



Artificial Intelligence (AI) in Agriculture and Accountability (Liability): A Legal Perspective

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Abstract. Artificial intelligence is rapidly transforming agricultural sector resulting in precision farming, increased productivity through resource management. Hence, it is necessary to examine this integration from legal perspective focusing on accountability for losses caused. The literature existing till date primarily emphasis on technological advancements of AI in agricultural sector. There is a considerable lack of literature focusing on legal complexities and challenges concerning the harm caused by AI driven decisions in agricultural sector. This research has adopted a mixed method approach developed with combination of doctrinal legal analysis and empirical fieldwork. A total of 49 stakeholders, including farmers, developers, legal professionals and policymakers constituted the primary data. The primary data includes perceptions about the liability for harm caused due to AI, the technical capacity of user farmers and operational risks involved in integration of AI in agricultural sector. The survey findings have shown that there is a substantial disconnect between the technological innovations in agricultural sector and the legal accountability for the harm caused due to such advancements. This research study has also identified the challenges relating the applicability of existing legal principles. It includes vulnerability of data security, unpredictable environmental factors lack of technical awareness among the end user farmers causing difficulties in establishing liability under the traditional tort law principles. Hence, the paper argued that a hybrid regulatory framework developed with the combination of elements of strict liability, risk distribution and mandatory insurance liability of government can ensure equitable accountability in integration of AI in the agricultural sector.

Keywords: AI Accountability, AI in Agriculture, Precision Farming, AI Tortuous Liability, AI Product Liability.

1 Introduction

The role of agricultural sector is undoubtedly pivotal contributing approximately 18% of GDP and also employing nearly half of the workforce of the country [1]. It is surprising, however that the sector has low productivity, largely depending on a monsoon rainfall, and vulnerable to other climate change vulnerabilities. The situation is further exacerbated by increasing food security challenges [2]. Hence, agricultural sector has significant potential to contribute more in the development of country, if technological advancements integrated in the sector. It gave rise to the use of Artificial Intelligence (AI) Technologies including machine learning, robotics, and data analysis systems to address the above mentioned challenges and enhance productivity by optimizing use of resources [3]. In a very short time, the integration of AI into agricultural sector has developed opportunities for precision farming, smart agriculture, and autonomous farming systems enabling the real time monitoring, predictive analysis and automation of processes increasing efficiency and reducing the environmental impact [4]. This integration also helped in achieving sustainable goals, specifically, the goals relating to food security and environmental sustainability [5].

However, along with the potential benefits, the integration of AI in agriculture has also raised significant concerns, specially about ethical governance, regulation, socio-economic inequalities and the accountability for losses caused due to such integration and limitations of the existing dispute resolution frameworks [6]. In light of this background, this paper aims to provide a comprehensive analysis of opportunities and challenges raised by integration of AI in agriculture with a particular focus on the legal, ethical, and regulatory frameworks encompassing liability under tort law.

2 Methodology

The researchers used both research methodologies, i.e., an empirical research design paired with critical doctrinal analysis. To evaluate contemporary perceptions of tortious liability, predictability, and operational risk in agricultural AI systems, empirical primary data was gathered from an intentionally structured group of forty-nine (N=49) domain-specific stakeholders. Participants were screened against minimum eligibility requirements: technical developers needed a minimum of two years designing or deploying machine-learning/hardware architectures for agricultural purposes, legal experts required active research or practice in technology/tort law, and farmers/users were required to have active operational experience with precision or smart farming platforms.

The texts were analyzed using three functional nodes including, firstly, environmental interfaces and data fragmentation; secondly, technological asymmetry of capacity barriers and lastly, casual attributability with systematic opacity. This achieved qualitative coding framework and inter-coder reliability. To mitigate possible substantive bias, the raw database was coded by two independent legal and technical researchers. The inter-coder reliability was statistically evaluated by using Cohen's Kappa coefficient. The alignment across all structural categories was ensured thereby. In this process the initial coding resulted in a strong overall baseline agreement (i.e. $\kappa = 0.84$). Just before finalizing the empirical findings, the authors have carried out some minor semantic divergences regarding the classification of joint technical liability v/s strict liability of product defects via an algorithmic arbitration protocol.

The primary data received in a survey from forty nine (N=49) stakeholders was cross-tabulated across all the core operational cohorts. It helps in understanding divergent structural roles influencing views of stakeholders on the liability of harm caused and technological capacity of user farmers. Due to the small sample size, this statistical analysis is based on Fisher's Exact Test (extended $R \times C$ contingency table). It has mitigated the sample size limits of traditional Chi-Square (χ^2) approximations. This is equally applicable to overcome small sample size across all segments.

A high rate of practical field exposure (i.e. 57.14% for n=28) of total respondents using or directly witnessing integration of AI in agricultural sector. It is to be noted that in the technology developer segment this exposure reached a very high rate (i.e. 89.47 for n=17 and in the legal professional segment it is lowest (i.e. 29.41% for n=5). This analysis highlights an experiential gap between the technology creators and legal professionals. When assessing current deployment domains, 38.78% (n=19) of the respondents have identified precision crop production as the primary vehicle for AI, closely followed by operational efficiency and resource management at 34.69% (n=17).

3 Literature Review And Research Gap

The literature on the application of AI in Agriculture has shown that the use of AI is gradually increasing with the support of governmental initiatives and private sector innovations. AI is being used in schemes like crop insurance programs to estimate yields and reduce costs. According to Giri A *et al.*, the key contributions of the use of AI in Agriculture in India revolve around improved crop productivity, reduced dependence on monsoon, enhanced farmer income, and efficient resource management [1]. Agriculture is highly weather-dependent. Hence, farmers need short-term weather forecasting as well as climate change modelling. AI plays a crucial role in climate-resilient farming by predicting weather patterns and minimizing environmental risks [5]. AI-powered image recognition systems and applications also detect various plant diseases with greater accuracy than human intelligence [7]. AI-powered systems detect abnormalities in crops and also recommend appropriate treatments and pesticides [8]. AI technologies monitor soil conditions of a large-scale area through sensors and remote sensing tools to provide information on soil moisture, temperature, nutrient levels, and accordingly help in enhancing soil health by promoting sustainable agriculture [9]. Similarly, the AI-based irrigation systems use

sensor data to optimize water usage and reduce water wastage, which help in improving crop yield. Such AI-based systems control water usage by analyzing soil moisture, weather conditions, and crop requirements and ensure that crops receive the precise amount of water at the right time, reducing water wastage [10]. Actionable insights are being provided by AI-powered decision support systems (DSS) so that farmers can decide upon crop selection, risk assessments during crop growth stages, along with yield predictions and market price forecasting. These systems enhance decision-making and thereby improve farm profitability. Some AI models, such as deep neural networks and ANNs based on environmental and agronomic data, are being widely used for that purpose [11].

However, the poor design and configuration of AI systems may cause harm and unintended consequences in digital agriculture by breaching privacy and leading to data theft [12]. Accountability of farmers, sellers, and developers is unclear in case an AI decision causes loss to agriculture, such as loss of crops, excessive spraying, and harm to livestock [13]. The liability for damages caused by the use of AI systems is primarily governed by tort law. It provides remedies for harm caused by wrongful actions [14].

The literature mentioned above indicates a potential research gap as it predominantly focuses on technological advancements, efficiency enhancement, precision farming, and sustainability outcomes, and the legal accountability dimensions of AI-driven agricultural practices remain significantly underexplored. The existing literature on the use of AI in agriculture has shown that there is a noticeable lack of comprehensive analysis addressing tortious liability and attribution of responsibility when AI systems malfunction or produce erroneous outputs leading to crop loss, environmental damage, and economic harm. Another significant research gap lies in the absence of a context-specific legal framework regulating the multi-stakeholder complexity where developers, service providers, hardware manufacturers, and end-users interact to resolve issues of evidentiary challenges, access to algorithmic data, accountability logs, and a regulatory framework of strict liability, hybrid liability, and mandatory insurance.

4 The Potential Benefits And Risks Of Using AI In Agriculture

The use of AI seems to be increasing mainly due to some prominent benefits like time saving, soil analysis, detection of diseases, and overall encouraging sustainable farming. With the use of AI, the user can analyze the type of soil so that they can decide the type of crops and when they can perform harvesting [15]. Similarly, early disease detection helps farmers to save time by adopting the best strategies to fight diseases. It reduces human efforts by monitoring the health and diseases of animals. AI-based technologies have large potential opportunities for efficient resource management, risk minimization, and improved financial decision-making. For example, precision irrigation minimizes the use of water, which is cost-saving. AI can identify leaks in irrigation or water supply with the help of sensors, and prompt action can be taken. [11].

The main potential risks associated with the use of AI in agriculture revolve around technical risks, lack of accountability, poor design and configuration, etc. It may result in a privacy breach leading to data theft. AI tools are used to work on behalf of human beings or make decisions on their behalf. AI is not advanced enough to think about what is morally right and wrong. Hence, a question arises about who is accountable or responsible, whether regulators, technology developers, or users [16]. AI may bring many benefits for agricultural producers, the environment, and consumers, but also significant risks. The accountability of farmers, sellers, and developers is unclear in case an AI decision causes loss to agriculture, such as loss of crops, excessive spraying, and harm to livestock [13].

5 Tortuous Liability For Losses Caused By Use Of AI

For shouldering the tortuous liability, the traditional tort law requires the existence of five mandatory elements including conduct, wrongfulness, fault, causation and harm [17]. In this framework the standard of 'reasonable man' plays very crucial role deciding whether the defendant has acted with a due care [18]. While applying this to the tortuous liability for the harm caused by the use of AI, such a framework raises a fundamental question i.e. should tortuous liability be assessed based on the conduct of the AI system or the human actors involved in the integration of AI in agricultural sector?

According to the traditional tort law principles the AI should be treated as a tool and not as a independent legal entity/ artificial person. It means the tortuous liability should be always attributed to human intelligence either which designed or deployed or operates AI systems. This approach is based on legal fiction that the AI does not directly causes accident and the accident is outcome of actions by individual with human intelligence [19]. The validity of this argument can be discussed further in applying this legal fiction for the integration of AI in agricultural sector.

It is to be understood that all AI technologies rely on collected data, processing tools and predictive analytics. It includes the use of sensors, drones and machine learning algorithms developed for making decisions [9]. While applying it in agricultural sector, all these technologies face risks resulted due to data accuracy, system reliability and environmental unpredictability. Therefore, all AI technologies fully depend on the correctness and reliability of large datasets and different algorithmic models procuring, in some cases inaccurate and unintended outcomes. It may result in financial losses, environmental damages and even physical harm to human beings.

5.1 Negligence And Liability

Under the tort law jurisprudence, the failure to take care of duty amounts to negligence whenever there is a duty to take care. In this analysis one of the most important elements of negligence is the foreseeability. It determines predictability of the harm caused along with the possibility to avoid such harm [20]. It is to be noted that application of these theoretical/ jurisprudential principles in the practical realities in the field of agricultural sector is very complex. The AI systems integrated in agricultural sector, hence, often functions as 'black boxes' within decision making processes resulting in a lack of transparency. Therefore, it becomes very difficult to determine how a particular decision was made by the AI system which complicates the identification of 'fault' as required for shouldering tortuous liability [21]. It complicates the assessment of foreseeability as it is difficult to predict specific outcomes of integration of AI in agricultural sector. This gave rise to one of the apparently valid arguments that the harm caused by the use of AI systems was unforeseeable and hence, not actionable as negligence under the tort law.

On this line of thought, it is to be noted that the unpredictability of AI systems is not entirely inherent and it may be result of design choices made by the developers while prioritizing efficiency over transparency. Hence, the counter argument is - it is unjust to allow the developers to evade liability on the grounds of unforeseeability. Therefore, it is argued that this is the right standard for AI liability, and in the context of using AI in agriculture, foreseeable risks associated with the AI systems must include malfunctioning, inaccurate data, inaccurate data analysis, and improper recommendations.

It is also to be noted that the use of AI in agriculture involves an interplay between multiple stakeholders like developers, manufacturers, data providers, service providers, and end-users. This complicates the attribution of liability as the harm may result from the interaction of several stakeholders [22].

5.2 Vicarious Liability

The principle of vicarious liability is based on the principal-agent relation. The principal is liable for the civil wrong of the agent, as the agent is acting on behalf of the principal, and he is acting as per the direction given by the principal. In case of crime, the liability of the principal is limited to the crime committed by the agent. The principal is liable for the crime committed by the agent only if the principal is equally involved in committing the crime.

This approach, contradicting with the earlier arguments, imposes liability on person who deploys AI for commercial purpose, even though they are not at the direct fault. Under this vicarious liability principle, the employers and operators are treated liable to the actions of their agents. While applying this principle to the integration of AI in agriculture sector, this principle raises issues about attribution of liability to developers, operators or end user farmers as they all play their limited role in 'deploying' AI systems in agricultural sector.

5.3 Product Liability And Strict Liability

The product liability approach developed under tort law treats AI systems as a product and hence argues that the manufactures are to be held liable for any defects causing harm to the end user farmers. This liability exists irrespective of careful behaviors on the part of manufacturers. In certain cases this principle also presumes the harm caused without requiring proof of fault [23]. Hence some considered this the most suitable approach for complex technologies like AI [14].

However, there exists a counter argument that treating technologies as products or services remains a constant debatable issue creating legal challenges. On this line of thought the dynamic and adaptive nature of AI complicates the matter undoubtedly. Despite of such challenges in integration of AI in agricultural sector, some researchers believe that the strict liability principle may enhance the burden of victim compensation on the manufacturers and developers [23]. It will solve the problem of difficulty of proving causation and fault due to which most of the AI-related damage claims are unsuccessful.

Access to evidence also plays a crucial role in establishing liability for the harm caused. All relevant information, such as system logs and algorithmic data, may be inaccessible due to proprietary restrictions [24]. Hence, the Courts need to adopt innovative approaches to access and appreciate the evidence.

6 Liability Of Stakeholders As Per Existing Legal Norms

AI systems can cause harm in a variety of ways such as incorrect decision-making, faulty recommendations, or operational failures. Recently, integration of the Internet of Things (IOT) has exposed AI technologies to cyber-security risks due to unauthorized access and data manipulation. This may affect agricultural operations, leading to more losses. Similarly, liability issues become more complex due to the autonomous and self-learning nature of AI systems, which may act unpredictably and beyond direct human control [14]. This creates a situation where developers cannot predict how their AI will learn, change its behavior from experience, and arrive at “its own” decision [23]. In agriculture, it may result in incorrect crop treatment, overuse of chemicals, or even machinery accidents.

There are mainly two stakeholders in terms of legal norms of tortious liability, firstly the developer, and secondly, the user or operator. As developers play a critical role in designing AI technologies, they are responsible for ensuring the safety and reliability of AI systems. The liability of developers may arise when harm is caused due to some design defects, inadequate testing, or failure to implement sufficient safety measures [25]. The developers may also be held accountable for creating AI systems that lack transparency and hence increase the risk of unforeseen harm.

The individual farmer or agricultural enterprise using AI technologies may also bear liability if the AI fails due to lack of reasonable care [26]. Hence, the users shall bear a duty to verify the working of AI systems before deploying and ensure proper maintenance throughout its natural duration of life. This concept of ‘duty to verify’ requires farmer users to exercise due diligence while relying on any AI outputs.

7 Data Collection And Analysis

The researchers collected data from a total of 49 stakeholders as stratified into four distinct, mutually exclusive categories to facilitate group-level comparative analysis. *Firstly*, farmers/users (n=9, 18.37%) representing agricultural producers with practical operational experience managing commercial crops using smart technologies. *Secondly*, agri-tech enterprise & software developers (n=19, 38.78%) representing software engineers, system architects, and technical service providers developing algorithmic systems for agriculture. *Thirdly*, the legal professionals and academicians (n=17, 34.69%), who represent practicing advocates, legal consultants, and academic researchers with a focused area of torts, cyber law, and digital governance, and *lastly*, the government and regulatory officials (n=4, 8.16%), who represent policymakers and government departmental officials having a focus on smart governance and policy standardization.

7.1 Treating Software Errors As “Defective Products” Under Tort Law

The present survey has a question i.e. should an AI software error (e.g. misinterpreting soil pH leading to crop loss) be treated strictly as a ‘defective product’? While analyzing the risk perceptions, defective product classification and liability allocation the following key variables were cross tabulated against the structural cohorts-

Table 1. Cross-Tabulation on Treating Software Errors as “Defective Products” Under Tort Law. [Fisher’s Exact Test p-value < 0.001; 95% CI for Legal Agreement: 56.6% to 96.2%].

Stakeholder Cohort	Strongly Agree / Agree	Neutral	Disagree / Strongly Disagree	Total (n)
Farmers / End-Users	77.78% (n=7)	11.11% (n=1)	11.11% (n=1)	9
Tech Developers	15.79% (n=3)	21.05% (n=4)	63.16% (n=12)	19
Legal Professionals	82.35% (n=14)	5.88% (n=1)	11.76% (n=2)	17
Government / Regulators	75.00% (n=3)	25.00% (n=1)	0.00% (n=0)	4
Total Sample	55.10% (n=27)	14.29% (n=7)	30.61% (n=15)	49

The above cross-tabulation has shown a highly polarized legal v/s technical divide with statistical significance (i.e. $p < 0.001$). In this case the agreements of legal professionals and end user farmers are 82.35% and 77.78% respectively. The agreement is in favor of a strict product liability framework. This seems to be based on the shared protective instinct of treating algorithmic failures as product defects, which shifts the burden of proof away from the vulnerable end user farmers. However, it is to be noted that this approach bypasses the complex task of establishing negligence within the software ‘black box’ feature. On the other hand, the significant strata of technology developers (i.e. 63.16%) do explicitly reject this. It seems to be based on the argument that the algorithms operate within highly volatile and unpredictable ecosystem which needs dilution of liability of technology developers.

7.2 AI Drone Misidentification And Liability Allocation

The present survey has a question i.e. who should be held liable if an AI drone misidentifies a healthy crop as a weed and destroy it? While analyzing the liability allocations, following key variables were cross-tabulated against the structural cohorts-

Table 2. Cross-Tabulation on Drone Misidentification and Liability Allocation. [Fisher’s Exact Test p-value < 0.042; Significant at $\alpha = 0.05$].

Stakeholder Cohort	Joint Software/ Hardware	Sole Software	Sole Hardware	User/ Farmer	Total (n)
Farmers / End-Users	66.67% (n=6)	22.22% (n=2)	11.11% (n=1)	0.00% (n=0)	9
Tech Developers	52.63% (n=10)	10.53% (n=2)	21.05% (n=4)	15.79% (n=3)	19
Legal Professionals	76.47% (n=13)	23.53% (n=4)	0.00% (n=0)	0.00% (n=0)	17
Government / Regulators	50.00% (n=2)	50.00% (n=2)	0.00% (n=0)	0.00% (n=0)	4
Total Sample	63.27% (n=31)	20.41% (n=10)	10.20% (n=5)	6.12% (n=3)	49

The above cross-tabulation demonstrates clear majority across all cohorts (63.27% overall) gravitated the joint liability of software and hardware developers. This majority consensus suggests a widespread understanding among the stakeholders about the operation of modern agricultural AI. This understanding underlines AI as a product of integrated cyber-physical systems based on software inputs and physical actuations which are deeply dependent on each other.

It is to be noted that there is a significant fraction of technology developers (15.79%, n=3) shifting the liability of harm to the user farmers, highlighting improper operation or failure to monitor the AI devices in real time by the user farmers as a cause of harm caused by the failure of AI. One more notable thing in this analysis is that not a single legal professional or government regulator has accepted liability of user farmers in this scenario. This is because of the understanding that the rapid automated mechanical harm is an event that exceeds any reasonable capacity for any real-time human interventions. This survey has also exposed that there is a fundamental challenge regarding the operational safety of agricultural AI (38.78%, n=19) as all stakeholders strongly disagreed with the statement that farmer users are currently trained to supervise or override an AI decision whenever a malfunction occurs. To further examine the reality of this finding, this variable was cross-tabulated against the mandatory duty to verify AI outputs.

7.3 Farmer Capacity V/s. Legal Duty To Cross Verify Uncommon Outputs

The survey has a question: Should Farmers Be Legally Required to Cross-Verify Outputs? While discussing the liability of farmer users, some key variables were cross-tabulated against the structural cohorts as below-

Table 3. Cross-tabulation on Farmer Capacity v/s. Legal Duty to cross-verify Uncommon Outputs. [Fisher’s Exact Test p-value < 0.001; Highly Significant]

To Supervise/ Override AI (n)	Strongly Agree / Agree	Neutral	Disagree / Strongly Disagree	Total (n)
Sufficiently Trained (n=11)	72.73% (n=8)	18.18% (n=2)	9.09% (n=1)	11
Neutral/Undecided (n=15)	26.67% (n=4)	46.67% (n=7)	26.67% (n=4)	15
Untrained/Incapable (n=23)	8.70% (n=2)	13.04% (n=3)	78.26% (n=18)	23
Total Sample	28.57% (n=14)	24.49% (n=12)	46.94% (n=23)	49

This cross-tabulation has clearly established that all stakeholders who acknowledge the lack of technical training to supervise AI operations also strongly reject (78.26%, n=18) the idea of imposing a legal duty to cross-verify outputs of AI technology. This finding fairly highlights a clear “capacity verification paradox” because the traditional tort law principles propose that end-users should maintain such a duty to verify. It is true that imposing this legal duty on farmer users who lack specialized technical training creates an unfair and unmanageable legal burden. Because if farmer users cannot interpret complex algorithmic outputs, then any legal requirement to cross-verify transitions will result in shifting reasonable safety standards into an absolute liability trap. This emphasizes that there is a need to develop tort law principles around strict developer accountability or a mandatory insurance model rather than such a legal burden on untrained farmer users. Such insurance may be provided by the government to encourage use of AI in agriculture.

8 Thematic Content Analysis Of Open-Ended Text Submissions

The open-ended content of the survey was analyzed using a thematic content analysis method based on three primary structural nodes, namely, ‘node A’ of dynamic causality and overlapping ecological fluctuations, ‘node B’ of fragmented technical infrastructure, and ‘node C’ of the “black box” transparency barriers.

The ‘node A’ respondents focus on the environmental variables changing constantly, sometimes hourly. It is extremely difficult to find out whether the failure of AI is due to a hidden software bug or an unexpected change in soil moisture or a sudden micro-climatic shift. The ‘node B’ respondents focus on the nature of data, creating severe logistical hurdles for data collection, storage and processing in real time, which may be disrupted by spotty connectivity or hardware limitations in remote rural regions. The ‘node C’ respondents focus on the lack of adaptive context of highly reactive historical data collected in rapidly changing weather conditions. Further, the lack of transparency in AI decision making processes makes it difficult to prove whether a harmful outcome was a foreseeable error by the developer or an entirely unpredictable natural occurrence or outcome of faulty handling by the user farmers.

9 Conclusion

Highly promising opportunities are offered by the integration of AI in agriculture, along with the complex challenges for traditional tort law remedies for deciding liability for the harm caused by such AI. The doctrinal analysis and empirical cross-tabulation in this study demonstrate that the traditional principles of foreseeability, negligence, and product defects face severe challenges if applied to learning algorithms of AI. A legal framework must evolve to address these challenges. The policymakers shall consider a hybrid approach of limited strict liability for structural software flaws along with mandatory insurance funded by government initiatives. It is the only way to achieve equitable distribution of the operational risks among the software developers and AI systems providers which can protect the untrained end user farmers maintaining a clear and supportive pathway for future innovations in the integration of AI in agricultural sector.

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