Explainable AI in Farming: Configurations of Human-AI Joint Decision-Making

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1 Introduction and Background

Agriculture is making leaps in digitalization and artificial intelligence (AI) systems with autonomous machines, sensor data, and decision support systems (Liakos et al., 2018; Smith, 2020). Understanding and improving how farmers interact with AI requires research that looks beyond AI in laboratory settings and into the application of AI in the field (Huysman, 2020; Jussupow et al., 2021). One key issue is explainability which paves the way for successful AI deployments (Gregor & Benbasat, 1999; Thiebes et al., 2021). Explainability refers to the effectiveness of AI's explanations (e.g., user interfaces, documentation, or manuals). This study focuses on the comprehensibility of explanations and specifically user interfaces for end-users. End-users often cannot comprehend how AI systems reach their decisions (Waardenburg et al., 2020). However, explainability is crucial for using AI in joint decision-making (Asatiani et al., 2021).

Human-AI joint decision-making happens through configurations of Human-AI agency, which are continuously and mutually shaped (Suchman, 2007, 2012). Recent research found that a translator role is required who mediates between end-user and AI system (Gal et al., 2020; Jussupow et al., 2021; Waardenburg et al., 2022). The translator role addresses comprehensibility in domain-specific contexts. What remains unclear is how human-AI joint decision-making occurs when explanations influence it. Research into how AI explanations are embedded in the organization and integrated into decision-making procedures is lacking. How humans engage with AI systems and make sense of explanations in the domain context has seen little empirical work until now (Abdul et al., 2018; Benbya et al., 2021). These issues are urgent for small businesses, where human actors rely on AI explanations. Therefore, this study asks: *How do configurations of human-AI joint decision-making emerge, and how do explanations influence these configurations?*

2 Methods: Interviews and Experiments on the Farm

This study addresses the agricultural context, focusing on family-owned, resource-constrained, small businesses that cannot afford human-AI translators. Agriculture is a growing high-tech industry characterized by technological innovation with political and economic importance for the Netherlands (Topsector, 2022). Data collection takes place on a demo farm that produces crops and operates under scientific supervision. Hence, the study focuses on crop yield and disease prediction (Inoue, 2020; Navrozidis et al., 2018; Pantazi et al., 2016, 2019). Figure 1 shows an example.

The study's scientific method follows a sequential two-phases mixed-methods design (Venkatesh et al., 2013). First, it is qualitatively explored how human-AI configurations emerge and how decisions are made by observing participants' use of AI systems. To understand the motivations during use, post-hoc interviews are conducted (Kaplan & Maxwell, 2005; Rowley, 2012). Second, based on the interviews and observations, technological and organizational interventions are derived and prototypically implemented on the farm. An experimental evaluation is performed on whether the interventions improve the explanations' comprehensibility (Schulz et al., 2010).

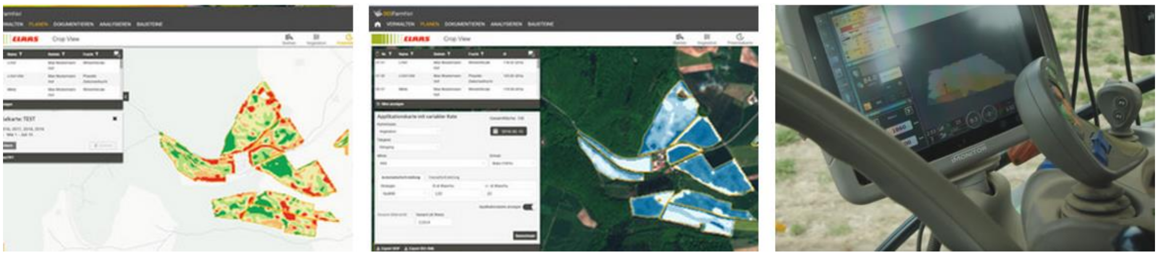

Figure 1. Cloud-software FarmNet. The farmer can set up his acres and compute the vegetation level based on current and historical sentinel-2 images in the application (left image). Based on the vegetation level, the system automatically optimizes the amount of fertilizer for each 10x10m square, which the farmer can adjust based on experiential and context knowledge (e.g., current fertilizer prices or weather conditions) (center image). The estimation is transferred to the tractor, where the farmer can choose in real-time if s/he wants to follow the recommended fertilizer amount or deviate from it (right image).

3 Preliminary Results (as part of preparing phase 1)

Six interviews with farmers and agricultural manufacturers have already taken place. The farmers' lifelong experience matters over technological innovations: "*I have worked on this field for more than 25 years. The farmer's eye fattens the cattle, not a faulty tool.*" Farmers appreciate innovations in engineering, which they understand due to their expertise. However, they are skeptical about innovations in information technology. They question the systems' validity "*if it's cloudy, the satellite tool is giving wrong results*," and the opacity of the back-box algorithms. Furthermore, they understand their farm as a business. They doubt the AI systems' profitability and are unsure how these systems would integrate with their farm infrastructure: "*ultimately, my farm is a business, and these systems are expensive with diminishing returns and high maintenance costs. I cannot repair it myself.*". Information technology affinity and age seem relevant, as a younger interviewee mentioned his excitement for AI-based systems. Young farmers enroll in higher education and study agriculture at universities, which might change farmers' perspectives toward new technologies in the future.

The interviewees from agricultural manufacturing describe being unable to provide an outlook on the financial benefits to farmers: "*we cannot guarantee productivity gains, as the technology is new*". The interviewed companies mostly sell new systems to large enterprises in Eastern Europe instead of small family-owned businesses because the technologies are oversized for small farms. The interviewed organization struggles with the digital transformation and selling digital services: "*we build a lot of engineering technology and sensors but are unsure what we can do with the collected data*."

4 Discussion and Implications: Accessible AI

Comprehensibility of the algorithmic mechanisms is the key barrier that prevents farmers from working with AI systems (Asatiani et al., 2021). Statistical capabilities are lacking on the farmers and manufacturing sides (Klerkx et al., 2019). Agricultural companies are still figuring out what they can do with the data they are collecting. Comprehension may also help to estimate the financial returns of AI systems. Lastly, the farmer's identity as the sole decision-maker affects the human-AI joint decision-making (Klerkx et al., 2019; Strich et al., 2021).

Therefore, the deployment of AI explanations should account for the experience and authority of the farmers. 'Identity-aware' user interfaces should be developed and evaluated (cf. Liu et al., 2003; Schaffer et al., 2019). Comprehension can increase the farmer's trust in AI systems and make them more effective (Thiebes et al., 2021). Explanations should build on top of the farmers' engineering expertise. The trend towards higher education in agriculture may accelerate future innovations in AI for farming. Public policy can support higher education programs for farmers and manufacturers. Manufacturers should build the capability to quantify and explain the benefits of novel AI systems.

This study contributes to recent research on end-user centered explainable AI in farm work (Abdul et al., 2018; Cheng et al., 2019). It extends the understanding of configurations of human-AI joint decision-making with implications for (1) user interface design, (2) and how organizations can deploy AI systems with explanations. This novel understanding contributes to the transfer of AI systems into practice. Advancing the effectiveness of AI explanations is crucial for making AI systems accessible to many industries (Ågerfalk, 2020). This study's insights may be generalized beyond farming and SMEs towards foundational insights into human-AI configurations.

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