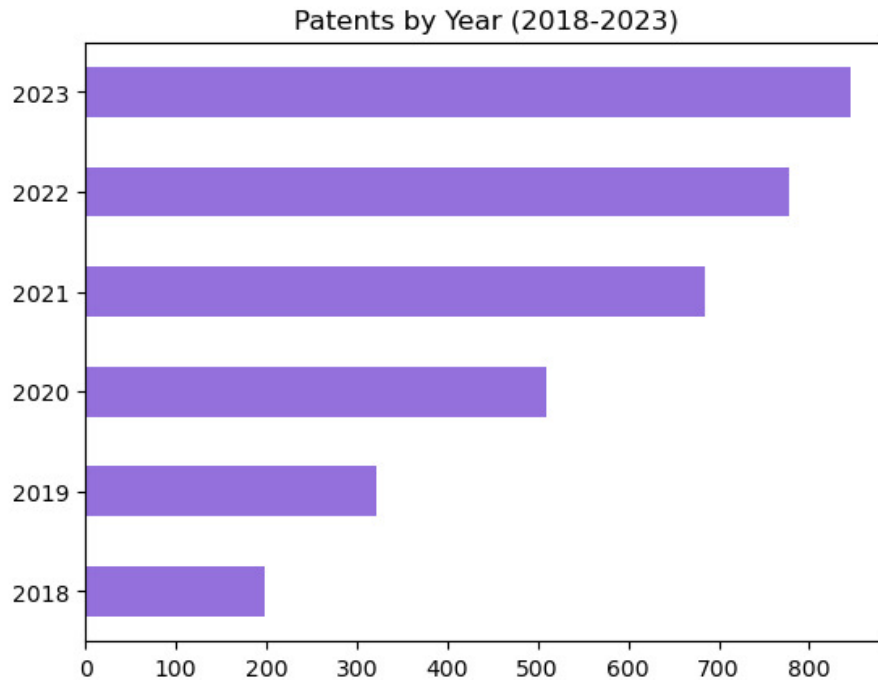


Figure 5. Total AI in food patents 2018-2023

Source: RAND Europe analysis 2024

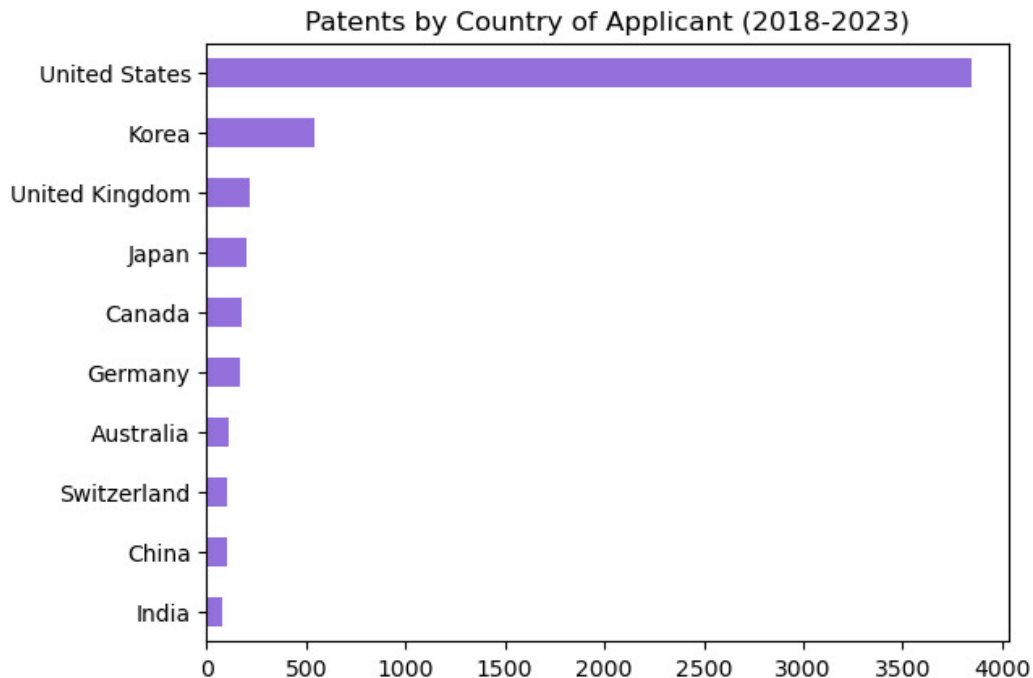


Figure 6. Number of patents by country of applicant

Source: RAND Europe analysis 2024

The academic literature review found a similar preponderance of research concentrated at the early stages of tool development rather than investigating application. We found mention of 24 prospective tools being developed with input from UK researchers, but there is no evidence that these are yet used outside of a research context (see [Table 2](#)). In contrast, we found only four academic use cases. However, outside of academia, we did find evidence that AI tools are being used within the UK food system.

Grey literature uncovered references to 13 different use cases within the UK at each point of the food system. These included, alongside the case studies we elaborate on below, AI being used to: track biodiversity on farms (Shang, 2023); direct agricultural robots (Barclays, 2020, p. 33); aid in recipe creation (Wood, 2023); and automatically reduce the prices of products in grocery shops as they approach their sell-by date (Ross, 2023). The diversity and spread of these use cases across the food system, in comparison to the relatively low volume of research into use as surfaced by our methodology, could be interpreted as a gap in the systematic implementation of AI tools in the UK food system.

Table 2. Relation of prospective tools found to the stages of the food system

Stage of food system	PubMed search (n=6)	Web of Science search (n=18)	Total found
Food supply	1	3	4
Food production	1	1	2
Food processing	1	4	5
Food distribution	1	2	3
Food consumption	1	3	4
Food waste	1	4	5
Whole system	0	1	1

Source: RAND Europe

3.2. Emerging trends of AI use in the food system

Industry and academic interest is focussed on future and emerging trends of AI

Horizon scanning of grey literature provides a snapshot of six weeks during which much of the hype in the sector was focussed on predicting AI trends in the food system. As displayed in [Table 3](#), the category of results with the largest number of associated articles was those that discussed general trends in AI use, or which made predictions about future use. These articles made only very brief reference to specific tools or actors in this space, instead largely concentrating on country-wide themes or summaries of emerging technologies.

Table 3. Horizon scanning results

Category	Number of results
Overview of trends and predictions	68
Investment or business news	25
Description of new tool (applied)	40
Description of new tool (prospective or uncertain)	15
Challenges and risks to AI	5
Other	2

Source: RAND Europe

There were also, however, a substantive proportion of articles focussed on specific AI tools inside or external to the UK (36%, n=55), either as applied use cases or prospective tools. The majority of these articles came from industry and business news rather than academia. 73% were press releases or industry news announcing the application of a new kind of AI technology by a specific company, or a new partnership between companies in order to deploy a specific AI tool. The remaining 27% (n=15) contained all the academic articles we unearthed, and either described a tool not yet in use, or failed to note where or by whom a technology had been implemented. This indicates that academic and industry interest is on synthesising general trends in AI use and predicting applications, with primarily industry leading discussions of actual use. This is consistent with the limited academic outputs surfaced by our methodology.

Necessarily, the information we found in this report on the use of AI in the UK food system came from limited, publicly available, sources. The focus was also largely limited to the practical impact of rolling out AI rather than on challenges, barriers, and responsible use. Most of the industry publications about a specific tool referenced or duplicated the originating company's press releases, with a few including interviews with company spokespeople. Articles were also likely to focus on the shareholder value of relevant companies, how its increasing use of AI may affect that, and subsequent implications for competitors. This provides little sense of the complexity that may surround the implementation of AI tools, including both barriers and facilitators to implementation, nor of unexpected impacts. Only a handful of the articles in the horizon scan mentioned challenges to roll-out or risks of increased use of AI.

Challenges with use of AI in the food system are focussed on the labour market and algorithmic bias

While only a minority of results from the horizon scanning mentioned issues with AI use in food systems, some challenges were identified. Firstly, job losses were a concern. Supermarkets in the UK mentioned cutting costs by investing in AI and replacing workers (Matheson & Williams, 2024;

PA Media, 2024), and the US had the second-highest level of layoffs for the month of January since records began in 2009, with food production companies accounting for the largest swathe of job cuts, which Challenger, Gray & Christmas ascribed to both advancing costs and AI adoption in the sector (Henney, 2024).

Another topic of concern was on the consequences of failures in AI. A report on an AI tool used in welfare schemes in India found that legitimate claims to subsidised food had been removed (Sambhav et al., 2024). The AI algorithm was trained on data held in several government databases to create a profile of claimants, but errors in source data led to bad algorithmic decisions. This is a critical concern for any AI: that the data it is trained on may be biased or inaccurate. And while this example did not occur in the UK, it is a reminder of the potential risks of widespread adoption without transparency and accountability mechanisms in place.

Thematic assessment revealed a large focus on food production, supply and waste

Thematic categorisation of the horizon scan outputs provided distinct focus areas in the food system where AI is being mentioned (see [Table 4](#)). Some articles may have been double counted where they addressed multiple themes, and, as some articles addressed no pertinent themes, the number of articles listed does not reflect all articles scanned.

Table 4. Horizon scanning themes

Theme	Number of articles	Primary source
Agricultural technology for supply and production	45	Industry and academia
Preventing food waste	18	Industry
Addressing climate change	17	Industry and academia
Food development and quality control	9	Industry and academia
Disease detection	7	Academia
Consumer use	6	Industry
Packaging or labelling	2	Industry
Authenticity	1	Industry

Source: RAND Europe

Topics that largely refer to agricultural technologies focussed at the supply or production stages of the food system (as described in 4.3 below). were the most common. This was followed by articles discussing the potential or use of AI to prevent food waste, and discussions of the potential of AI to mitigate climate change across the whole food system. This was a common pattern across the horizon scan and the literature review.

Box 5. Spotlight on food waste

Food waste was a common theme in the horizon scanning, with airlines, supermarkets, and production lines described as implementing technologies to prevent food waste through predicting purchase habits and determining how quickly food will rot (Caspern, 2024; Maszczyński, 2024; Waste 360, 2024). Of the prospective tools found in literature, food waste, along with processing, had the highest hit rate of new tools, with 22% (n=5) of the total tools found aimed at automating the processing of food waste. This could indicate that preventing food waste is a driver of industry adoption of AI tools, and that research and innovation into the optimisation of processing what food waste is produced is being conducted.

Box 6. Spotlight on production and supply

Agricultural technology or precision agriculture was a major theme of the horizon scanning outputs where technology was focussed on food production and supply. Half of the systematic reviews in this study discussed AI used in the supply or production of food within agricultural settings. The grey literature search surfaced six production and supply tools, all for use within agriculture. This is also very topical given the UK's recent Precision Breeding Act, the first of its kind, allowing genetic editing to be utilised for food production (*Genetic Technology (Precision Breeding) Act 2023*, 2023). This is at an early stage with a lot of current work focussed on implementation of the act. This will no doubt spur further research and tool development given AI's critical role at the intersection of gene editing (Zakaria et al., 2023).

3.3. AI utility within the UK food system

There appear to be forms of AI-focussed academic research and industry activity occurring across all stages of the food system, despite the low volume of academic use cases surfaced. Below we set out the major trends in current use and research, as well as indicating potential future developments as described in systematic reviews, and as compiled from horizon scanning and analysing the distribution of prospective tools. We also provide case studies of current use at each stage (see [Figure 7](#)), where we have attempted to qualitatively suggest the possible ease of scaling each specific tool. This judgement is based only on the information we could gather, largely from grey literature searches, around barriers and facilitators to, and opportunities for, scaling and implementation. We were unable to thoroughly research other factors which will have a significant impact on scaling – for example market dynamics, or consumer or producer appetite – and so these judgements must be considered postulation rather than prediction.

3.3.1. Food supply



Figure 7. Case studies across the food system

Source: RAND Europe

Our findings suggest that, globally, a large proportion of research into the use of AI within the food system is concerned with predicting and maximising the efficiency of the growth and supply of food. In 2020, a systematic literature review into machine learning applications in agricultural supply chains found that 42% of the research papers they discovered were focused on use in the supply phase (Sharma et al., 2020). This includes technologies for monitoring different agricultural variables, crop yield and soil property prediction, and irrigation management. Two of the other six systematic reviews found were also largely concerned with Precision Agriculture and Agriculture 4.0 or 5.0 technologies, either within the coffee sector (Sott et al., 2020), or in smart farming (Agrawal et al., 2023). Primary benefits to this kind of technology include an increased ability to manage water resources with greater efficiency, deciding how and when to sow and harvest crops (Sharma et al., 2020), and mitigating the effects of ‘outlier events’, like wars or pandemics on food supplies (Agrawal et al., 2023).

None of this research touched on UK-use cases, and largely avoided describing how tools are embedded in any specific geographic location. This makes it difficult to understand both how widely used they are in the UK, compared to other localities, and to understand any barriers or enablers for implementing at scale. However, general problems in implementing more data-driven agricultural supply chains, which are likely to be felt at other stages of the food system also, include concerns around data privacy, security, accuracy and access (Sharma et al., 2020). As an industry, agriculture is also subject to more uncontrollable environmental factors than many other industries where risk is easier to model (Sharma et al., 2020). While data on weather forecasts, for example, may not be subject to the kinds of biases that more human-focussed or generated data might be, the difficulty in creating a controlled environment for testing means that the adoption of machine learning technologies will need to be preceded by very extensive testing in very different environments, suggesting that wide adoption of AI in food supply is likely to be slow (Sharma et al., 2020). As understanding how local geographic and

environmental conditions interact with AI technologies is likely to be critical for allowing for widespread use, the lack of research into implementation in situ is a significant gap.

Multiple systematic reviews suggests that large amounts of data are being generated by digital technologies currently at use in the food system, including by Internet of Things and sensor technologies (Yadav et al., 2022), combined with drones and connected devices (Sharma et al., 2020). However, this data requires structuring and meaningful analysis, which is likely to be the major barrier to adoption at scale. Nevertheless, as outlined in the case study below, some investment is being made within the UK to improve data-sharing and organisation.

Box 7. Agrimetrics Data Marketplace case study

Agrimetrics Data Marketplace is a tool that focuses on supply levels in the food system. It was developed in 2019 in response to realising the value trapped in the data of agri-food organisations (*About Us | Agrimetrics*, 2023). It helps to address some of the core challenges in the agri-food sector with AI at the supply stage (including data access and data sharing) by functioning as a collection of linked agri-food data that can be easily shared, accessed, and monetised (Barclays, 2020, p. 32).

Agrimetrics is used in multiple ways, and is particularly interesting as a use case as it helps to address some of the issues with data sharing and accessing during the supply stage by deepening integration of data into agrifood processes. Agrimetrics Data Marketplace is predicated on an open architecture to allow users to access a breadth and depth of data in one place, in one interface that is easily searchable. Moreover, the use of AI to collate and harmonise data from multiple sources saves extensive time in data transformation. Data exchange privacy is also able to be controlled by the user whilst help is given to manage the integrity and security of data and data governance systems (Barclays, 2020, p. 32).

An example of a use case of Agrimetrics is the predictive service of CropLens AI (*AI Identifies Crops from Space with 90% Accuracy*, 2022). This is a proprietary algorithm that identifies crop types from space using Machine Learning algorithms. It offers predictions of the types of crops that are growing in the UK, based on a model developed by Agrimetrics and observations of field boundaries from space from Sentinel-1 Synthetic-Aperture Radar (SAR). It then assigns the crops into 5 categories of Oilseed Rape, Winter Wheat, Winter Barley, Grass and “other” to ascertain supply levels (*CropLens AI*, 2024).

CropLens AI is allowing easier, faster and more affordable insights to be generated much earlier in the season: it offers near real time predictions of the types of crops growing in the UK since predictions are updated every 6 days, in accordance with attributing the latest SAR acquisitions to UK fields. And the overall model precision of the algorithms used in CropLens AI is 67% in October (beginning of the growing season), but increases to 90% in July, August and September (end of the growing season). Part of this high precision is due to the algorithms being trained and tested against real world observations, made possible by the wide spread of data captured by Agrimetrics.

Usage of the tool is also increasing amongst retailers. For instance, Airbus now use Agrimetrics as an exclusive reseller of their whole earth observation portfolio (this includes their Airbus Crop Analytics, an advanced set of crop/field analytics that includes leaf area index, leaf water content, and soil water saturation) for the UK agricultural market.

Moreover, Agrimetrics does not only help with yield prediction, but hosts multiple different AI tools and datasets across its platform, including solutions to disease and pest prediction, optimising nitrogen applications, and irrigation (Morrison, 2020). ClearSky, a University of Hertfordshire founded cutting-edge AI outfit, also uses the Data Marketplace to market uninterrupted optical data to calculate measures such as Normalized Difference Vegetation Index. Moreover, Agrimetrics provides tools and support for code developers who join the marketplace, allowing them access to documentation and sample data, which allows for high levels of engagement with the tool with minimal buy in needed upfront.

This suggests that increased use of the platform could be very viable. Agrimetrics has been appointed the Data Innovation Partner to the Agriculture and Horticulture Development Board (*AHDB Appoint Agrimetrics as Data Innovation Partner*, 2022), and received a substantial initial seed fund investment of £90 million from the UK's strategic innovation agency, Innovate UK (Barclays, 2020, p. 32). This has made Agrimetrics one of four centres for agricultural innovation, and helped enable Centres to build new infrastructures and innovation and capitalise on leading UK research and expertise (e.g. Crop Health and Protection, Centre for Innovation Excellence in Livestock, Engineering and Precision Technologies, and Agrimetrics) (*Agri-Tech Centres*, 2021). These centres are intended to allow industry to cooperate with and access new research, and may provide a useful model to how, outside of academic publishing, innovation in AI in food is being implemented at scale.

3.3.2. Production

The production stage of the food system deals with turning raw materials into food. This includes harvesting, picking, disease detection and livestock management. We did not discover substantial amounts of academic research into AI use cases in food production, although many references to the potential of agricultural technology were made. Systematic reviews discussed smart farming (Agrawal et al., 2023), with an emphasis on the potential that a combination of sensor technologies and drones with other Internet of Things elements has to produce an 'intelligent web of interoperable entities' controlling agricultural processes (Sharma et al., 2020). Other emerging technologies described include deep-learning coffee bean inspection models and machine learning alert systems to identify pests (Sott et al., 2020). As well as this, another example included non-invasive machine learning models used to estimate the water content of plants, which is being developed, if not yet used, in the UK (Zahid et al., 2019). However, these other tools were not situated in a particular geographic context.

Outside of academia, agricultural technology was by far the largest theme to emerge from the horizon scanning, with primarily industry articles being written about its use. Use cases described small robots and drones being used on farms for a variety of tasks, and AI used for disease detection in cows was also mentioned: a new technology from the start-up MyAnIML, which uses facial recognition and deep learning to determine animal health through images of cow muzzles, was recently corroborated by a study from the United States Department of Agriculture (*First-of-Its-Kind Technology Analyzes Cow Muzzles to Predict Illness*, 2024; Startland News Staff, 2024). Outside of industry, the horizon scanning also surfaced some academic work on prospective tools for disease detection in plants (Shafik et al., 2024), including classifying potato leaf disease (Charisma & Adhinata, 2024), as well as rice, wheat, and maize diseases (Joseph et al., 2024) and detecting spider mites on labrador beans (Liu et al., 2024).

While many AI-driven technologies rely heavily on high computing power, it appears that the majority of the food production sector AI use also requires an investment in robotics and sensing technologies. The scale of adoption of these kinds of technologies is unclear based on this study, however large-scale adoption in the UK is not evident at present and could be considered expensive. Individual farmers with limited capital, knowledge or skills are likely to struggle to adopt the technologies (Sott et al., 2020), and accessible support with repairs is likely to be needed.

Box 8. Summer Berry Farm Company and Tortuga AgTech case study

Autonomous fruit picking robots utilised by the Summer Berry Farm Company are an example of a tool employed in the production stage of the food system (Holland, 2023). The robots were developed and trialled in 2020 through a partnership between the Summer Berry Company in the UK and Tortuga AgTech (who function as partners) (*Robotics*, n.d.). Following this successful trial stage, there has been an increased roll out of the number of robots operating in the business. For instance, the Summer Berry Farm Company now has over 50 robots working on their strawberry fields and glasshouses across their British farms.

The robots help increase efficiency in picking and harvesting crops through performing a variety of labour-intensive tasks on the farm. For instance, 15 robots operate autonomously and so need only one human supervisor. They can pick for up to 16 hours a day when the spring harvest begins and can operate both indoors and outdoors (Tortuga, 2023). The robots also help the farms survive labour shortages as, in a post-Brexit climate, there are less EU migrants to pick and pack crops, such as in the remit of fruit picking (Kollewe, 2022). Quality is also greater, with the robots able to pick the fruit with 98% accuracy and cause less bruising or crop damage than humans (Tortuga, 2023). Additionally, the robots can help save grower money; provide greater plant-level information to growers to generate better operational, agronomic, and commercial outcomes on the farms; generate forecast reports; and help fight pests (using UV light technology for mildew and mite control) (*Robotics*, n.d.).

However, there are many challenges associated with this tool which are likely to make its scale up difficult, especially outside the remit of fruit picking. For instance, the same tool may not be suitable for every customer or company (Tortuga, 2022). This is because customers and companies each have different economics and variability in their cost, performance and reliability metrics. Tortuga developed these robots specifically for Summer Berry Farm Company's location (with mud, dust, rain and unreliable internet) and needs (including how much and where robots needed to add value, and where trade-offs across cost, performance and time could or needed to be made), and so it may not necessarily be able to be deployed at other locations or for other tasks while remaining cost-effective over manual operation. Deep operational, agricultural, and manufacturing expertise is needed to develop a technology that will help grower customers at scale; the likelihood of this one tool being rolled out across many different agricultural contexts, and remaining economically attractive, is low. Tortuga is instead an argument for a slower scale up, with technology developed for specific contexts. This is reflected in the landscape of multiple failed robotics companies that have struggled to commercialise despite offering exciting technologies (Vanderborght, 2019), and the

difficulties experienced by robot developers in integrating hardware and software to make complex robots (Marcus, 2012; Sparc, 2016).

3.3.3. Processing

Processing in the food system includes activities for ensuring quality and the manipulation of food through preservation, packaging, or transforming from one edible material into another. In the academic literature, we found no use cases of AI in food processing, but we did find three prospective tools being developed within the UK, which largely focused on sorting and quality control: deep learning models to classify fruit (Salim et al., 2023); tags that can be used to automatically sort, weigh and calculate the charge for fruits (Sharif et al., 2023); and sensors to identify when powdered foods contain allergens (Rady et al., 2019). This focus on using AI to help automate the sorting of foods and quality control was also echoed in the grey literature search which produced the use case outlined below. The horizon scanning generated evidence of more activity occurring in industry globally, particularly at the food development stage, something we did not see referenced in the academic searches: Givaudan and Nuritas are using AI to discover how peptides can enhance food flavour (Selby, 2024), and multiple companies are attempting to use AI to help convert plant proteins into food products, although this technology is still in its infancy (Taylor, 2024). Similarly, the grey literature search found reference to Waitrose using AI to help develop recipes for their new Japanese range (Wood, 2023).

Box 9. TOMRA Food case study

TOMRA is a Norwegian company with a global presence, founded in 1972 to design, manufacture and sell machines to automatically collect used beverage containers. Between 2011 and 2018 they acquired multiple companies possessing patented technologies for food sorting, and by 2022 had become one of the world's leading food sorters (*TOMRA Recycling and PolyPerception Announce New Collaboration*, 2022). Today they have developed automated sorting solutions in two additional areas: recycling, where they use sensor-based sorting technology to prepare materials for recycling; and food, where their technology grades, sorts, peels and analyses both fresh produce and processed foods (TOMRA, 2024)

The spread of TOMRA's technology is wide both geographically and across food types; they have developed machines suitable for sorting fresh and dried fruit, nuts, seeds and grains, vegetables, confectionary, coffee, meat, seafood and pet foods. Within the UK, sugar confectionary company Swizzles Matlow used a TOMRA optical sorter to automate sorting of 'Drumstick Squashies' by detecting, and removing, defective products based on colour and outline (TOMRA, n.d.-c). GA Pet Food Partners and J G Pears animal by-products processor both use a TOMRA sorter to removed foreign bodies from raw materials (*Customer Story from GA Pet Food Partners, United Kingdom*, n.d.; TOMRA, n.d.-b), and the Jersey Royal Company utilises a sorter to help pack and ensure the quality of Jersey Royal new potatoes (TOMRA, n.d.-a).

In 2016 Zeina Foods, a nut packing company in Yorkshire, began using a TOMRA sorting product, the NIMBUS, to help with their roasting, cleaning and distribution of pistachios among wholesales. After utilising the NIMBUS for two years, Zeina Foods reported processing approximately 5,000 tons of pistachios a year, compared to the approximately 730 tons they processed before its installation. As well as allowing for their business to operate at scale, the NIMBUS also allows them to improve the quality of their final product, as it is able to accurately identify and remove foreign matter (like glass, stone or shells) from the pistachios despite the challenges offered by the nuts' multi-faceted and multi-coloured surfaces. The model is also able to classify by biological characteristics to detect and remove aflatoxins and hard-to-find nut defects. The same model of machinery is used by GA Pet Food partners to sort pet food.

Capacity to scale TOMRA sorting technologies seems very high; Zeina Foods is a growing but still medium-sized family-owned operation (Zeina, n.d.), with around 18 employees as of March 2024, but they were able to purchase and implement TOMRA technology (*Zeina Foods | LinkedIn*, n.d.). TOMRA is also constantly developing new machinery, appropriate for use by different food groups. The horizon scanning revealed that TOMRA has just launched three new AI-powered sorting solutions, including a blueberry pre-grader that uses AI modelling to distinguish between clusters and groups of

berries, a deep learning technology for grading apples, and a deep-learning grading platform for cherries which is able to identify half cherries, open sutures, cosmetic blemishes and stem pulls (Haynes, 2024). As well as developing tools optimised for use with differing food groups, TOMRA also offers a high level of support to combat a skills-gap which may deter investment in their offer. They have a service department based in the UK who can help with preventative maintenance, supplying spare parts, and offering upgrades to (TOMRA, 2024). They also offer an 'Academy' to train operators in how to use and understand TOMRA machinery (*TOMRA Academy*, n.d.).

3.3.4. Distribution

This stage of the food system deals with the sale and distribution of packaged and prepared food, and the use of AI in transportation, storage, and inventory. The academic and grey literature for this element of the food system is relatively thin, with the fewest use cases associated with this area. Outside of the UK, the horizon scanning revealed that UAE-based company, VERITY ONE, is using AI and blockchain as part of an advanced retail management system to recall fake honey (Reiser, 2024). This echoes the prospective tool we found in development within the UK analysing when and where food packaging codes are scanned to reveal anomalies in supply chains caused by food fraud (Jiménez-Carvelo et al., 2022). However, Jimenez-Carvelo et al. suggested that, in 2022, while implementing AI to detect patterns of fraud has been used in other areas (like biology, medicine and credit card fraud) it had not yet been used in food supply chains. VERITY ONE may have implemented this technology, or have been using a similar tool, but this suggests that AI in food fraud detection is likely to be an emerging area globally, and currently be under researched and potentially underutilised in the UK.

Otherwise, two other prospective tools are being developed by researchers in the UK: a smart shelf system for assessing food quality (Song et al., 2024), and an artificial neural network model to precisely estimate the temperature of food products that are stored in multi-temperature refrigerated transport vehicles (Zou et al., 2023). Beyond assessing food authenticity and quality, AI is also being used to predict consumer behaviour and adjust distribution accordingly, as seen in the case study in [Box 10](#).

We feel that the current developments at the intersection of production, distribution and consumption might have been masked in the methodology deployed and could be underrepresenting AI utilisation in this space. For instance, a high-level grey literature search on niche use cases in production surfaced two examples of note that were featured very

low in the list of outputs generated in the search due to being labelled as examples of 'food management'. One of the examples was the use of the retailer app called 'Too Good to Go' which allows retailers to manage excess inventory of products that are near expiry and incentivise consumers to purchase these at a significantly reduced price to avoid waste (Nott, 2024). The other example was the use of a platform called ChocoAI for the retailer Crowbond Food, wholesale suppliers, who were able to utilise the AI platform to streamline and manage order processing with efficiency gains and without increasing their labour workforce (Choco, 2024). This is a notable example of AI enabling small industry players to grow and increase their market share.

Box 10. Ocado case study

Ocado has developed a 'Smart Platform' (OSP) that harnesses various technologies, including AI, robotics and automation, to aid in more effective and efficient distribution of food, and to help with purchasing and eating decisions by working towards consumer interest and behaviour (Marr, 2022; *The Ocado Smart Platform (OSP)*, 2023).

To help with efficient distribution, Ocado uses automated warehouses with robots that pick and pack groceries. Fleets of bots collaborate (in what is known as 'The Hive') to pick a 50-item order in under 5 minutes (*The Ocado Smart Platform (OSP)*, 2023). They then carry this order to a station where orders are packed, and loaded ready for dispatch. Following this, Ocado employs 'Last Mile Technologies' that use AI to optimise the load of every vehicle for grocery deliveries, through accounting for traffic conditions, vehicle weight, emissions, and vehicle fuel level to ensure the quickest route to customers (Marr, 2022).

Ocado also uses technologies to help with purchasing decisions, and to work towards consumer interest and behaviour through having a personalised online journey (*The Ocado Smart Platform (OSP)*, 2023). For example, automated warehouses help predict what customers want and need and adjust orders from suppliers accordingly. Their AI, through insight into real time availability, helps to understand what products are in stock so that they can give customers the groceries they expect. Their grocery-specific smart features also are personalised to individual customers, enabling customers to find new choices through intelligent suggestions, help find their favourites, provide reminders for frequently purchased products at checkout, and anticipate when they are running low. Overall, OSP contributes to more choice, fresher food, and increased convenience and flexibility for customers to generate 'delightful customer experiences'.

Another benefit of the OSP is also a reduction in food waste through AI powered demand forecasting and replenishment. For example, the OSP determines the food that customers want and need so that Ocado can then accordingly adjust orders from suppliers. This is at a large scale, with the platform assessing up to 20 million forecasts per day to reduce any overstock and waste (*The Ocado Smart Platform (OSP)*, 2023). In addition, machine learning algorithms help to attain the optimal time for customer discounts to get rid of their inventory or help Ocado manage and monitor their donation effort of produce that is nearing expiry. Artificial intelligence and machine learning also help Ocado to reduce food waste by making sure that their products are both stored and delivered at temperatures that safeguard against the likelihood of their spoilage (Marr, 2022). Together, machine learning, artificial intelligence, and data analytics help Ocado to reduce its food waste to losing only 1 in 6,000 produce items.

However, it is difficult to assess the potential ease of scale up for this tool. Tools from the private and the commercial sector often lack information and transparency on barriers and challenges, and concentrate instead on opportunities and successes. Therefore, conclusions on ease of scaling cannot be drawn from the available information, and further research is required to establish this.

3.3.5. Consumption

This stage of the food system deals with the decisions made by individuals to consume food. Like distribution, there is limited evidence of AI activity at this stage. In the academic search we found one systematic review which mentioned the possibility of smart devices and Internet of Things technology allowing customers to access data about food, to improve supply chain visibility and transparency, while also capturing data about consumers' behaviour when buying (Sharma et al., 2020). We also unearthed an academic study into a Diabetes Platform which helps consumers plan their diets (see [Box 10](#): Nutrition platform case study).

The horizon scanning generated more articles into consumer-facing AI, although the focus of these was almost entirely on tools home cooks can use within their kitchen. Tools discussed include: smart cooking assistants and smart thermometers (Hillary, 2024); smart fridges which can identify their own contents, note approaching expiration dates, and recommend recipes to use up available food (Lynch, 2024); smart food storage solutions which can monitor temperature and humidity levels; and automated sterilising systems for surfaces and utensils (Murrell, 2024).

Box 11. Nutrition platform case study

The grey literature searches produced multiple examples of AI technology being used to help guide individual food consumption choices. The Deli Society's AI helps match consumers to products sold on their platform (*What Impact Will AI Have on Retail?*, 2023); the EprObes project is using AI to develop personalised nutrition plans for children (Holland, 2023); and ZOE, founded in 2017, is an AI driven nutrition platform that creates a personalised eating plan according to an individual's physiology, based on the results of gut health, blood fat tests, and 14 days of blood sugar monitoring (Kollewe, 2023).

Academic research has been carried out into a similar platform, unnamed, that was referred to by Diabetes UK between September 2020 and April 2021 (Bul et al., 2023). This web-based AI driven nutrition platform was powered by deep learning and natural language processing, and helps with food consumption, interest and behaviour choices for people with diabetes. The tool helped participants become more confident in meal planning (after an 8 week period), make healthier food choices (after an 8 week period), improved their shopping experiences and helped them to plan meals more efficiently (18/23; 78%). To do this, the platform was tailored to the behaviour of the individual (e.g., recipes they view, share, shop or save), their behaviour preferences (e.g., diet, foods they like and dislike, favourite dishes), and their context (e.g., supermarket deals, user inventory, trending recipes) to inform the AI to produce personalised recipe suggestions, meal plans, shopping lists and purchase options. Moreover, the platform connects various data points about ingredients and their relationship to each other, recipe properties and budget and availability of produce across supermarkets to produce a positive user experience.

There appears relative potential to scale AI technology to help guide food consumption choices. For example, there were only minor challenges identified with the use case of the diabetes management platform including the platform being cumbersome (9/21; 43%) and unnecessarily complex (7/21; 33%) in some cases, due to information overload across the platform features, and having American measuring units and ingredients, or some participants experiencing minor usability issues. Moreover, participants identified that the platform would only help in diabetes management if users followed through and actioned the healthy habits indicated on the platform. However, the study was predicated only on a small before and after study without a control group, and without the name of the platform it is difficult to see if it still running; certainly, Diabetes UK's website is no longer advertising or linking to it. The wider selection of consumer-focused AI tools which emerged from the grey literature searching, however, suggest that this kind of tool can be scaled and is likely to become more widely used. There is relatively widespread adoption of Zoe, with 130,000 people having signed up before November 2023 (Kollewe, 2023). However, test kits cost nearly £300 and must be purchased with a membership plan that

starts at £24.99 per month (Holland, 2023), while subscriptions to the Deli Society start at £40 a box (The Deli Society, 2023), which suggests that access is unlikely to be equitable across socioeconomic status.

3.3.6. Waste

Food waste appears to be a prolific research area; we found one systematic review on the use of AI in converting food waste into methane (Workie et al., 2023), and three academic articles looking at the use of AI in preventing or processing food waste in the UK (Jagtap et al., 2019; Jagtap & Rahimifard, 2019; Ramanathan et al., 2023). Food waste was also one of the largest themes to emerge from the horizon scanning, with 18 articles discussing it. The literature and use case examples suggest that AI is playing a role at three different points: preventing excess food waste at processing stages; optimising collection of food waste; and improving the efficiency of converting food waste into other useful materials.

Preventing food waste was a key driver of global AI use, as discussed in the horizon scanning, and technology can be incorporated at multiple different stages of the food system to allow for this. The case study, below, describes technology being used in both the preparation of food, and to monitor waste after consumption – i.e. once the food has been bought. As with learning about consumer behaviour in the consumption and distribution stages, this information can be used to shape food management strategies, from how much retailers order to how much farmers grow or manufacturers produce.

AI in waste sorting is a relatively well-established technology; for example, the Greyparrot Automated Garbage Monitoring System monitors and analyses live image feeds of waste flows to detect food-grade packaging (Workie et al., 2023), and is present in 14 countries including the UK (Greyparrot AI, 2024). The grey literature search also identified companies (PolyPerception and TOMRA recycling) which are utilising waste sorting technologies to identify food waste at waste processing centres (*TOMRA Recycling and PolyPerception Announce New Collaboration*, 2022). Outside of the UK, AI is being used widely in waste collection activities, with smart waste bin technologies first introduced in 2010 (Workie et al., 2023). AI to optimise waste collection operations, through route-planning for example, is still in development although it has been trialled in the United Arab Emirates (Abdallah et al., 2019).

The final potential use of AI in waste management is in aiding in its decomposition and reuse as biogas, as part of anaerobic digestion. This is a widely used technology already, with the UK's Poplars food waste

processing plant utilising anaerobic digestion in combination with AI technologies to control odours (Workie et al., 2023). However, future developments may include using AI to reconfigure digesters to react to different types of food waste, and forecast performance. This technology is still in its infant stages however, and there is a large technological and management gap between this and its use on an industrial-scale (Workie et al., 2023).

Still, it is possible that the next ten years may see AI integrated throughout the food waste collection-to-reuse cycle, with smart bins identifying food as soon as it is thrown away, then collected in an optimum way to reduce travel time and CO₂ emissions by AI-assisted rubbish collectors, and then automatically sorted and refined into valuable methane gas within anaerobic digestion plants. This kind of coordination will require both greater research into some of the technologies involved at the transporting and digesting phases, and a particular attentiveness to the practical needs that emerge when implementing at scale. Currently, interest in optimising food waste seems high, with multiple competitors emerging at each stage of this process. This has the potential to lead to individual tasks being optimised but creates difficulty in coordinating a disposal to reuse cycle.

Box 12. WinnowVision and IKEA case study

WinnowVision is a patented smart bin technology (Mekhsian et al., 2023). It uses a camera, set of smart scales, and machine learning technology to learn to recognise different foods being thrown away, and calculate the financial and environmental cost of this discarded food to commercial kitchens (Winnow, n.d.-a). In early 2015, IKEA installed Winnow into two pilot sites in the UK to determine if food waste could be reduced by giving workers digital measurement tools and analysis. In 2019, WinnowVision's additional AI element was launched at IKEA's flagship store in Greenwich, with cameras determining what food had been thrown away rather than manual input being needed (Zornes, 2022). IKEA was prompted to use WinnowVision by their internal strategic commitment to cut food waste by 50% across operations before the end of August 2020 (Klupacs, 2019), and achieved this across all stores in 2022 (Zornes, 2022). They use the technology to identify: the top errors contributing to food needing to be thrown away; which foods were not being ordered and so had to be disposed of; and patterns in customer preferences in order to avoid overproduction (for example, if it is warm, people are more likely to buy food they can eat outside, like wraps or hot dogs, which led IKEA kitchens to adjust production levels according to weather forecasts) (Winnow, n.d.-b). The primary benefit to the technology is a large reduction in food waste: according to Winnow's data, a typical kitchen wastes between 5-15% of food they purchase, largely due to overproduction, and WinnowVision's ability to make forecasting decisions has saved approximately 45,000,000 meals and 78,000 tonnes of CO₂ (Winnow, n.d.-a).

WinnowVision is now being used at scale by both IKEA and other companies. As of August 2020, WinnowVision has been rolled out in IKEA stores in more than 30 countries, and installed in 23 IKEA UK and Ireland stores (Zornes, 2022). Winnow is also used by many other large corporations in businesses like hotels, contract caterers, casinos and cruise ships (*Food Waste Reduction | Winnow*, n.d.). Noted facilitators to implementation include strong internal leadership by adopting companies, clear internal communication around a goal that can be definitively measured, and the opportunity for shared learning between adopters (Zornes, 2022). However, differing market priorities and attitudes towards sustainability can be barriers to roll out, as can differing team cultures or structures (Zornes, 2022). The other potential issue to seeing widespread adoption of WinnowVision or a similar technology is cost; currently WinnowVision is used by very large corporations with multiple kitchens. Small or medium businesses are not likely, in the immediate future, to invest in this technology, and as it is patented, competitors for smaller-scale operations may also struggle to emerge.

Otherwise, there appears to be potential for Winnow to adapt its technology for wider use, either outside of commercial kitchens, or with a focus on collecting different or more specific data. For example, currently Winnow is rolling out

a plate waste solution which uses a motion sensor camera connected to a scale to automatically recording food waste from plates, rather than after it has been put in the bin (*Food Waste Management Software* / *Winnow*, n.d.). This allows greater insight into customers' eating habits. Smart bins however also have potential to be scaled beyond commercial kitchens. Wang et al. (2021) have developed a proof of concept for waste classification using deep learning at the start of rubbish collection. This technology utilises gas and ultrasonic wave sensors, rather than cameras, to identify the amount of food waste in bins. But, as Workie et al. (2023) note, further research is needed on strengthening the transport of food waste from source to processing or anaerobic digestion site before any such technology could be implemented, so we are unlikely to see this deployed in the immediate future.

4. Conclusions and recommendations

4.1. Research into AI in food within the UK is focused upstream of application and implementation

There is emerging evidence on the application of AI tools within the food system in the UK. However, the evidence base seems to be fairly limited, especially with regards to information on AI tool scalability, challenges and barriers. The US appears to be dominating the AI food sector based on the volume of academic outputs and patent activity generated over the last six years however there are niche areas where other market dominate such as precision agriculture in China via use of autonomous drones. Globally there is a large volume of research into AI and food systems being conducted, and the UK is a major contributor to the corpus of research. However, evidence from UK researchers seems to be more concentrated at the pre-implementation phase than on studying the implementation of tools in industry.

4.2. Research and activity is prevalent in food supply and production and food waste

Emerging trends in both the use of AI tools and research into AI within the food system in the UK is primarily focused on food supply and production, or food waste. There are scalable tools that could predict or maximise the efficiency of the growth and supply of food, hampered primarily by concerns around data organisation and sharing. Tools at the production stage were more likely to involve complex, and likely expensive, robotics specialised to particular tasks, as well as drones and sensors.

Within food waste, we found evidence of both activity and research aimed at preventing food waste, and at processing it in the most efficient and effective way. The UK has a lot of the infrastructure required for automatic anaerobic digestion of food waste, with anaerobic plants already using AI for other tasks, and AI-sorting in waste treatment centres already occurring. It is possible that an entirely automated disposal-to-reuse pipeline could one day be implemented, although some elements of this chain require further research, and coordination may be a systemic barrier.

Within the areas of food processing, distribution, and consumption, there was limited evidence of application-focussed efforts in the academic outputs. However, evidence from the grey literature searching and horizon scanning suggests there is growing development and interest in these tools for both individual consumers, particularly in the form of Internet of Things technologies for use within home kitchens, and for wholesale retailers and food suppliers. These kinds of tools may have a greater impact on the rest of the food system if more widely developed and used, as the ability to predict consumer behaviour shapes growth and production strategies. As it is, retailers are also adopting food management tools to help prevent overproduction and waste, although this appears to be a crowded market, making coordination of data sharing difficult.

4.3. Drivers of AI adoption in the UK include improving sustainability, understanding of consumer behaviour and food safety

Sustainability appears to be a large driver of interest in AI within the industry publications captured by the horizon scanning. Mentions of mitigating climate effects through predicting environmental changes appeared to be of prevalent concern, and a desire to prevent food waste and engage in a more environmentally friendly, as well as efficient, work were key motivators for developing and using tools.

Understanding consumer behaviour was also a key motivator for the consumption and distribution case studies we unearthed, although little of this was discussed in the academic work included in the study. Food safety was less frequently mentioned, although it appeared to be most crucial to the processing stage of the food system, about which we generally found limited information. The use of AI to gauge the authenticity of food was not a key outcome for any of the case studies nor mentioned in the systematic reviews we found. However, its presence in one prospective tool and one of the horizon scanning articles suggest that this is a type of tool that is being developed and used outside of the UK; further investigation may be warranted.

4.4. Future developments

A recent report by a think tank compared the labour market and hiring trends as a proxy for forecasting growth of AI across multiple industries; they found that the UK food sector was the fourth fastest adopter of AI technologies (Watkins, 2023). While this assessment is very narrow and fraught with limitations in its interpretability, combined with our study outputs the use of AI in food appears to be on an upward trajectory both in the UK and globally. Given the focus on sustainability and food security in the context of national security and resilience and preparedness, it is likely that AI adoption and utility will be crucial for food and wider agricultural practices, however at present this appears to be spurred by industry.

There are however significant uncertainties in this sector that should be considered when determining trends. For instance, geopolitical conflict disrupting food supply chains, exogenous shocks like Brexit, Covid-19 and systemic large-scale change such as climate catastrophes should be considered alongside the use of disruptive technologies like AI. Food systems, and AI as an enabling technology, is thus a dynamic ecosystem and our limited study provides a few snapshots of potential future developments.

Our study has highlighted that sustainability, primarily in the context of food waste and climate adaptation, will be of huge importance in this sector where further utility of AI tools could be explored. There is significant industry interest already in this space and demand could create market incentives for further development and competition. Food production and supply is also experiencing significant developments especially with significant global investments in precision agriculture. Based on the UK's Precision Breeding Act 2023, and the ongoing debates on the EU GMO directive, there will be a flurry of activity in field trials and crop development based on new gene editing techniques where use of AI will be a crucial enabler. This could create a proliferation of AI uses in food authenticity applications, which are currently limited. This will no doubt also be a relevant agenda politically, given the challenges surfaced during the Russia-Ukraine war highlighting food insecurity, and with the UK importing 46% of its food. Other drivers also include changing of cultural norms which has seen a big surge in a demand for alternative proteins. AI driven synthetic biology platforms and biofoundries could play a critical role in meeting these market demands.

Food production will remain a globally competitive landscape with food production and supply also seeing developments in AI assisted drones for precision agriculture and geo surveillance which have implications for food security as well as national security. AI will doubt play a critical role here as well.

4.5. Challenges and risks to implementation

The challenges to and risks of implementation of AI in the food system were difficult to characterise given the lack of implementation use cases in academic literature and given that industry focussed use cases rarely explored challenges and risks. However, some themes that have emerged across case studies and industry scanning are: risks to sector jobs due to replacement with AI; difficulties experienced by companies selling AI tools that may become outdated and unsustainable; the social consequences of failures in AI when determining food distribution based on inaccurate or biased data; the expense of specialised AI tools, and need for skills in both use and repair; concerns around data privacy and sharing, as well as how to meaningfully organise disparate data.

The risks and challenges of use of AI in the food systems remain underexplored and require a more comprehensive assessment.

4.6. Areas for further research and wider recommendations

Our study revealed some key areas for future research as well as wider recommendations which are applicable to multiple stakeholders operating across the varied facets of the food and agriculture ecosystem such as DEFRA, UKRI, UKHSA and FSA.

Recommendations

1. Government institutions may consider proposing guidelines or codes of conduct, akin to the US executive order, to generate more transparency in the use of AI and underpinning algorithms in the food industry. Our study, while limited in scope, highlights the lack of evaluations and transparency prevalent in the commercial sector on use of AI. This is likely due to proprietary reasons or other sensitivities. Nonetheless there is a need for transparent assessment of how algorithmic decisions are driving food distribution and consumption.
2. There is a need for more planning and investment in capacity building to support adoption of AI tools and technologies across the food supply chain. Given the largely traditional make up of the sector, there is a need to assess areas where biggest capacity and workforce support might be needed for high impact and to enable adoption of technology. This is likely to require a concerted effort across multiple government institutions to upskill and train the agriculture/food sector workforce. As labour intensive processes

become unsustainable against the labour shortages, a combination of automation and workforce upskilling and development will be critical.

3. **More cross-disciplinary efforts are needed to assess AI utility where food systems interact with other areas** such as climate mitigation in crops, antimicrobial resistance mitigation and tracking of pathogens in food and the environment. Adoption of AI and its use cases are blurring the disciplinary and sectoral boundaries further, with food at a critical nexus of environment, health, and security.
4. **More efforts demonstrating economic and social benefits of technology adoption are needed to engage with the public, and the food industry at large to drive technology acceptability underpinned by robust evidence outlining both risks and benefits.** The lack of transparent evaluations, reporting and cost benefit analysis of AI tools in the food sector create challenges in scaling and adopting of such tools and technologies and furthermore they limit public acceptability.

Areas for further research

1. **More systematic research into the use of AI in the UK food system is needed.** While we found evidence of a significant body of research into AI in food systems, its focus was primarily on discovering potential new tools across the food system, with very limited attention towards researching the implementation and use of those tools in the field. Further analysis into this could provide useful insights into understanding what type of research is being progressed across the distinct components of the food system, what impact developing AI might have on food safety, and, especially if driven primarily by industry, whether it is possible to access or influence that research. There is a need to review whether the food of developments at the intersections of the food system components to assess new and emerging markets such as food management which might be masked by current structures
2. **More research on industry practices and challenges on AI use and scalability is needed.** Given that industry led examples of AI use in food systems were prevalent in this study, it would be useful to further understand the drivers, challenges and barriers of these use cases by engaging directly with industry. Current evidence is limited likely due to commercial interests and sensitivities. This type of engagement could provide useful insights for leveraging

AI more equitably or understanding the scalability challenge. The study could also develop methodology for evaluating AI implementation in this setting.

3. **Gap analysis and stakeholder engagement could identify opportunities for tool development.** While the focus of this study was on identifying use cases within a fairly limited scope, a systematic gap analysis identifying needs where AI could add value to the UK food system would be a welcome driver for tool development. We found no evidence that such a rigorous gap analysis into AI use across the food system in the UK has been carried out. A challenge-led approach by identifying where AI could unlock opportunities could be useful for both academia, regulators, and the private sector to identify where further investments and developments could be fruitful.
4. **Global capabilities assessment could identify opportunities for the UK.** Given the work ongoing globally where AI is increasingly being utilised in the food system, a study focussing on international case studies to provide insights for the UK may be beneficial for government to assess market conditions and feasibility of enabling the work to take place in the UK.
5. **Developing rules of engagement for the use of AI tools in the food system could create transparency in the use of AI in the food sector.** The lack of transparency around algorithmic inputs and decision-making has the potential to cause significant harm. As tools appear to largely be being developed in industry, outside of public sector or academic scrutiny, research could usefully explore what codes of best practice for implementing new tools in the context of food safety, authenticity, and sustainability might look like.



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Supplementary Materials

Appendix A

Download: <https://science.food.gov.uk/article/123638-use-of-ai-in-the-uk-food-system/attachment/245853.docx>
