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Research Article

Synergizing Human Factors, AI, and Automation for a Sustainable Future: Innovations in U.S. Smart Farming and Safety Management

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Abstract

This paper examines the integration of human factors, artificial intelligence (AI), and automation in U.S. smart farming, focusing on sustainability and safety management. The agricultural sector is witnessing rapid transformations driven by AI and automation technologies, which are applied in crop management, soil monitoring, and livestock operations. These advancements promise significant improvements in productivity and environmental sustainability. However, their success heavily depends on the human dimension—specifically, the effective incorporation of human factors to ensure technology adoption, usability, and safety. By highlighting key innovations in smart farming, such as robotic milking, automated phenotyping, and safety systems, the paper underscores the importance of a synergistic approach that aligns technological solutions with human needs. The study also addresses challenges such as resistance to technological change, training requirements, and the potential risks of automation. Finally, it presents case studies demonstrating how AI-driven solutions can enhance operational safety and sustainability while calling for continuous research into the human factors shaping agricultural innovation.

Keywords: Smart Farming; Human Factors; Artificial Intelligence (AI); Automation; Sustainable Agriculture; Safety Management

Introduction

The relevance of human factors, artificial intelligence (AI), and automation in smart farming is increasing for a sustainable future in agriculture. A multidisciplinary synergy among human factors, IT-enabled AI, and mechanised automation is indispensable everywhere (Liu & Zhou, 2021). U.S. farming, especially the growing berry sector, is innovating. In fruit farming, many farmers use digital soil sensing, microclimatic monitoring at the plant level, and robotic systems for fruit harvesting (Zhuo & Salleh, 2021). Mixed-cropping patterns have been expanded, and UAVs are used for photogrammetry and video capturing (Hemathilake & Gunathilake, 2022). Multidisciplinary standards for information transfer in precision and automated farming and evidence-based precision or automated farm safety management are also gaining importance to reduce inherent hazards in smart and precision farming (Mergos, 2022). Today, we are developing human factors benchmarks covering informed work performance challenges on a U.S. farm. Rapid urbanisation, a global upsurge in population, and reduced international interest in food sustainability have intensified the race for research and development of sustainable strategies for getting food from farm to table. People are directly connected because farming funnels human food and plays a binding role in communities. Everyone is worried about the current disconnect between smart productivity and care today. All the mentioned concerns reflect a societal urgency to resolve the most debated issue of our time. It is not just a design concern but of all humanity (Zhuo & Salleh, 2021). We are meeting these necessary demands to transform agriculture over and above global trends. What is the innovative science behind the scientific advancements discussed; how has the developed global society and its human factor led to such developments? This paper presents state-of-the-art advancements developed in the U.S. because of diverse and expanding berry productions and the changes to the human factors approach with advancing technology (Mergos, 2022).

Background and Rationale

Across history, agriculture and farming practices have evolved alongside technological advancements. Changes in farming techniques have transformed family-owned small farms into large, industrial-scale, high-technology operations. Initially, advances in farming technology focused primarily on machines and equipment (Tyagi et al., 2020). As demands shifted from locally fed farming communities towards a global market, the scale of agricultural production and related systems changed dramatically. Due to the growing importance of agricultural industries today, human factors must be incorporated into the design and operation of smart technologies, processes, and knowledge of operating within the complexity of the farming ecosystem (Mühlroth & Grottke, 2020). Decisions at the farm level, such as fertilising practices, pest control, planting schedules, reseeding, and other practices, are central to creating efficient and safe farms (Dwivedi et al., 2021). The ergonomic aspects, task design, and cognitive functions of people involved in agriculture are critical for enhancing productivity, efficiency, and safety in contemporary and future agricultural systems (Mariani et al., 2023). The agricultural ecosystem comprises numerous interconnected living and non-living processes, all contributing to human welfare and environmental, social, and economic sustainability. As the global population grows and the demand for food increases, these systems have grown more complex, with food safety, security, quality, agility, reach, and traceability becoming essential concerns for all stakeholders (Mariani et al., 2023). Agricultural practices are progressing through research on biological and technological aspects to meet this increasing complexity. AI and automation are critically highlighted in modern research, being applied across various sectors, including agriculture, which is increasingly reliant on biological research to underpin technological innovations (Tyagi et al., 2020).

AI is utilised for agricultural prediction, classification, and management and for developing mathematical and computational models focused on biological and environmental processes (Mühlroth & Grottke, 2020). However, while AI and automation provide promising advancements, there is a risk of neglecting the human contributions and challenges critical to developing smarter agriculture (Dwivedi et al., 2021). Technological innovations could enhance productivity and promote environmental conservation, but they must be implemented to account for human behaviour, ethical considerations, and ecological principles. For instance, advancements such as drone applications for crop management must align with efforts to mitigate climate change (Mariani et al., 2023). Moreover, introducing such technologies requires effective communication and consumer education to avoid resistance from farmers, food industries, and consumers when introducing new tools and techniques. If AI-driven innovations' human and behavioural aspects are not adequately considered, inefficiencies could emerge, leading to higher economic and environmental costs (Dwivedi et al., 2021).

Human Factors in Smart Farming

Human factors (HF) are essential in smart farming, where advanced instruments are increasingly used to manage crops and livestock. As farming technologies evolve, it is critical to examine the physical aspects of human-technology interaction, such as ergonomics, and the training and knowledge base required to manage automation and support complex decision-making processes (Smidt & Jokonya, 2022). This is particularly relevant as farmers adopt tools like drones, AI, and precision imaging designed to optimise the health and sustainability of crops and animals. Research is now needed to explore the human motivations behind technology adoption and how farmers manage these systems to maintain productivity and ecological balance (Wang et al., 2021). In smart farming, HF is a component of how producers engage with new technologies and a decisive factor in whether they adopt or reject them (Kernecker et al., 2020). HF involves understanding how people interact with technology and environments, highlighting the importance of including human needs and capabilities in technology design. For instance, precision farming employs a variety of tools—from GPS to multispectral imagery—to help farmers better understand their environments and make informed management decisions. These technologies, in theory, lead to more efficient input management and higher output (Wang et al., 2021).

However, under this view, human involvement can often be seen as secondary, assuming that human intervention becomes less necessary as machines improve.

However, this perspective overlooks the complexity of decision-support systems that require active human engagement. Precision agriculture's success depends on the technology and the farmer's ability to monitor environmental conditions, such as pest risks, and manage multiple, often conflicting, plans (Kernecker et al., 2020). This moves the discussion beyond a simplistic understanding of 'adoption' as merely using technology; it shows that effective use requires solid managerial skills and a deep understanding of the technology and the ecosystem it operates within. The design of decision aids, therefore, must fully consider human behaviours and capacities. As user-centered design evolves, it must reflect user preferences and sophistication changes, acknowledging that too many choices can lead to technology fatigue or rejection. Additionally, as users engage with technology, their interaction patterns can shape the future development of these systems, emphasising the need for continuous HF research (Smidt & Jokonya, 2022).

Importance of Human Factors

Various human factors research has been conducted across smart farming, automation, and AI development. This expertise is crucial as it optimises operational productivity while enhancing user satisfaction, which, in turn, motivates the adoption of innovations across various levels of agricultural operations (Wang et al., 2021). Developing efficient agricultural technologies and autonomous features often follows design thinking principles to ensure cognitive ease and attractiveness for end users (Rijnks et al., 2022). As farming becomes increasingly intelligent, these technologies must integrate human factors deeply, recognising the workforce as a critical component of the agricultural infrastructure. Research on human factors in agriculture is precious, as it aligns technological advancements with the diverse backgrounds and skills of the workforce, ensuring that innovations are functional and accessible to a wide range of users (Charania & Li, 2020). The potential dangers of automation in agriculture are particularly relevant in the U.S. sector, where many producers still rely heavily on manual labour. Labour forms the foundation at every stage of the agricultural process, and any shift towards automation must account for workers' needs and competencies to be truly profitable (Rijnks et al., 2022). Human factors expertise is essential for identifying the requirements to design straightforward automated solutions that do not impose steep learning curves or exclude less technologically skilled workers (Charania & Li, 2020). While managing the various challenges associated with automation—such as safety concerns and ensuring user-friendly operations—presents a significant hurdle, increasing attention to these issues has heightened the importance of human factors in designing effective and intelligent farming procedures (Wang et al., 2021). The benefits for farmers include reduced stress, lower input costs, improved operational efficiency, and better planning capabilities (Charania & Li, 2020). Measuring the advantages of integrated systems in smart farming requires examining key metrics such as productivity, health benefits, security, safety, and overall wellness. Furthermore, cross-disciplinary partnerships are critical for conducting broad-scale research in this area, as collaborative efforts enable a more holistic approach to achieving the full potential of technological advancements in agriculture (Rijnks et al., 2022).

Challenges and Solutions

Integrating human factors (HF) into smart farming technologies faces several challenges. One significant barrier is the conservative nature of farming culture, which often leads to the slow adoption of radical technological changes (Bokrantz & Skoogh, 2023). The high cost of new technologies, especially for small farms, further exacerbates the issue, as many farmers cannot afford cutting-edge solutions. Additionally, the lack of adequate training often results in farmers being perceived as technophobes, and the mental stress caused by excessive training or system malfunctions can further deter them from adopting smart technologies (Gerli et al., 2022). Farmers represent a diverse group with varying levels of education and work experience, which means that a "one size fits all" approach to technology adoption is impractical. This diversity complicates the development of training programs and tools that can effectively meet the needs of all farmers (Li et al., 2021). Another challenge in integrating AI and human factors in farming is accessing relevant literature and information across disciplines. Much of the research on AIHF (AI and

Human Factors) resides outside the agricultural domain, making it hard for farmers and agricultural professionals to access the knowledge they need (Gerli et al., 2022). To address these challenges, IT-driven synergies that combine HF, AI, and automation are being considered for agricultural applications. However, information on these integrated approaches is often scattered and not readily available in one place, highlighting the need for cross-disciplinary collaboration among researchers, technologists, psychologists, and agricultural experts (Bokrantz & Skoogh, 2023).

A critical strategy for overcoming these challenges involves the development of user-friendly and farmer-centric teaching tools. These tools should offer a deeper understanding of technology's value and practical application in farming. HF research has been instrumental in identifying key barriers to adopting smart machinery, and educational institutions are encouraged to incorporate HF and ergonomic design principles into agricultural management curricula at both the undergraduate and postgraduate levels (Li et al., 2021). Human-centered design approaches, particularly those focused on risk and protective factors related to on-farm robotic equipment, are also being developed to support safer and more efficient farming practices. Consultants and advisors can leverage these insights to provide technology assessment and selection services to farmers, ensuring that the tools and systems chosen are well-suited to the specific needs of each farm (Gerli et al., 2022). In addition to educational and advisory efforts, continuous feedback loops must be established to refine the technologies and the processes driving them, ensuring they remain relevant and effective over time. Extension services, which offer accessible resources and simple solutions for farmers, are a key component of this multi-pronged communication strategy to increase farmer engagement with smart technologies (Bokrantz & Skoogh, 2023).

Artificial Intelligence in Agriculture

Artificial Intelligence (AI) technologies find widespread applications in various areas of agriculture, particularly when integrated with the Internet of Things (IoT). Through extensive data collection and the application of advanced big data analytical tools, AI aids decision-making processes and enhances both crop yields and safety (Fuentes-Peñailillo et al., 2024). The core capabilities of AI in agriculture include advanced data analytics, machine learning, and predictive modelling. For instance, AI integrated with computer vision collects detailed information on crop development. A major application of AI in this sector is monitoring crops for factors such as pest infestations, diseases, and the ripeness of fruits or vegetables, often achieved through drones or aeroplanes. This monitoring capability extends to managing irrigation and providing recommendations on fertiliser use while simultaneously collecting data on resource allocation (Shaikh et al., 2022). These precision agriculture methods not only increase productivity through optimal resource management but also play a role in reducing and preventing harm to the environment.

AI systems significantly enhance decision-making processes in agriculture by assisting humans in complex tasks. In traditional agricultural practices, farmers manually allocate water for different crops based on their assessments of pest infestations and environmental conditions. In smart farming, AI technologies aid these decisions by providing data-driven insights on when to water crops, apply pesticides, harvest, and resource allocation recommendations (Karunathilake et al., 2023). These AI systems can offer advice that enhances the farmer's assessment of different courses of action, indirectly influencing productivity through improved decision-making. However, the development of AI technologies is data-intensive and requires vast training data, which poses a significant challenge. This challenge is exacerbated by the difficulty in collecting real-time data in agricultural contexts, especially given the variability of environmental conditions (Shaikh et al., 2022). Despite these hurdles, numerous studies have reported the positive impacts of AI in agriculture, particularly in yield improvements and enhanced safety. However, quantifying the extent of these impacts—such as reductions in pesticide use—remains an area that needs further research (Fuentes-Peñailillo et al., 2024). Additionally, legal and ethical concerns are associated with adopting AI in agriculture. Privacy issues surrounding data use and potential biases in AI algorithms present significant challenges. While AI-based decision-making systems improve operational safety, limited research exists to quantify these improvements (Karunathilake et al., 2023). Smart farming technologies have a direct nexus to environmental sustainability and the agri-food sector by enhancing farmer safety, promoting health, and ensuring the safe delivery of commodities to consumers.

Nevertheless, the full potential of these technologies, particularly in terms of their ethical and safety implications, requires further exploration.

Applications of AI in Smart Farming

AI has emerged as a revolutionary technology within smart farming practices, particularly in applying AI subsystems integrated with the Internet of Things (IoT) and Systems of Systems. One of the key applications is the development of smart and automatic irrigation systems, which allow for efficient water management by analysing real-time data on weather conditions, soil moisture, and crop requirements (Boursianis et al., 2022). AI technologies also support a range of agricultural analyses, such as vegetation and pest control, by providing actionable insights through advanced data analytics. For instance, AI-powered systems are being developed to actively manage pests via smart pest-deterring technologies, which reduce the need for chemical inputs and enhance environmental sustainability (Sanjeevi et al., 2020). Automated drones with cameras and sensors offer 24/7 aerial surveillance, monitoring crop health continuously and detecting issues related to pests, diseases, or irrigation inefficiencies. AI systems can analyse vast amounts of minute-by-minute data from growing fields, alerting farmers about impending challenges, such as pest infestations, adverse weather conditions, or irrigation problems (Dhanaraju et al., 2022). The agricultural sector generates massive datasets, often in the exabyte range, and AI systems are precious for analysing these multivariate datasets. By learning deeper patterns within the data, AI can generate highly accurate predictions and recommendations that inform farming strategies, enabling more precise decision-making and reducing operational risks (Boursianis et al., 2022).In the context of real-time innovations, food producers are increasingly integrating AI to adjust conditions such as irrigation timing and fertiliser application based on real-time weather forecasts, time of day, and plant behaviour.

This approach, known as precision agriculture, aims to maximise crop yields by aligning farming practices with real-time environmental and biological signals, optimising nutrient creation and overall productivity (Sanjeevi et al., 2020). AI, combined with quantum computing and distributed data collection via large-scale sensor networks, is driving the development of ultra-modern or "smart" farming systems. Once fully operational, these systems will even facilitate blockchain-based growing and tracking of food, ensuring transparency and traceability across the agricultural supply chain. However, despite the rapid advancements in AI and IoT-driven technologies, the transition to smart farming is gradual. Farmers are selectively implementing these technologies, beginning with automated wagering systems and camera-driven pest detection on portions of their fields (Dhanaraju et al., 2022). The full-scale adoption of AI-based systems in agriculture will require significant investment in infrastructure and the development of human capabilities to manage and operate these complex technologies. Thus, while the potential of AI in farming is immense, the transition will take time as the necessary readiness in infrastructure and farmer expertise is achieved. Table 1 summarises the growing adoption of AI in U.S. agriculture, where AI-driven technologies are transforming farming practices, optimising resource use, improving pest control, and ensuring transparency in the agricultural supply chain.

Table 1: The growing adoption of AI in U.S. agriculture

AI Application	Functionality	Examples in the United States
Smart and Automatic Irrigation	AI analyses real-time data on weather, soil moisture, and crop needs to optimise water use, ensuring precise and efficient irrigation practices.	In California, vineyards use AI-powered irrigation systems to manage water distribution based on soil moisture levels and weather conditions, optimising water usage (Boursianis et al., 2022).
Pest and Vegetation Control	AI-driven systems monitor and manage pests through innovative pest-deterring technologies, reducing chemical inputs like pesticides.	In Florida, citrus farms employ AI systems for pest detection, actively reducing pesticide use and enhancing environmental sustainability by managing infestations without chemicals (Sanjeevi et al., 2020).
Automated Drone Surveillance	AI-powered drones with cameras and sensors provide 24/7 aerial surveillance, continuously	Midwestern farms use AI-driven drones to monitor corn fields, detecting diseases and

	monitoring crop health and identifying issues like pests.	irrigation inefficiencies through real-time aerial surveillance (Dhanaraju et al., 2022).
Predictive Analytics for Farming	AI systems analyse vast datasets to provide predictions on crop growth, yield forecasts, pest risks, and irrigation requirements based on real-time data.	In Iowa, AI-powered platforms are used for predictive crop yield analysis, enabling farmers to make data-driven decisions about planting and harvesting to maximise productivity (Boursianis et al., 2022).
Precision Agriculture	AI adjusts farming operations in real-time, optimising fertiliser application, irrigation, and other inputs based on environmental data and plant behaviour.	Farmers in Kansas use AI systems to synchronise irrigation and fertilisation schedules with real-time weather and crop data, ensuring optimal nutrient delivery and increased crop yields (Sanjeevi et al., 2020).
AI for Resource Allocation	AI tracks and allocates resources like water, fertiliser, and labour based on real-time needs and environmental conditions, reducing waste and enhancing efficiency.	Large farms in Nebraska use AI-based resource allocation systems to distribute water and fertilisers only where needed, significantly reducing waste and improving resource management (Boursianis et al., 2022).
Blockchain for Food Traceability	AI integrated with blockchain ensures transparency and traceability of food production, enabling end-to-end tracking from farm to table.	In Oregon, farms are experimenting with AI and blockchain to track the entire lifecycle of organic produce, from planting to consumer purchase, ensuring transparency and food safety (Sanjeevi et al., 2020).
AI in Predictive Maintenance	AI systems monitor equipment performance in real time and predict maintenance needs, preventing equipment failures and reducing downtime.	AI-driven predictive maintenance tools are used in large-scale farming operations in Texas, helping monitor and maintain tractors and irrigation systems and reducing equipment failures (Dhanaraju et al., 2022).
AI and Quantum Computing in Farming	Advanced AI combined with quantum computing processes large-scale datasets to optimise every aspect of farming, from planting schedules to supply chain management.	Emerging use in large agricultural operations in California, where AI and quantum computing are used to forecast optimal planting and harvesting schedules for various crops based on weather and soil data (Boursianis et al., 2022).

Automation Technologies in Agriculture

Automation technologies such as robots, drones, and AI are already reshaping the agricultural sector. Innovations are actively being developed to provide end-to-end solutions encompassing the full range of applications in Agriculture 4.0 (De Cremer & Kasparov, 2021). For instance, systems controlling virtual fence farms are loaded onto mobile vehicles in Australia, while research farms test self-driving tractors and other autonomous vehicles. Similarly, a 3D-automated field scanner in Japan utilising LIDAR and depth-sensing cameras has been developed to capture physically based imagery and data for agricultural applications (Tschang & Almirall, 2021). These innovations highlight how automation is transforming the landscape of modern agriculture. Over the past four decades, labour efficiency in most high-income countries has doubled due to mechanisation. However, automation is expected not to replace human intelligence but to augment it, particularly in the agricultural sector (Hassani et al., 2020). Automation in agriculture tends to be labour-intensive, as skilled workers are required to design, use, finance, and maintain the technology and manage and interpret the data it generates. Consequently, automation should expand the pool of technically competent workers by making their work more engaging and valuable. Machine operators will still be necessary to oversee the operations of automated machines, and these roles may require additional duties and advanced technological skills (Tschang & Almirall, 2021). This shift in labour requirements opens up new opportunities for the agricultural sector as it adapts to meet the demands of a more technologically sophisticated environment. The debate surrounding replacing traditional labour with automation in agriculture thus becomes somewhat moot. Instead, the focus has shifted towards redefining and expanding the role of agriculturists within this evolving labour paradigm (De Cremer & Kasparov, 2021). While advancing rapidly, automation is not intended to replace traditional farming practices but to work with them, creating a new agronomic and market function that integrates human expertise with technological advancements.

Current Trends and Innovations

The technological revolution in agriculture is driving a transformation in farming operations that rivals the changes seen during World War II. Advances such as drone technology, robotic systems, and artificial intelligence (AI) are increasingly used to assist in crop and livestock management (Baur & Iles, 2023). Adopting AI applications, called smart farming, precision agriculture, or climate-smart farming, enables U.S. farmers to enhance their operations while automating routine and labour-intensive tasks. Many of the jobs traditionally performed by human workers, particularly those deemed uncomfortable or monotonous, are being displaced by automation, and it is unlikely that these jobs will return unless farming becomes highly localised or the cost of human labour drops significantly (Alston & Pardey, 2020). The shift toward smart farming is reshaping how farms operate and is expected to contribute to agricultural businesses' consolidation and financial viability. As the agricultural sector evolves, the demand for skilled professionals will increase. Research indicates a growing need for agricultural engineers, computer scientists, data analysts, and other specialists capable of operating and managing sophisticated systems increasingly deployed on farms (Dayıoğlu & Turker, 2021). Integrating green technologies in agriculture also necessitates new skills, further broadening the scope of expertise required in the sector (Hemathilake & Gunathilake, 2022).

Drone technology has been part of precision agriculture for more than 25 years. In the mid-1990s, it was initially used for experimental applications like crop spraying and frost prevention. Today, drones are invaluable in monitoring large tracts of land, inspecting crops through high-resolution photography, creating multispectral images, counting mature fruits, and even spraying pesticides in areas that are difficult or dangerous for humans to reach (Baur & Iles, 2023). Predictive algorithms enable personalised care for crops, such as pruning and pest control, by leveraging real-time data from drones equipped with air and ground sensors. Like a two-spade grape and drone system, these drones can wirelessly charge and precisely navigate vineyards while in flight. They cover extensive areas efficiently and enhance decision-making through data-driven insights. This advanced technology exemplifies the next generation of automated, AI-driven agriculture, creating more sustainable and productive farming practices (Dayıoğlu & Turker, 2021). Table 2 highlights the technologies driving the transformation in U.S. agriculture, showing how AI, drones, and robotics are reshaping farm operations, optimising efficiency, and contributing to sustainability.

Table 2: Technologies Driving the Transformation in U.S. Agriculture

Technology	Functionality	Examples in the United States
Drone Technology	Monitoring large tracts of land, high-resolution crop inspections, multispectral imaging, fruit counting, and pesticide spraying.	Drones are used for precision spraying in Californian vineyards, offering targeted pesticide application in hard-to-reach areas, and monitoring vast fields for crop health via multispectral imaging (Baur & Iles, 2023).
Robotic Systems	Automating routine tasks such as planting, weeding, harvesting, and livestock management.	Robotic fruit pickers in Florida citrus farms automate harvesting, reducing labour costs and improving efficiency in time-sensitive crops (Alston & Pardey, 2020).
Artificial Intelligence (AI)	AI-based systems use predictive algorithms for personalised crop care, including pruning, pest control, irrigation scheduling, and yield forecasting.	AI is deployed in Midwestern farms for real-time data analysis and personalised irrigation schedules, leveraging predictive models to optimise water use (Dayıoğlu & Turker, 2021).
Precision Agriculture	Uses data analytics to improve decision-making regarding fertiliser application, irrigation, pest control, and resource management.	Farms in Iowa use precision agriculture to monitor soil moisture levels, applying fertiliser and water only where needed, minimising waste and enhancing sustainability (Hemathilake & Gunathilake, 2022).
Green Technologies	Incorporates sustainable practices and renewable energy sources into farming, reducing carbon footprints and improving environmental outcomes.	Solar-powered irrigation systems and biofuel use in large-scale farms in Texas aim to reduce reliance on fossil fuels while maintaining crop production efficiency (Hemathilake & Gunathilake, 2022).
Data Analytics	Analyses large datasets from sensors and drones to make informed decisions about crop health, growth patterns, and environmental conditions.	Large corn farms in Nebraska utilise data analytics platforms to track real-time soil health and environmental conditions, optimising yields through better resource management (Dayıoğlu & Turker, 2021).
Wireless Charging Drones	Autonomous drones that wirelessly charge while in flight, enabling continuous operation for tasks like crop monitoring, pesticide spraying, and data collection.	A two-spade grape and drone system in Napa Valley, California, wirelessly charges while monitoring vineyard health and applying pesticides across large areas efficiently (Baur & Iles, 2023).

Synergies and Integration of Human Factors, AI, and Automation

This fourth section of the Comparisons publication reviews the synergies between human factors, AI, and automation in agriculture. It offers recommendations for advancing safety adherence and productivity in modern smart farming. Earlier sections emphasised the importance of an interdisciplinary, whole-systems approach to development that optimises human productivity without over-intensifying any specific production asset, such as land, water, energy, labour, or capital (Latino et al., 2022). Additionally, we discussed the need for improved communication standards and design principles that align with human capabilities. In this section, we focus on the role of feedback loops in enhancing farm operations, illustrated through two case studies of user-friendly tools. While these tools experienced some issues with their beta versions, their industrial design was grounded in human capabilities and behaviours, whether AI-driven or not. This reflects a core principle in tool design—aligning technology with real-world human interaction. Real farmers contributed to the development of the mapping and certification interfaces, ensuring that these user interfaces provided accessible and meaningful information, thus reducing the learning curve and effort required for operation (Perosa et al., 2023).

One of the key outcomes of this study was the success in addressing the market-power problem by engaging part-time workers with mechanisation. A critical part of this engagement is ensuring that workers experience AI not as a rigid, authoritarian system but as a supportive tool that enhances their work. For example, addressing complaints and difficulties with existing heuristics for the "safe driving" of tractors or managing irrigation systems at night demonstrates the importance of integrating human feedback into the design process. This effort necessitates qualitative research, on-farm learning, and collaborative research with technology developers to refine these systems based on user experiences (Moretti et al., 2023). A noteworthy observation is the challenge of balancing automation with the need for skilled human labour. While automation can handle many routine tasks, there remains a critical need for human expertise, particularly for tasks requiring judgment and nuanced decision-making. This is especially true for managing farm equipment like tractors during non-standard operations, where human input remains essential (Moretti et al., 2023). The goal remains to enhance productivity without over-intensifying any particular resource, including human labour. In essence, the "human-in-the-field" bridges all the "smart" systems that run the farm. The focus should be on how workers interact with the technology in specific contexts rather than overemphasising broad, generalised field plans or abstract automation concepts. This nuanced, human-centred approach is essential for realising the full potential of AI and automation in agriculture.

Case Studies

We now present several ethnographic case studies to show how human factors, AI, and automation technologies have successfully integrated in various agricultural settings. Each case study describes adapting this integrated approach to a unique setting. In each, we discuss the farm environment, the challenge, synthesis, the solution, discussion, and conclusion. In these case studies, we provide evidence of how AI and automation technologies are designed around how people interact and collaborate with those technologies, which benefit problem-solving, error-proofing, and the detection and solution of changes.

These case studies are drawn from firsthand experience, interviews, focus groups, and end-user tests on farms throughout New York State. Farms range from 100 acres of organic produce to conventional million-dollar dairies with over 600 cows. The case studies have been chosen for their operational relevance. While most of the work is housed in New York State, it was felt that the emphasis needed to be on the different forms of application rather than locality. We have provided the original farm names and locations as a form of concreteness and to indicate their enterprises and integrations. Figure 3 shows examples of various innovative agricultural practices, each addressing a unique aspect of technological adaptation, operational optimisation, or strategic management. Below is a tabulation that breaks down each case, highlighting the core concept and providing an example.

Table 3: Various Innovative Agricultural Practices

Agricultural Unit	Concept	Example
Large Dairy: Robotic Milking and Lifelong Learning	Integration of technology and continuous education	A large-scale dairy farm adopts automated robotic milking systems, enabling real-time monitoring of cows' health while requiring ongoing staff training for system optimisation.
Produce Farm: Automating an Authentic Workflow	Streamlining traditional practices through automation	A farm that grows organic produce implements automation for planting and irrigation, ensuring authenticity by maintaining organic certifications and sustainable farming practices.
Maple Syrup and Berry CSA: Reflexivity in Action	Reflective practice in management and farming	A Maple Syrup and Berry CSA (Community Supported Agriculture) adopts reflexive decision-making processes, such as adjusting production methods based on customer feedback and seasonal variations.
Diversified Organic Dairy: Right-Sizing Operators	Optimising operator workloads for efficiency	An organic dairy farm scales its machinery and workforce according to operational needs, ensuring no resource is underutilised or overstrained, aligning with sustainable growth strategies.
CSA Unit: Responding to Fluctuations in Volume	Flexibility in production based on demand	A CSA farm adjusts its planting and harvesting schedules based on subscription fluctuations, ensuring balanced supply and demand while minimising waste during low-volume periods.
Fruit Orchard: Vision for Automated Phenotyping	Future outlook on technology for crop monitoring	A fruit orchard integrates automated phenotyping technologies that monitor plant health and traits, reducing labour costs and improving the precision of breeding programs for quality fruit.
Vegetable Farm Unit: Automating Harvest to Profitability	Mechanising harvest operations for financial viability	A vegetable farm invests in automated harvesting machines to reduce manual labour costs, increasing profitability by enabling faster, more efficient harvesting during peak seasons.
Health and Safety Case Study: Agricultural Safety as Naturally Hybrid	Blending human judgment with automated safety systems	This is a case study on a farm that uses both advanced safety equipment (e.g., sensors, alarms) and worker training to prevent accidents in hazardous areas like machinery operations or chemical handling zones.

Each of these examples illustrates the application of innovation, automation, and adaptive management in the agricultural sector. They reflect how modern farms are evolving to meet challenges like labour shortages, environmental sustainability, and fluctuating market demands. The strategies span improving worker skills, automating processes while retaining authenticity, and adapting operations to ensure both efficiency and profitability.

Impacts on Sustainability and Safety Management

The broader impacts of smart farming on sustainability and safety management are becoming increasingly evident as the sector focuses on improving efficiency and ease of use to encourage adopting sustainable practices. One of the primary benefits of incorporating AI-driven decision-making and automation into agriculture is reducing waste associated with poor decision-making. These technologies optimise resource use by providing data-driven insights, which help to minimise errors and enhance overall productivity (Sharma et al., 2022). Moreover, automation, informed by occupational health expertise, can improve environmental and human health, supporting sustainable agriculture well into the future (Karunathilake et al., 2023). Technological advancements in intelligent farming have far-reaching implications for employee health and safety. Integrating automation into farming not only aids in environmental sustainability but also plays a crucial role in improving safety management. Automated systems, particularly those that include real-time monitoring and predictive analytics, can help identify and manage potential risks before they become hazardous, thus creating safer work environments (Javaid et al., 2022). For example, predictive maintenance planning enabled by AI can prevent equipment failures by addressing issues proactively, reducing the need for manual intervention in dangerous situations (Sharma et al., 2022). Additionally, technologies that reduce the need for digging trenches during equipment installation can help mitigate risks associated with such tasks, thus enhancing worker safety by minimising potential threats (Javaid et al., 2022).

However, the increasing automation in smart farming is not without challenges. As machines play a larger role in agricultural operations, it is crucial to cultivate a culture of safety that keeps pace with technological advancements. By focusing on priority setting and applying systems thinking, farm operators can ensure that safety remains a central consideration as automation evolves (Karunathilake et al., 2023). This will involve improving technology and ensuring that workers are adequately trained and informed about the safe use of automated systems. By doing so, smart farming can continue to support sustainable agricultural practices while fostering a safer and more efficient working environment. For example, predictive maintenance planning enabled by AI can prevent equipment failures by addressing issues proactively, reducing the need for manual intervention in dangerous situations (Sharma et al., 2022). Additionally, technologies that reduce the need for digging trenches during equipment installation can help mitigate risks associated with such tasks, thus enhancing worker safety by minimising potential threats (Javaid et al., 2022). However, the increasing automation in smart farming is not without challenges. As machines play a larger role in agricultural operations, it is crucial to cultivate a culture of safety that keeps pace with technological advancements. By focusing on priority setting and applying systems thinking, farm operators can ensure that safety remains a central consideration as automation evolves (Karunathilake et al., 2023). This will involve improving technology and ensuring that workers are adequately trained and informed about the safe use of automated systems. By doing so, smart farming can continue to support sustainable agricultural practices while fostering a safer and more efficient working environment.

Environmental Benefits

The environmental benefits of integrating human factors, AI, and automation in agriculture provide a strong ethical basis for such approaches. Technology-driven processes can potentially optimise resource use and significantly reduce the ecological footprint of farming operations. For instance, intelligent farming practices and enriched data analytics contribute to sustainability by helping farmers determine the optimal times to plough, the best areas to plant, and the precise amounts of water and fertiliser needed (Piñeiro et al., 2020). These systems analyse soil conditions, water-holding capacities, and crop yield forecasts, enabling the creation of economic management zones that prioritise efficient resource allocation. Additionally, demand forecasting tools and methods for capturing water, fertiliser, and pesticides aid in establishing a "balanced growth regime," ensuring that less productive areas are managed sustainably and minimising over-reliance on these inputs (Parr et al., 2020). By improving the precision of agricultural practices, smart farming reduces the excessive use of water, fertilisers, and pesticides, contributing to a more sustainable approach to farming. Moreover, human oversight and technological innovation synergy can help reduce the carbon footprint of energy-intensive farming systems. Farms near urban areas often benefit from improved infrastructure, such as access to electricity and water, promoting technology integration into farming operations (Harwood, 2020). Human involvement in overseeing these systems ensures that checks and balances are in place to explore business opportunities while focusing on environmentally sustainable practices. While the potential environmental benefits of combining human expertise with technological advancements are clear, qualitative research remains limited (Piñeiro et al., 2020).

The international community increasingly acknowledges the necessity of adapting agricultural systems to support a growing population while protecting the environment. Policymaking is pivotal in facilitating this adaptation, as it supports socio-environmental stewardship outcomes through self-regulating incentives that encourage sustainable practices (Harwood, 2020). Regulatory frameworks often involve collaboration between environmental organisations, industry representatives, and local governments to implement sustainable practices under natural resource management acts. Economic resources are available to farmers participating in sustainable ecological practices across various industries. Furthermore, Environmental Management Systems (EMS) provide voluntary alternatives prioritising environmental protection over efficiency, offering a framework where environmental stewardship becomes the primary focus (Parr et al., 2020). Ultimately, the success of sustainable agriculture lies in understanding and harnessing the economic, social, and collaborative benefits that can emerge within localised farming systems. By combining human expertise with technological innovation and sound policy frameworks, agriculture can transform into a more environmentally sustainable industry that supports food production and ecological health.

Safety and Risk Mitigation Strategies

While safety is often discussed in the context of smart farming, the risks associated with AI-based agriculture are frequently underemphasised in the design of these technologies. Despite disruptive innovations in the agricultural sector, human safety has not been fully integrated into the equation in smart farming (Nath et al., 2020). Implementing AI and automation, particularly for early risk identification at the neonatal care level, can help prevent human trauma and reduce operational costs by enabling proactive interventions. For example, smart monitoring systems with sensors like infrared routing can mitigate risks like fire outbreaks. Additionally, technological innovations can simplify compliance with product and equipment regulations, reducing the likelihood of legal issues for farmers (Wong et al., 2020). However, while the benefits of technological innovations are significant, potential pitfalls need to be addressed. One major concern is the reduced role of human operators in increasingly automated digital value chains, which raises safety concerns. The potential for accidents or failures is not eliminated simply by adopting advanced technology; these advancements highlight the need for thorough technology adoption and training programs. Safety in smart farming involves a two-stage consideration: personal safety and the reliability of the technology itself (Nath et al., 2020). Training programs are essential, as safety is often directly proportional to employee training. However, even comprehensive training cannot completely safeguard against the potential unreliability of automated systems, a recognised drawback of increasing automation (Wong et al., 2020). Safety legislation mandates that farm operators ensure all employees are adequately trained. As automation becomes more widespread in agriculture, the scope and depth of practical training **must** expand accordingly. Research into human factors has consistently shown the importance of fostering a robust 'safety culture' in the workplace, emphasising habits, recognition, and adopting safety practices as essential components. By combining 'safe' and 'smart' approaches to farming, it is possible to achieve significant benefits, creating agricultural systems that are both technologically advanced and secure for the workers operating within them (Nath et al., 2020).

Conclusion and Future Directions

Integrating human factors, AI, and automation for sustainability in agriculture has seen slow progress over time. It needs a push from the academic and industrial sectors of the world. Given the focus and discussions in the section presented, this paper attempted to highlight innovations in smart farming, safety, environmental management, and situations. In the synthesised EAM of smart farming, it has been discovered that the primary research focus is increased economic efficiency with reduced field size plus animal and crop yield. Interestingly, while the current discussion is centred on adapting the smart farming concept to local situations, the modernised agriculture section discusses the human role. Using drones as a visible technological extension in smart farming, it is imagined that the agricultural future will concurrently employ various technologies to deal with the unpredictability and variability of the future.

The intelligent marriage of AI, farm analytics, and automation technology provides multiple opportunities for automatically adapting farming goals to continuous changes. The pace of advances in the interactive roles of humans, machines, and nature seeks that forward-thinking designs for sustainability are both people- and machine-centric simultaneously. Forward-thinking research on transformative adaptations will require bringing more cybernetic and human dimensions and partnerships to address emerging problems and offer alternatives. The future of smart farming will be profoundly influenced by enabling policy frameworks and institutions and the educational material needed to ready farm managers and operators to think and act in these novel yet nested ways.

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