Configurations of Human-AI Work in Agriculture

Adoption and Use of Intelligent Systems by Agricultural Workers

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Abstract: Agriculture is making leaps in digitalization and the development of artificial intelligence (AI) systems, e.g., decision support systems, sensors, or autonomous vehicles. However, adoption and widespread use of these technologies remains below expectations with negative consequences for digitally advancing the agricultural industry. Therefore, this study investigates the configurations of human-AI work, in particular, human-AI decision-making. Configurations describe the interactions between workers and intelligent systems, emphasizing the adoption and use of technologies *in-situ*. This study targets agricultural farms in Germany, collecting qualitative data at small-medium-sized businesses. From this data, the paper examines how configurations of human-AI work emerge and how explanations influence these configurations in the context of agricultural work. Theoretical contributions include a new understanding of how agricultural workers adopt and work with AI to make decisions. Practical contributions include more accessible AI systems, easing transfer into practice, and improving agricultural workers' interactions with AI.

Keywords: explainability, adoption and use, decision-making, human-AI interaction, work, farming

1 Introduction

Agriculture is making leaps in digitalization and artificial intelligence (AI) systems with autonomous machines, sensor data, and decision support systems. However, despite technological advances and high spending on developing novel AI-based systems, the adoption and use of these technologies remains below expectations in agricultural practice [WFPD18]. The lacking adoption and use results in little value being captured. Especially small-and-medium sized agricultural companies fall behind in innovation and economic performance [KlJL19].

The lagging adoption and use of new technologies such as AI impedes the digitalization in agriculture with severe impacts on reaching sustainability and climate goals. Adoption at scale and effective use of these novel technologies would enable precision farming and sustainable intensification, with a profound impact on climate change, sustainable soil, and groundwater quality due to reductions in fertilization.

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The novel characteristics of AI-based technologies and the idiosyncrasies of farmwork render it unclear if established theories on technology acceptance can sufficiently explain the scant adoption and use of AI in farming [GiBS22, WHHJ22]. Jobs, tasks, and norms in farming follow a different paradigm, and the boundary conditions of existing theories may be violated [KlJL19, WFPD18].

Therefore, this short paper asks: "*Why do agricultural workers not adopt and use novel intelligent (AI-based) systems?*" The question is addressed by conducting qualitative interviews with agricultural workers and manufacturers. The theoretical lens of *configurations* is used for analysis. Drawing from Suchman [Such07], configurations are defined as the individual interactions with technology *in-situ*, emphasizing humans' choice for adoption and use practices. As this text is a short paper, the preliminary results focus on the adoption aspect of such configurations.

2 Methodology

Empirically, we address the research question by conducting informal, unstructured interviews about the adoption and use of machine-learning-based technologies. These unstructured interviews allow for a rich qualitative analysis of how choices about adoption are made [BeGM87, Fisk04]. It follows guidelines by Myers and Newman [MyNe07]. Open coding was performed by the first author alone, following the steps by Saldana [Sald09]. The qualitative data was broken down into discrete parts and then compared "for similarities and differences" [Sald09, p.81].

Fig. 1: Left: Predict vegetation levels from satellite images and optimize fertilizer using machine learning. Right: Transfer fertilizer estimations to tractor for precise distribution.

As configurations are contingent on the application domain's boundary conditions, the research question must be inquired in context [MiHS17]. This study focuses on the empirical context of North Rhine-Westphalia and Lower Saxony, which is characterized by family-owned farm businesses (SMEs) that are resource-constrained with up to five workers. Data collection focuses on arable farms that produce crops under recurring observations by scientists. Intelligent systems under study include crop yield and disease

prediction systems [Inou20]. Figure 1 shows an example of machine-learning-based functionality that was discussed with the interviewees[4].

Four unstructured expert interviews with farmers and one with a farm advisor, as well as two expert focus groups (five people each) with agricultural manufacturers took place in 2021. In total, eleven hours of interviews were conducted (cf. Table 1).

#	Occupation	Agricultural workers	Duration
1	Farmer	1	1 hr
2	Farmer	2	2 hrs
3	Farmer	4	1 hr
4	Farmer	2	2 hrs
5	Farm Advisor	n/a	1 hr
6	Agricultural Manufacturer	n/a	2 hrs
7	Agricultural Manufacturer	n/a	2 hrs

Tab. 1: Interviews and Expert Groups.

3 Preliminary Results

According to the interviewees, the farmers' lifelong experience matters over technological innovations, with one interviewee reciting an old proverb in their statement: "*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 criticize the opacity of the back-box algorithms.

Furthermore, they understand their farm as a business. Although the interviewees can appreciate the value propositions of the technologies, they doubt the AI systems' profitability. They 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 their excitement for AI-based systems. Young farmers enroll in higher education and study agriculture at universities, which might change agricultural workers' perspectives toward new technologies in the future.

The interviewees from agricultural manufacturing describe being unable to provide an outlook on the financial benefits to the agricultural workers: "*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

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[4] https://www.claas.de/produkte/digitale-loesungen/farm-management/365farmnet (accessed 2022-10-20).

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

Comprehensibility of the algorithmic mechanisms is the key barrier that prevents agricultural workers from working with AI systems. Whereas previous research suggests that a lacking explainability leads to ineffective use [AsMN21, Hüll21], our findings highlight that lacking explainability impedes adoption altogether and agricultural workers are hesitant to procure AI-based precision farming technologies.

While research has focused on the users' lacking skills for effective human-AI work [KlJL19], our findings show that statistical skills are lacking both on the agricultural workers and manufacturing sides. Agricultural companies are still figuring out what they can do with the data they are collecting and analyzing [KlHü18]. Comprehension may also help to estimate the financial returns of AI systems.

Lastly, the farmer's identity as the sole decision-maker affects the use of AI for decision-making. This is in line with existing research from other domains, which found changes in professional role identity, for example, in finance [StMF21]. However, agricultural workers' identity is not just about a professional role but rather a life identity, *a calling* [KlJL19]. Hence, the identity shift from manual laborer towards manual laborer plus knowledge worker is more fundamental—as our research shows. Therefore, the deployment of AI explanations should account for the experience, authority, and identity of the agricultural worker. 'Identity-aware' user interfaces should be developed and evaluated [LiWH03, SOMR19].

Comprehension can increase the agricultural worker's trust in AI systems and make them more effective [WHHJ22]. Explanations should build on top of the agricultural workers' 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 extends the understanding of configurations of human-AI work with implications for designing AI-based systems and deploying AI-based systems with explanations in organizational settings. Thereby, it contributes to recent research on end-user-centered AI by looking at the context of agriculture [AVWL18, CWZO19]. This novel understanding contributes to the transfer of AI systems into practice.

5 Conclusion and Next Steps

Based on unstructured interviews, we develop an understanding of configurations of human-AI work. This study's insights support the statement from Ågerfalk [Åger20], showing that the comprehensibility of intelligent systems is crucial for adoption and use. Consequently, explanations and potentially the effects of higher education in agriculture may offer a remedy to the lagging adoption. Furthermore, the findings show that the idiosyncrasies of agricultural work, including the agricultural workers' identities and the quantifiability of financial benefits are relevant.

This preliminary study has some limitations. Only the first author coded a small sample of qualitative data. All interviewed farmers were from small farms. Hence, generalizability to other farm businesses and agricultural workers may be impeded. Our next steps are to derive ideas for technological and organizational interventions, prototypically test and experimentally evaluate them with agricultural workers—following established RCT protocols [ScAM10]. Specifically, interventions that improve the explainability of these technologies are in focus because they affect trustworthiness, transparency, and comprehensibility as the necessary conditions for widespread adoption and use of intelligent systems by agricultural workers. Advancing the effectiveness of such AI explanations is crucial for making AI systems accessible to the agricultural industry and reaching climate and sustainability goals.

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