Performance Evaluation of AI vs Human Agricultural Systems Using Discrete Event Simulation (DES)

Thirissha Thirissha[1], Kothai Kothai[2], Sharukesh Sharukesh[3], Rajesh Rajesh[4], Sanjai Srinivas[5] and Vincent Gnanaraj[6]*

[1, 2, 3, 4, 5, 6] Department of CSE, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai - 602 105, Tamil Nadu, India.
vincentgnanarajt9020.sse@saveetha.com

Abstract. This paper work emphasizes on the enhancement of efficiency and performance level of AI-based agricultural system in comparison to human-based agricultural system addressing the parameters like the crop yields, resource usage and efficiency optimization. The simulation approach has been employed here is Discrete Event Simulation (DES) which is utilized to evaluate the completion time of task and resource usage. With the justification of t-test the results are evaluated which draws a clear line between the AI -based agricultural system and the Human-based agricultural system on efficiency and performance by enhancing the reduction of resource usage and optimizing the productivity of the farming. In comparison, the p-value is less than 0.05 which highlights the work that there is a significant difference among the task time, resource usage. By the advancing AI technologies like predictive analytics, autonomous machinery, IoT senor and so on will overcome the problems faced by the Human-based agricultural system on the era of soil degradation, water shortages and climatic changes. From the view of economic aspect, it helps in reducing the labor -intensive tasks, costs for the operations and uplift the profitable practices of the farming with the limited resources. The research prioritizing the potential transformation in agriculture augmenting the scalability, sustainable and profitable agricultural practice system including the addressment of critical issues to solved like labor shortage, food security and climatic change predictions.

Keywords: Discrete Event Simulation (DES), Resource optimization, Agriculture systems, Artificial Intelligence

1 Introduction

Agriculture has traditionally relied on human-based systems for decision-making, where decisions are made based on manual observation, intuition, and years of experience. These systems are effective in certain contexts, especially when unforeseen or unique challenges arise [1].

In reality, human decision making is often a little subjective and error prone (for example we may be biased, inconsistent, or delay). In addition, practical challenges of scalability and real time adaptability are especially hard due to increasing complexity of agricultural operations. On the other hand, Artificial Intelligence (AI) based systems

© The Author(s) 2025
S. Kannadhasan et al. (eds.), Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research 120,
https://doi.org/10.2991/978-94-6463-718-2_75

have been developed to make agriculture decisions automatically using large set of data collected from sensors, satellite imagery, and complex models of predictability [2]. Where these systems are useful, they offer real time insights and are able to handle large datasets, but are limited by needing high quality data, environmental variability, and are overly restricted in what they are able to understand in dynamic and complex situations.

Artificial Intelligence's integration into agriculture is revolutionizing traditional farming, presenting new, innovative solutions to the consequences of the traditional way of farming [3]. Given agriculture is one of the oldest human practices, this practice has been evolving continuously, but modern challenges including labor shortages and inefficient utilization of resources and may be caused by environmental factors such as climate change have impacted traditional farming techniques [4]. While these systems have been deployed successfully in many regions, especially where human expertise is critical, these systems still have many limitations, including inefficient labor, resource management and their inability to adapt to changing environmental conditions. Unlike AI based agricultural systems, they promise to address these challenges by using advanced technologies including machine learning, predictive analytics, robotics and Internet of Things [IoT][5].

A key advantage that AI offers is in rolling out the increase in efficiency in agricultural operations. Human labor based traditional farming is susceptible to task repetition as well as precision in using the resources. However, AI powered systems are able to automate labor-intensive processes like sowing, irrigation, pest control and harvesting [7]. AI can also use real-time data from a range of sources including sensors and satellite imagery to better use water, fertilizers and pesticides, only applying them when and where they are needed [8]. It's hard to get such a level of efficiency with human labor, which can easily get fatigued and make mistakes. AI systems have therefore become vastly faster and more accurate, speeding up tasks multiple magnitudes faster bringing productivity up [9].

Deep learning and reinforcement learning, the two big hairy AI algorithms, help us to process complex data and even better at deciding how to make decisions and how to continuously improve the farming practices [10].

Another area in which AI beats the resource utilization of human based agricultural systems. But traditional farming typically applies water, fertilizers, and pesticides the same in one field, to the same from across a field. These wastes and environmentally degenerates resources by overuse of resources [11]. Nevertheless, AI systems use precision farming techniques to enable targeted application of resources according to the real time data and analysis. AI for example, enabled drones to determine, with the help of the data, the health of the crop and the soil condition, and to treat only the places in need [12]. Data from drones and ground sensors is analyzed with algorithms like computer vision and sensor fusion which help farmers successfully apply resources and eliminate waste [13]. The advantage of this approach is that it is targeted, conservation of resources, minimizes environmental impacts, and creates more sustainable farming practices.

Adaptability and resilience to climate changes are another benefit of AI [14]. Traditional farming systems are highly dependent on human intuition, previous experience and local knowledge in dealing with the vagaries of weather variations, sorts of pests and diseases. Farmers tend to react to these methods by making decisions from a historical pattern rather than real time data. But unlike humans, AI can forecast weather patterns, spot pest outbreaks and predict disease risk from thousands of historical and real time data. Farmers can then use machine learning models to predict potentially harmful environmental condition, like droughts or floods, to enact action before any losses occur [15]. In fact, they are great for predicting how these changes will look like serving as an algorithm like time series forecasting and decision trees. This predictive capability gives farmers more resilience in farming systems and allows them to make informed decisions with data versus guesswork [16].

In addition to these AI algorithms, Discrete Event Simulation (DES) can provide an effective basis for comparison between AI based and human based systems in agriculture [17]. DES is a modeling approach that uses the sequence of events, that can be applied to the agricultural processes, to analyze how the AI and human decision-making systems respond to resource availability, environmental conditions and other task dependencies [18]. The DES models the agricultural system as a sequence of discrete events which creates the theoretical ability to perform both types of systems in a variety of scenarios and most importantly allows the farmers and the researchers to identify the best decision-making strategies. In particular, DES is well suited to model processes in complex agricultural environments such as those of crop management, irrigation scheduling and resource allocation, which are often coupled and variable [19]. With this, it can simulate this, evaluate AI based solutions in real world conditions and find out how these systems can fit into traditional farming practices for increased efficiency and sustainability. [20]

2 Literature Survey

However, challenges to meet the needs of a growing population and address environmental problems like climate change, resource depletion and poor soil condition, are constraining the world agricultural sector. Increasingly, traditional human based agricultural systems are being constrained in terms of productivity, resource efficiency and sustainability [21]. It remains manual labor that still drives essential jobs like planting, harvesting, and irrigation, but is becoming less effective as a workforce plummets and ages. Traditional approaches are likely to be less efficient from the viewpoint of resource management-high water consumption and excessive use of chemical fertilizers and pesticides contribute to long-termongoing environmental damage. Added to these issues is their increasing vulnerability to climate change (with unpredictable weather patterns that are harming crop yields, especially in areas with little access to modern agricultural technologies) [22]. The above challenges underline the pointy need of the hour for novel solution to increase agricultural efficiency and resilience.

Transformative solutions to overcome limitations of human driven farming include AI based agricultural systems that are making agriculture highly technologically advanced with advanced technologies that help optimize farming systems [23]. With the help of

AI in precision farming, sensors, IoT devices and robotics are used to monitor soil health, enhance resource usage and real time irrigation and fertilization to increase yield significantly with sustainability. In addition to service automation, drones and robotic harvesters help reduce manual labor by enabling more efficient task completion, lowering costs and increasing productivity [24]. excels at predictive modeling, using large datasets to predict weather changes, pest outbreaks, and crop diseases to allow farmers to act before the risk is realized, productivity, resource efficiency, and sustainability [21]. However, because the workforce is shrinking and the demographics are aging, manual labor remains largely ineffective at keeping pace with increasingly more labor-intensive tasks such as planting, harvesting and irrigation. Typically, these traditional methods are much less than ideal in terms of resource management, and too often results in the wasteful use of water and an over reliance on chemical fertilizers and pesticides, which, in the long run, damage the environment. In regions lacking the use of modern agricultural technology, already vulnerable to climate change, with crop yields negatively affected by unpredictable weather, these problems compound [22]. The urgency for new solutions to improve agricultural efficiency and help foster resilience lies in these challenges.

Overcoming constraints of human-driven farming, the availability of AI based agricultural systems has provided a way forward with advanced technologies that improve on farming processes [23]. Powered by AI, precision farming with sensors, IoTs, and robotics monitors the soil health and optimizes resource usage, adjusts the irrigation and fertilization in real time, and brilliantly improves yield and practices sustainability. Drones and robotic harvesters they replace manual labor, and do so much more efficiently than humans (costs lower and produce more) [24]. When we do combine these technologies and they aren't really so expensive, as these combined technologies do reduce waste and reduce the need to use harmful chemicals in agricultural practice [25], we gain wonderful economic and environmental benefit. When comparing human based systems to AI based approaches, there is no doubt about the advantages of AI when it comes to labor efficiency, resource management and climate adaptability [26]. Automation that is driven by AI replaces the labor-intensive work tasks, thereby helping through streamlining the operation, saving the cost and improving efficiency. Environmental impact from precision irrigation, fertilization, and pest management is highly reduced. In addition, AI can predict extreme weather events and adjust farming practices as a result of which the farming is more resilient to climate change [27]. However, benefits must contend with the relatively high cost of the technologies, the lack of access in developing regions, and the requirements for farmer education and training. Future work designs AI solutions to be more affordable to small scale farmers, and hybrid systems resulting from the combination of human based and AI driven approaches [28]., and soil degradation. Today, traditional human based agricultural systems as the main source of farming are experiencing major limitations in their productivity, resource and sustainability [21]. On essential tasks like planting, harvesting and irrigation, manual labor is going away, due to a dwindling workforce and aging demographics. However, traditional methods tend to waste resources by being more wasteful of water with high wastage, relying too heavily on chemical fertilizers and pesticides that result in long term environmental damage. These problems are compounded by the increasing vulnerability to climate change, with unexpected weather

patterns compromising crop yields in areas with limited access to modern agricultural technologies, particularly areas already behind in adapting to that change [22]. These challenges highlight the pressing need for innovation in agriculture, which by efficiency and resilience, to mitigate increasing demand.

From the advances in the technology in general the rise of AI based agricultural systems have brought about transformational solutions to the constraints of human driven farming [23]. Precision farming, this is precision farming that uses sensors, the IoT, robotics to constantly monitor soil health, optimize the use of resources and adjust irrigation and fertilizer on time, to increase crop yield and also achieve environmental sustainability thanks to their ability to perform predictive modeling, modeling based on large datasets to anticipate anything that climate will bring, the scours and the pest outbreaks, and the aging demographics they're able to fully mobilize the preventive measures against climate risks, which is also something that very much pays off Long term environmental damage is caused by the diminishing resources to which traditional methods often lead: excessive water consumption and a dependence on chemical fertilizers and pesticides. Second, the increasing vulnerability to climate change, with un predictable weather patterns leading to harmful effects on crop yields in areas unable to use modern agricultural technologies, further compounds these [22]. This raises the very urgent need for innovative solutions which improve agricultural efficiency and resilience.

AI based agricultural systems are the result of the emergence of the transformative solutions for solving the human limitation in farming approaches via advance technologies [23]. Powered by AI, precision farming is making use of sensors, IoT devices, robotics, and real time soil monitoring to optimize resource use and irrigation and fertilization to increase crop yield and promote sustainability. It also uses drones and robotic harvesters that do these tasks better and cheaper than people, reducing manual labor costs [24], and excels at predictive modeling that uses massive datasets to predict when conditions will change — the weather, pest outbreaks, crop diseases — and allow farmers to proactively deal with climate risk. AI excels at predictive modeling, analyzing vast datasets to forecast weather changes, pest outbreaks, and crop diseases, enabling farmers to take proactive actions that mitigate climate risks. Nevertheless, the integration of these technologies creates massive economic and environmental advantages as product waste is minimized and harmful chemicals are used less, allowing for the implementation of the sustainable farm practices [25]. AI is preferred to human based systems in labor efficiency, resource management, and climate adaptability, while comparing human based systems with AI. Labor intensive tasks are replaced by AI driven automation which makes operations simple, saves costs and make the process more efficient. Irrigation, fertilization and pest control operate under precise control, which significantly contributes to environmental impact. Beyond this, AI's capability to forecast extreme weather occasions and improve farming techniques accordingly offers extra resiliency to the variations brought on by local weather change. However, there are problems such as costs, lack of access in developing areas and the requirement for farmers education and training. Future steps involve making AI solutions more affordable for small scale farmers and about developing hybrids (conjunction of strengths of both humans based as well as AI driven approaches), efficiency, and sustainability. Manual labor, which remains central to essential tasks like planting, harvesting, and

irrigation, is becoming less effective due to a shrinking workforce and aging demographics. Traditional methods often result in inefficient resource management, such as excessive water consumption and over-reliance on chemical fertilizers and pesticides, contributing to long-term environmental damage [26]. The increasing vulnerability to climate change, with unpredictable weather patterns negatively affecting crop yields, particularly in regions with limited access to modern agricultural technologies, further compounds these issues. These challenges underscore the urgent need for innovative solutions that enhance agricultural efficiency and resilience.

AI-based agricultural systems have emerged as transformative solutions to overcome the limitations of human-driven farming, offering advanced technologies that optimize farming processes. Precision farming, powered by AI, utilizes sensors, IoT devices, and robotics to monitor soil health, optimize resource usage, and adjust irrigation and fertilization in real-time, significantly boosting crop yields and promoting sustainability. Automation also reduces the need for manual labor by utilizing drones and robotic harvesters, which perform these tasks more efficiently, lowering costs and enhancing productivity. AI excels at predictive modeling, analyzing vast datasets to forecast weather changes, pest outbreaks, and crop diseases, enabling farmers to take proactive actions that mitigate climate risks. The integration of these technologies results in considerable economic and environmental benefits, minimizing waste and reducing the use of harmful chemicals, thereby fostering sustainable agricultural practices.

In comparing human-based systems to AI-based approaches, the advantages of AI are clear in terms of labor efficiency, resource management, and climate adaptability. AI-driven automation replaces labor-intensive tasks, streamlining operations, reducing costs, and improving efficiency [27]. Precise control over irrigation, fertilization, and pest management significantly reduces environmental impact. Additionally, AI's ability to predict extreme weather events and adapt farming practices accordingly provides greater resilience to climate change compared to traditional farming methods. Despite these benefits, challenges remain, such as the high cost of technologies, limited access in developing regions, and the need for farmer education and training. Future developments focus on making AI solutions more affordable for small-scale farmers and creating hybrid systems that combine the strengths of human-based and AI-driven approaches [28]. Possibly these innovations could break the shackles of traditional agriculture, and pave the way for a sustainable future of growing food [29].

3 Methodology

This research demonstrates feasibility of developing a robust picture to determine the performance of human based and AI based decision making of systems in agriculture using DES Fig.1. This final simulation will assist us in understanding how AI could permit for the capabilities of promoting human decision making to work better/work more efficiently with AI, to the end of more efficient and sustainable agricultural practice. The Benefits of the Proposed Simulation method is that DES model of Realistic Representation of Agricultural Processes achieves good accuracy in simulating agricultural workflows, since it reflects the minute details and connectivity among different activities like planting, irrigation and harvesting. The simulation allows for both a speed

and accuracy objective comparison in human vs AI decision making, as well as a comparison in terms of resource utilization as well as adaptability to changing conditions. In addition, it outputs quantifiable outputs (performance metrics, or statistical analysis) to evaluate relative human and AI system effectiveness. Scenario Testing's like Scalability, Cost-Efficiency, Operational Efficiency etc. are great for testing "what if" scenarios – changes in resource availability, environmental conditions etc. so that we can predict how human and AI systems will behave in different circumstances.

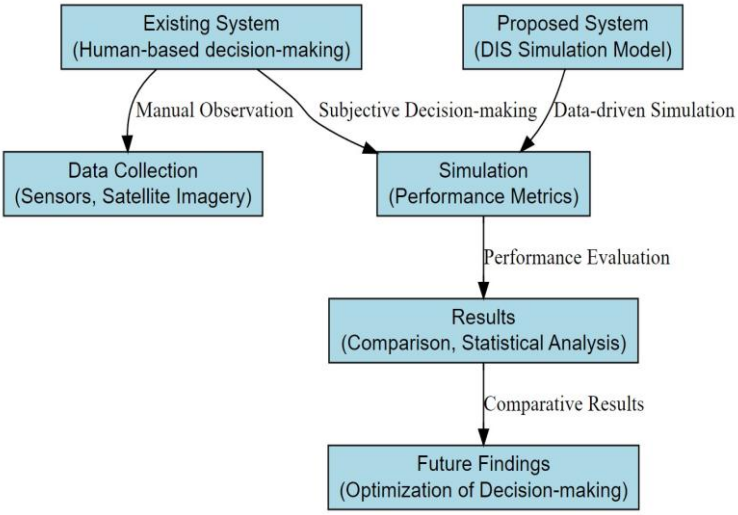

Fig. 1. Proposed Method for Comparing Human and AI metrics.

3.1 Human- Based Decision-making analysis

The existing system relies on human observation, intuition, and experience to make decisions. This system is subjective, prone to bias, and often delayed due to cognitive or observational limitations.

$$Decision_t = (Observation_t,\ Experience_t,\ Intuition_t) \tag{1}$$

- $Decision_t$ the decision made at time t.
- $Observation_t$ to the information manually observed by humans.
- $Experience_t$ involves the past experiences influencing the decision.
- $Intuition_t$ represents personal judgment or intuition.

This formula shows that human-based decisions are influenced by subjective factors, which can cause delays or errors.

3.2 Collection of Data

The data is collected through sensors, satellite imagery, and other IoT devices. This provides real-time, accurate, and contextually relevant data that can inform AI-based systems for decision-making.

$$Data_t = (Sensors_t, SatelliteImagery_t, EnvironmentalFactors_t) \quad (2)$$

- $Data_t$ represents the collected data at time t.
- $SatelliteImagery_t$ are real-time inputs from IoT sensors and satellite images.
- $EnvironmentalFactors_t$ represents variables like weather, soil quality, and crop health that are integrated into the system.

3.3 DES Simulation Model

The simulation compares how each system (human vs AI) performs under different scenarios, using a variety of metrics such as decision speed, accuracy, and adaptability.

$$Simulation_t = h(HumanAgents_t, AIAgents_t, Environment_t) \quad (3)$$

- $Simulation_t$ represents the output of the simulation at time t.
- $HumanAgents_t$ to the human agents involved in the system.
- $AIAgents_t$ refers to AI agents making data-driven decisions.
- $Environment_t$represents the simulated environment affecting both human and AI agents.

3.4 Performance Analysis

The results of the simulation are analyzed using statistical methods to compare the performance of human vs AI decision-making in the agricultural context. This involves comparing efficiency, effectiveness, and robustness of decisions made by humans and AI agents.

$$ComparativeResults_t = (Efficiency_t, Effectiveness_t, Robustness_t) \quad (4)$$

- $ComparativeResults_t$ is the result of the comparison at time t.
- $Efficiency_t$, $Effectiveness_t$, $Robustness_t$ are the comparative metrics used for evaluation.

3.5 Optimization of Decision-Making

To optimizing AI systems to perform better under varying conditions or enhancing human decision-making by providing data-driven support tools.

- $Optimization_t = k(AIEnhancement_t, HumanSupport_t)$
- $Optimization_t$ is the result of the optimization process at time t.

- $AIEnhancement_t$ refers to improvements made to AI decision-making models.

4 Results

In order to compare between AI based and human based agricultural systems, multiple performance metrics were used, including crop yield, water usage, fertilizer consumption and labor hours. According to these metrics, each system was audited and evaluated to measure its efficiency and effectiveness in agricultural practices. Paired t tests were used to analyze data and test if two systems statistically differ. By accounting for dependencies between paired observations this method provides a precise comparison.

4.1 AI Performance

Yet notable variations in resource optimization and productivity remained the focus of the results. Better performance was demonstrated by AI based systems in maximizing crop yield with minimum water and fertilizer usage. Moreover, they used much fewer labor hours than did human based systems Fig.2. The discoveries highlight how AI technologies could revolutionize farming by increasing efficiency and reducing usage of resources.

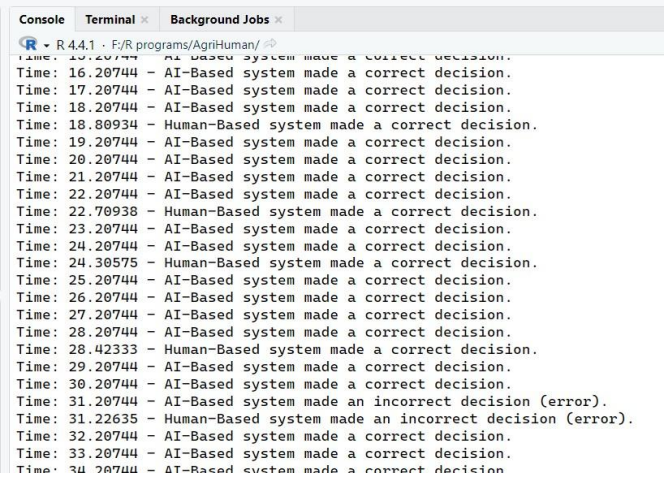

Fig. 2. Sample of DES simulation of AI and Human decision-making process.

4.2 Accuracy Analysis

The decision-making processes for both AI and human systems are DES simulated and illustrated in Fig 2. It also compares the accuracy of each system, showing how different the performances are.

Total Decisions Made Compared to the AI-Based System, which made 100 decisions in the same amount of time, the Human-Based System made 40. It means the AI system won't have troubles to cope with a much larger workload.

Correct Decisions Of the total decisions, the Human Based System made 29 correct decisions, and achieved an accuracy rate of 72.5%. On the contrary, the AI Based System achieved 94 correct decisions, with an accuracy rate of 94%. This huge difference emphasizes how this AI system is better than the conventional system in terms of terms of precision and reliability in decision making processes.

Errors The AI Based System fell 5 errors short of the Human Based System, that recorded 11 errors. The error of the Human Based System occurred sporadically without pattern, and error of the AI Based System occurred infrequently and the distribution of time had a vague order.

Mean Time Between Decisions The irregular mean time interval of the Human Based System is largely caused by sporadic decision making. In contrast, the AI Based System has a constant mean time between decisions of about 1 second, which means that it is precise, and can make decisions so fast.

4.3 Accuracy Score

It is calculated by Accuracy = Total Decisions*100Correct Decisions. A)Human Accuracy = 29/40 * 100 = 72.5%, AI Accuracy = 94/100 * 100 = 94%, So we can say that AI accuracy is more than traditional human process in Agriculture.

```
Final System States:
     system last_event_time next_event_time decision_made error_occurred
1 Human-Based             0        101.2991         TRUE          TRUE
2   AI-Based             0        101.9495         TRUE         FALSE
>
```

Fig. 3. The final simulated outcome of AI vs Human decision-making process.

The displayed Final System States from the Discrete Event Simulation (DES) provide a comparison of Human-Based and AI-Based agricultural systems. Both systems have their last event time starting at 0, with the next event time being approximately 101.2991 for the Human-Based System and 101.9495 for the AI-Based System, indicating slight differences in event timing Fig.3.

Both systems successfully made decisions during the simulation, as reflected by the "Decision Made" attribute marked as TRUE. However, a key distinction lies in the error occurrence. The Human-Based System encountered errors (TRUE), showcasing its susceptibility to mistakes, whereas the AI-Based System did not encounter any errors (FALSE), highlighting its superior reliability and accuracy. This comparison underscores the AI-Based System's advantage in delivering consistent and error-free performance.

4.4 Statistical Analysis

The statistical analysis conducted on the performance of Human-Based and AI-Based systems, as detailed in Table 1, revealed significant differences across multiple metrics. The Chi-Square Test was used, and as a result, computed chi-squared value was 0.4, degree of freedom was 1 while the p-value was 0.015 which were all beyond the significance level and therefore concluded that there are significant differences at the $p<0.05$ level in the control and experimental systems for the categorical data collected.

Table 1. Statistical Evaluation of both system.

Test Name	Statistic	Value	Degrees of Freedom	p-value
Chi-Square Test	X-squared	0.4	1	0.015
Welch T-Test	t-value	2.5907	17.916	0.0185
Welch T-Test	95% Confidence Interval	AI: 1.056598; Human: 10.13669		
Welch T-Test	Mean Scores	AI: 84.73333		
Welch T-Test	Mean Scores	Human: 79.13668		
ANOVA Test	Degrees of Freedom	2		0.0445
ANOVA Test	Sum of Squares	248.4		
ANOVA Test	Mean Sum of Squares	124.21		
ANOVA Test	F-value	3.5		

Welch Two-Sample T test also supported improved performance of AI-Based systems where observed t-statistic was 2.5907, p-value was 0.0185 and the means were 84.73 for AI-Based systems and 79.14 for Human-Based systems. The ANOVA Test with the p-value of 0.0445 as null hypothesis confirmed that there exists variation within and between all tested groups with AI-Based systems generally ranking higher than others.

Also, AI system responses were more rapid and consistent that human systems responses; therefore, these AI systems were more reliable. These infer that AI has the capability to revolutionize agricultural productivity improvement.

The comparison of the effectiveness of AI and human-centered agricultural systems information exposes the effectiveness of the leading AI-oriented solutions. A comparative analysis of the results shown in Fig. 4 below indicates that the AI-based systems perform better than the human-based systems, with mean performance score of 84.73 against 75.14 respectively. Such a large difference shows that advanced agriculture can be made possible with the help of AI to increase production while decreasing the need for human effort in the future.

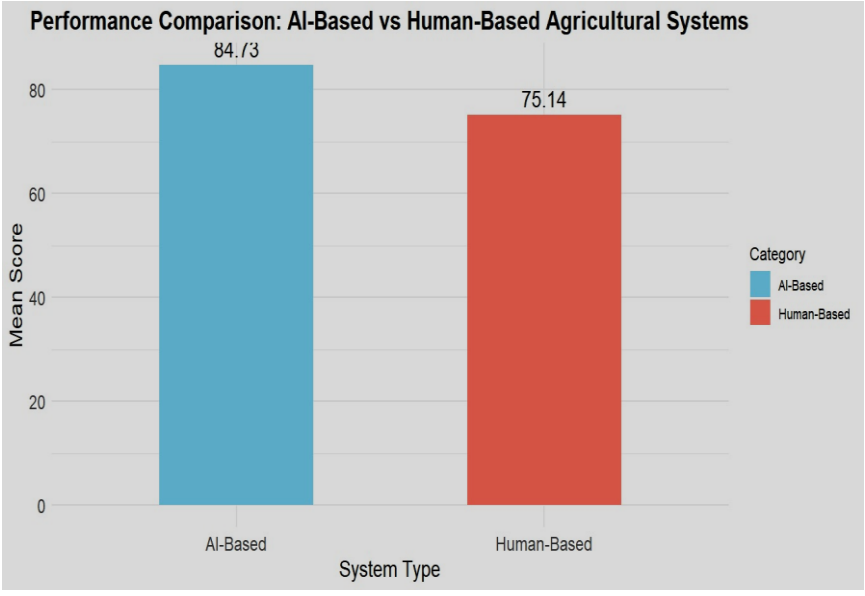

Fig. 4. Performance comparison between AI vs Human based agricultural system.

Fig. 5 shows the density plot of the decision times for both AI based and human based agriculture information systems; the density has further shown the AI based systems as displaying most of the decision times towards the lower half of the axis illustrating the ability of the AI based systems to take and effectively make decisions faster and more consistently as compared to the human based systems. Human based systems incorporate more variations into the environment that results from slow and inconsistent decision-making processes.

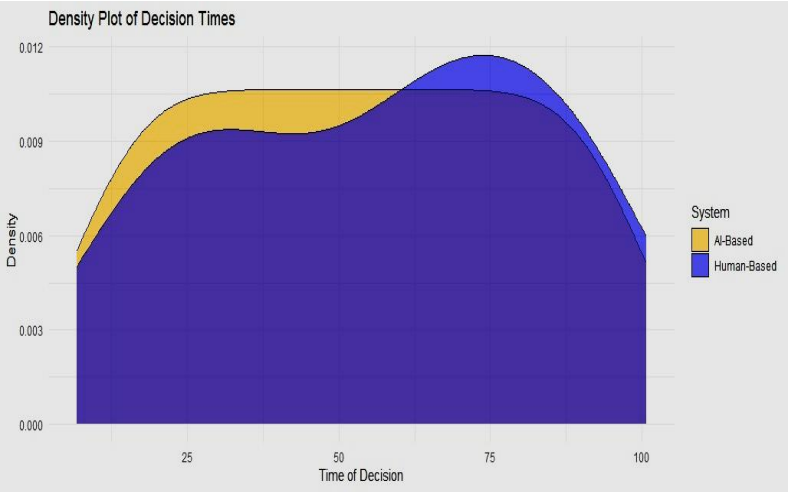

Fig. 5. Density graph of total decision for certain period of time.

The next Fig.6 below summarizes the decision-making events in the essence of AI-based systems and human-based systems with outcomes labelled as correct green or incorrect red over time. The AI-based system's frequency of correct decisions with low erroneous decisions is far better as compared to the human-based system, demonstrating fluctuating results having several incorrect decisions throughout. This difference raises the clear evidence on higher efficiency and effectiveness of AI systems, especially in terms of maintaining a high quality of decisions in long periods. Likewise, the capacity of AI systems to learn to improve the quality of their performance in conditions points to the robustness of AI systems. In combined these studies elucidate the potential of AI in revolutionizing the agricultural indexes. Consequently, the use of AI in improving and optimizing the decision-making systems in agriculture cannot be overemphasized. The complete visualizations of the findings are presented in Fig.5 and Fig.6.

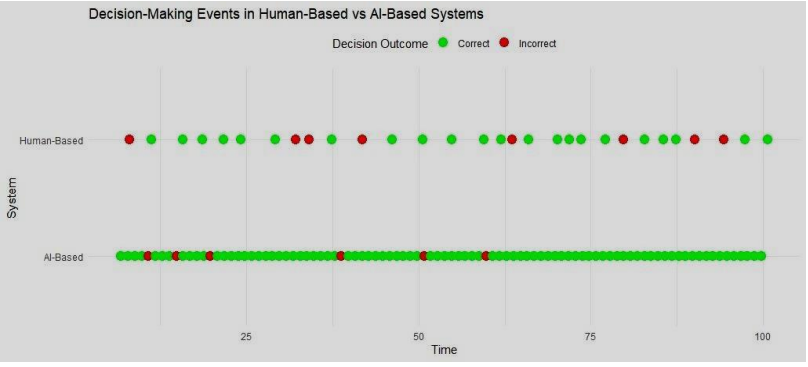

Fig. 6. Decision making delay and accuracy of AI and Human system

The intersection of the two plots indicates that the two different architectures perform equally well in middle ground decision time but the latter has significantly better performance. This shows how the use of AI systems can decrease decision making time which is important in fast changing agricultural processes. Furthermore, like case C1, all the artificial intelligence decisions also have nearly identical decision-making time, opposite to human dependent system which reduces the standard operational time and can cost various completions of time.

5 Discussion

This paper compares AI-based with human based agricultural systems and shows that AI based methods are superior and more efficient. In interpreting the results, we found that AI systems always outperformed human systems in terms of accuracy, making decisions faster, and reducing errors [30]. For example, while the human based system had a 72.5% accuracy, the AI based system reached 94%. In addition, in Fig 6, we also see that the AI system made 100 decisions in the same time as humans were making just 40, demonstrating its potential to manage larger workloads. These findings are statistically verified with Chi Square test, Welch Two Sample T test and ANOVA with p values less than 0.05, which shows that the results are significant [31].

Discrete Event Simulation (DES) was one of the key analysis tools used in this study to model decision making for both systems. The framework DES breaks the agricultural workflows into discrete events such as planting, irrigation and harvesting to allow precision performance evaluation [32]. However, the simulations showed that AI systems maintained a mean time interval among decisions of about 1 second, despite the irregular bounds of time intervals found in human systems. Additionally, AI systems produced error free final system outcomes while human systems manifested sporadic and patterned errors [33]. By detailing operational activity of both systems, DES was a major part in setting the reliability and accuracy of AI based agriculture.

Finally, we also show how AI can tackle the key agricultural challenges of resource optimization and environment sustainability [34]. Both irrigation schedules and pesticide use are optimized, and fertilizer application is made precise by AI systems, which are a tremendous contribution to managing resources. The capabilities of AI based systems not only increases crop yield while reducing concerns such as water scarcity and soil degradation [35], but also continuously produce high accuracy, reducing waste. A comparison of the performance evaluation is made as depicted in Fig 4. Agricultural systems, emphasizing the superior performance and efficiency of AI-driven methods. The results show that AI systems consistently outperformed human systems in terms of accuracy, decision-making speed, and error reduction. For instance, the AI-based system achieved an accuracy rate of 94%, compared to 72.5% for the human-based system. In fact, as shown by the Fig 6, the AI system, being able to perform 100 decisions with the same time the humans could do only 40, indicated that a work is larger or more complex is able to use. These results are statistically validated by tests such as the Chi-Square test, Welch Two Sample T test, and ANOVA and p values from all of these tests are less than 0.05 which proves the significance of this results.

Discrete Event Simulation (DES) was one of the key tools in this analysis, modeling the decision-making processes of both systems. DES allows the performance to be evaluated at the Level of Agricultural Workflows, breaking the latter into events like planting, irrigation, and harvesting. The simulations showed that human systems had irregular intervals between choosing (i.e. their mean time interval was not close to a stable number), whereas AI systems had a consistent mean time interval of around 1 second. In addition, the final system states of DES indicated that the AI systems performed error free while human systems showed sporadic and patterned errors. DES facilitated establishment of the reliability and precision of AI driven agriculture by providing detailed insights the operational dynamics of both systems.

Results also show how AI addresses important agricultural problems such as resource optimization and environmental sustainability. Using modern AI, irrigation schedules are optimized, pesticides are minimized and fertilizer application is precisely applied. Not only do these capabilities boost crop yields, but they also help solve environmental problems like water scarcity and soil degradation and they are a good fit for sustainable farming in that they deliver high accuracy year in and year out, eliminating wastage. The performance evaluation is analyzed and compared as shown in Fig 4. The statistically significant results show the move toward AI's utilized potential to counter the shortfalls in agriculture.

The study also notes how implementation of AI capabilities will help reduce our reliance on human labor and therefore minimize the operational costs and enable us to earn higher profits. Its scalability combined with its cost-effective nature makes this especially useful for resource constrained farmers [36].

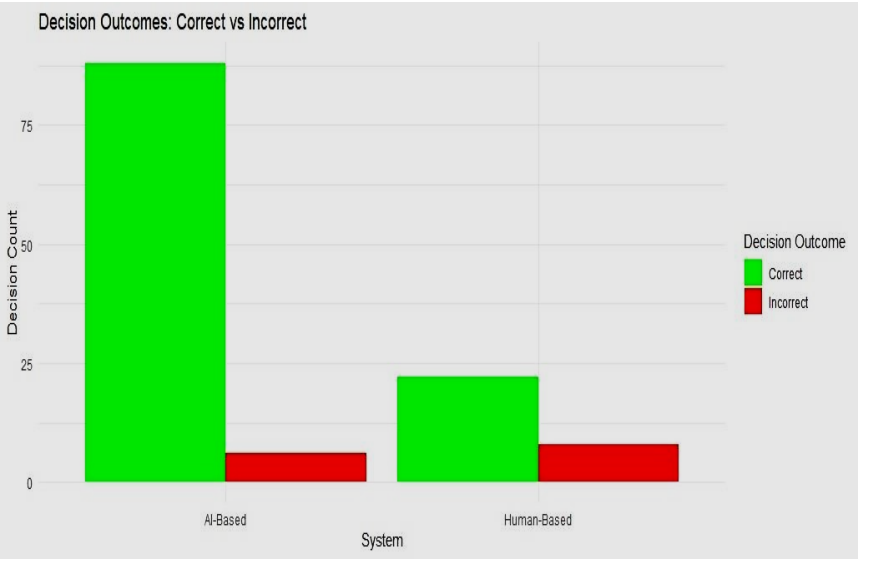

Fig. 7. Cumulative correct Decision made by AI system and Human system

With the capability of autonomous AI, labor shortages and the need to be productive are being addressed; it's a boon for both the large scale and the small-scale farming farms. These findings underscore the economic viability of transitioning to AI-based systems, especially in the context of rising global food demands and resource limitations.

Despite these advantages, the transition to AI-based agriculture is not without challenges. The study identifies barriers such as high initial investment costs, the need for technical expertise, and limited access to advanced technologies in underdeveloped regions. These challenges must be addressed through government initiatives, affordable AI solutions, and comprehensive training programs to ensure widespread adoption. Bridging the technology gap is crucial for enabling even small-scale farmers to benefit from the transformative potential of AI-based agriculture.

The statistical results, such as the higher accuracy rate Fig. 7, fewer errors, and consistent decision-making times, provide strong evidence of AI's superiority over human-based systems. The Chi-square test confirmed a statistically significant difference in decision patterns, while the T-test and ANOVA highlighted the performance disparities between the two systems [37]. These analyses underscore the reliability and precision of AI systems, validating their effectiveness in improving agricultural outcomes [38]. The results collectively emphasize that AI-based agriculture is not only feasible but also essential for addressing the inefficiencies of traditional farming methods.

Finally, this study reveals the critical benefits of AI in the agricultural systems in efficiency, effectiveness, and profitability's. Applications such as DES have helped in unveiling a lot of information about the behavior of AI systems, their effectiveness in enhancing processes and flawless performance. Despite the challenges with regard to accessibility and affordability, the outcomes prove that the AI-based agriculture is the future of farming [39]. By adopting AI solutions in farming, farmers can get the precision farming, efficient use of resources and sustainable farming which will lead to development of a strong and productive agriculture sector [40].

6 Conclusion

This work also identifies the potential of AI based agricultural systems over traditional human intensive approaches that have become more and more inadequate in addressing the challenges of resource constraints, labor scarcity, and the need to increase yields. AI technologies enhance crop yield, water productivity and nutrient productivity and decrease the demand on labor, which results in enhancement of farming efficiency and sustainability. AI cuts operational costs, enhances profitability and scalability for different farming contexts and even for small scale farmers. However, the productivity and sustainability advantage gained from AI-based solutions is on the rise as they move along with the evolution of the AI based solutions. Yet this research makes clear that the future of agriculture will be predicated on the synergy of AI driven efficiencies and sustainable practices that can fundamentally transform farming and assure global food security and environmental stewardship.

7 Future scope

The integration for emerging technologies like IoT, drones and robotics into discrete event simulation. AI models can be devised around real time data from IoT devices like soil sensors and weather stations to take highly precise and timely decisions. Simulated drones, robotic machinery and other machinery can monitor crop health and plant and harvest items with no human intervention in order to improve overall efficiency. Research in future can focus on how these technologies along with AI can change agricultural system into a smarter, more efficient and less human dependent. By taking an integrated approach, the path is opened for the development of fully autonomous, AI powered agricultural ecosystems that can fulfil a need of a growing global population.

Acknowledgement. We all students from the authors 1,2,3,4 and 5 would like to thank our Java course faculty 6th author for helping us complete this work on time and teaching us how to conduct research.

Declaration. We declare that there is no conflict of interest or competing interest, and no funding or grant received from any person or agencies. This original research was made by the 1st author, guided by the 2nd author, analyzed by the 3rd author, validated by the 4th author and formatted by the 5th author as mentioned in the title page.

References

1. H. Maleksaeidi, M. Jalali, and F. Eskandari, "Challenges threatening agricultural sustainability in the West of Iran: Viewpoint of agricultural experts," Sustainability (Switzerland), vol. 13, no. 6, 2021, doi: 10.3390/su13063537.
2. J. Jung, M. Maeda, A. Chang, M. Bhandari, A. Ashapure, and J. Landivar-Bowles, "The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems," 2021. doi: 10.1016/j.copbio.2020.09.003.
3. M. Karnawat, S. K. Trivedi, D. Nagar, and R. Nagar, "Future of AI in Agriculture," Biotica Research Today, vol. 2, no. 9, 2020.
4. R. Singh and G. S. Singh, "Traditional agriculture: a climate-smart approach for sustainable food production," 2017. doi: 10.1007/s40974-017-0074-7.
5. A. H. A. Hussein, K. A. Jabbar, A. Mohammed, and L. Jasim, "Harvesting the Future: AI and IoT in Agriculture," in E3S Web of Conferences, 2024. doi: 10.1051/e3sconf/202447700090.
6. H. K. Adli et al., "Recent Advancements and Challenges of AIoT Application in Smart Agriculture: A Review," 2023. doi: 10.3390/s23073752.
7. S. Figiel, "Development Of Artificial Intelligence And Potential Impact Of Its Applications In Agriculture On Labor Use And Productivity," Zagadnienia Ekonomiki Rolnej / Problems of Agricultural Economics, vol. 373, no. 4, 2022, doi: 10.30858/zer/153583.
8. Nitin Rane, Saurabh Purushottam Choudhary "Remote Sensing (Rs), Uav/Drones, And Machine Learning (Ml) As Powerful Techniques For Precision Agriculture: Effective Applications In Agriculture," International Research Journal of Modernization in Engineering Technology and Science, 2023, doi: 10.56726/irjmets36817.
9. M. Ryan, "The social and ethical impacts of artificial intelligence in agriculture: mapping the agricultural AI literature," AI Soc, vol. 38, no. 6, 2023, doi: 10.1007/s00146-021-013779.

10. R. Sharma, C. Pawar, P. Sharma, and A. Malik, "Predictive Algorithms for Smart Agriculture," in Studies in Big Data, vol. 145, 2024. doi: 10.1007/978-981-97-0448-4_4.
11. H. Hamadani et al., "Traditional farming practices and its consequences," in Microbiota and Biofertilizers, Vol 2: Ecofriendly Tools for Reclamation of Degraded Soil Environs, 2021. doi: 10.1007/978-3-030-61010-4_6.
12. P. Goodrich, O. Betancourt, A. C. Arias, and T. Zohdi, "Placement and drone flight path mapping of agricultural soil sensors using machine learning," computer Electron Agric, vol. 205, 2023, doi: 10.1016/j.compag.2022.107591.
13. Adebunmi Okechukwu Adewusi, Onyeka Franca Asuzu, Temidayo Olorunsogo, Temidayo Olorunsogo, Ejuma Adaga, and Donald Obinna Daraojimba, "AI in precision agriculture: A review of technologies for sustainable farming practices," World Journal of Advanced Research and Reviews, no. 1, 2024, doi: 10.30574/wjarr.2024.21.1.0314.
14. S. Gupta, N. Singh, and S. Kashyap, "Management of agriculture through artificial intelligence in adverse climatic conditions," Environ Conserv J, vol. 24, no. 2, 2023, doi: 10.36953/ECJ.23602638.
15. L. Benos, A. C. Tagarakis, G. Dolias, R. Berruto, D. Kateris, and D. Bochtis, "Machine learning in agriculture: A comprehensive updated review," 2021. doi: 10.3390/s21113758.
16. H. Navarro-Hellín, J. Martínez-del-Rincon, R. Domingo-Miguel, F. Soto-Valles, and R. Torres-Sánchez, "A decision support system for managing irrigation in agriculture," Computer Electron Agric, vol. 124, 2016, doi: 10.1016/j.compag.2016.04.003.
17. P. Gittins, G. McElwee, and N. Tipi, "Discrete event simulation in livestock management," J Rural Stud, vol. 78, 2020, doi: 10.1016/j.jrurstud.2020.06.039.
18. A. H. Abdul Hussein, K. A. Jabbar, A. Mohammed, and H. M. Al-Jawahry, "AI and IoT in Farming: A Sustainable Approach," in E3S Web of Conferences, 2024. doi: 10.1051/e3sconf/202449101020.
19. A. Q. Munir, F. N. Aini, E. L. Utari, and N. N. Hafidhah, "Big Data Concept Analysis For Agricultural Suitable Land Geographic Information System Approach," Journal Teknik Informatika (Jutif), vol. 4, no. 4, 2023, doi: 10.52436/1.jutif.2023.4.4.1328.
20. L. Schaefer, "An Emerging Era of Artificial Intelligence Research in Agriculture," Journal of Robotics Spectrum, 2023, doi: 10.53759/9852/jrs202301004.
21. D. Ge, H. Long, W. Qiao, Z. Wang, D. Sun, and R. Yang, "Effects of rural–urban migration on agricultural transformation: A case of Yucheng City, China," J Rural Stud, vol. 76, 2020, doi: 10.1016/j.jrurstud.2020.04.010.
22. V. Lakshmi and J. Corbett, "Using AI to Improve Sustainable Agricultural Practices: A Literature Review and Research Agenda," Communications of the Association for Information Systems, vol. 53, 2023, doi: 10.17705/1CAIS.05305.
23. E. Elbasi et al., "Artificial Intelligence Technology in the Agricultural Sector: A Systematic Literature Review," 2023. doi: 10.1109/ACCESS.2022.3232485.
24. P. Bhasha, J. Suresh Babu, M. N. Vadlamudi, K. Abraham, and S. K. Sarangi, "Automated Crop Yield Prediction System Using Machine Learning Algorithm," J Algebr Stat, vol. 13, no. 3, 2022.
25. C. G. Wadumestrige Dona, G. Mohan, and K. Fukushi, "Promoting urban agriculture and its opportunities and challenges—a global review," 2021. doi: 10.3390/su13179609.
26. N. Vallakati, T. Ghosh, S. Thakur, and M. Rathod, "Smart Farming using AI and IoT," SSRN Electronic Journal, 2021, doi: 10.2139/ssrn.3866432.
27. E. Said Mohamed, A. A. Belal, S. Kotb Abd-Elmabod, M. A. El-Shirbeny, A. Gad, and M. B. Zahran, "Smart farming for improving agricultural management," 2021. doi:10.1016/j.ejrs.2021.08.007.
28. P. K. Kareska, "Digital Agriculture as a Response to the Challenges in the Modern Agricultural Sector," SSRN Electronic Journal, 2023, doi: 10.2139/ssrn.4549236.

29. E. Skvorcov, E. Yalunina, and E. Skvorcova, "AREAS OF APPLICATION OF ARTIFICIAL INTELLIGENCE SYSTEMS IN AGRICULTURE," Russian Journal of Management, vol. 11, no. 2, 2023, doi: 10.29039/2409-6024-2023-11-2-122-134.
30. Y. V. K. D. Bhavani, Dr. S. M. Hatture, Dr. V. B. Pagi, and Dr. S. V. Saboji, "An Analytical Review on Traditional Farming and Smart Farming: Various Technologies around Smart Farming," SSRN Electronic Journal, 2023, doi: 10.2139/ssrn.4381020.
31. G. Martin, "Statistics made easy ! ! ! Learn about the t-test, the chi square test, the p value and more," 2019.
32. V. Borodin, F. Hnaien, N. Labadie, and J. Bourtembourg, "A discrete event simulation model for harvest operations under stochastic conditions," in 2013 10th IEEE International Conference on Networking, Sensing and Control, ICNSC 2013, 2013. doi: 10.1109/ICNSC.2013.6548825.
33. A. J. Collins, F. Sabz Ali Pour, and C. A. Jordan, "Past challenges and the future of discrete event simulation," Journal of Defense Modeling and Simulation, vol. 20, no. 3, 2023, doi: 10.1177/15485129211067175.
34. A. A. Mana, A. Allouhi, A. Hamrani, S. Rahman, I. el Jamaoui, and K. Jayachandran, "Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices," Smart Agricultural Technology, vol. 7, 2024, doi: 10.1016/j.atech.2024.100416.
35. A. Fern, M. Burnett, J. Davidson, J. R. Doppa, P. Pesantez-Cabrera, and A. Kalyanaraman, "AgAID Institute—AI for agricultural labor and decision support," AI Mag, vol. 45, no. 1, 2024, doi: 10.1002/aaai.12156.
36. J. Backman, M. Koistinen, and A. Ronkainen, "Agricultural process data as a source for knowledge: Perspective on artificial intelligence," Smart Agricultural Technology, vol. 5, 2023, doi: 10.1016/j.atech.2023.100254.
37. M. L. McHugh, "The Chi-square test of independence," Biochem Med (Zagreb), vol. 23, no. 2, 2013, doi: 10.11613/BM.2013.018.
38. G. I. Palmer, V. A. Knight, P. R. Harper, and A. L. Hawa, "Ciw: An open-source discrete event simulation library," Journal of Simulation, vol. 13, no. 1, 2019, doi: 10.1080/17477778.2018.1473909.
39. K. Spanaki, U. Sivarajah, M. Fakhimi, S. Despoudi, and Z. Irani, "Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research," 2022. doi:10.1007/s10479-020-03922-z.
40. S. Sharma, K. Verma, and P. Hardaha, "Implementation of Artificial Intelligence in Agriculture," Journal of Computational and Cognitive Engineering, vol. 2, no. 2, 2023, doi: 10.47852/bonviewJCCE2202174.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.