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Abstract

Organizations are deploying artificial intelligence (AI) to improve decision-making and performance. AI-enabled systems are used to automate the decision-making process or assist human choice by providing algorithmically generated information through predictive analytics and recommendations. However, the ability of these systems to improve organizational performance is constrained by biases within the algorithms. This study proposes to use organizational learning as a theoretical lens to understand how users perceive and respond to these biases using their experiential learning and cognitive search processes. The research is set within the agricultural context, as farm organizations are increasingly adopting AI-enabled systems to improve agricultural productivity and sustainability. However, because of complexities associated with the natural environment, algorithmic biases in the recommendation could threat these outcomes. The study proposes to conduct multiple case studies to explore how users of AI-enabled agricultural systems perceive algorithmic bias and develop coping mechanisms to improve agricultural performance.

Keywords

Algorithmic bias, agriculture, artificial intelligence, cognitive search, experiential learning.

Introduction

Data analytics, big data technologies, and artificial intelligence (AI) are being deployed to transform and improve organizational decision making (Chen et al. 2021). AI algorithms are used to automate or assist human decision making by providing algorithmically generated information through feature classification, predictive analytics, and recommendations (Kordzadeh and Ghasemaghaei 2021). Despite the value offered by AI technologies for organizational performance and transformation, their black-boxed algorithms may pose ethical risks to individuals, organizations, and society (Someh et al. 2019). In this respect, an emergent operational and ethical concern is that AI algorithms can reduce human subjective interpretation of data and embed human and social biases and deploy them at scale (Davenport et al. 2020).

Algorithmic bias can cause incorrect recommendations, leading to inaccurate decision making and subsequent negative consequences for individuals, organizations, and society, such as workplace discrimination based on gender and race (Akter et al. 2021) and financial losses when bias in lending practices favour bad credit risks (Talagala 2019). Bias can enter algorithms through flawed data sampling, dependence on historical data and misinterpretation of algorithmic recommendations (Kordzadeh and Ghasemaghaei 2021). Algorithmic bias can reduce the potential of AI for business and society; thus, the scientific community is encouraged to conduct more research around the detection and mitigation of algorithmic bias. Computational scientists have developed techniques to address this issue to some extent (Someh et al. 2019). However, information systems (IS) research has devoted limited efforts to addressing the organizational, social, and behavioural implications of algorithmic bias (Someh et al. 2019). This study proposes to address this gap.

Algorithmic systems are a sociotechnical phenomenon, and their outcomes depend on both the algorithmic output and how users make decisions with these outputs. Users interpret the algorithmic outputs based on their tacit knowledge, personal prejudices, transparency of algorithmic processes, and organizational rules and policies (Silva and Kenney 2019). Users may form both positive and negative perceptions of algorithmic outputs based on the outcomes associated with such outputs and these perceptions can have a significant influence on the extent to which users adopt algorithmic systems (Lee 2018). Furthermore, in contrast to human decisions that are made based on judgment and understanding, algorithmic outputs are derived from impersonal quantitative calculations and statistical models and on historical data (Lindebaum et al. 2020). The fact that these outputs are not generated by humans can also impact users' perceptions of the algorithmic outputs and their beneficial outcomes. In one agriculture setting, unmanned aerial vehicles provided a misleading count of the damaged plant population compared to farmers' on-field knowledge (Byrum 2017). If not addressed, such anomalies can cause delays in the replantation of damaged crops, leading to huge crop loss. Through past experiences, users can evaluate the anomalies in the algorithmic outputs, consider the next best action, and devise strategies to cope with these anomalies.

In this study, we draw on the distinction between two basic modes of organizational learning: experiential learning and cognitive search (Gavetti and Levinthal 2000). Experiential learning involves retaining past actions that produced desired results and discarding the actions that led to undesirable outcomes. In contrast, the cognitive search perspective posits that individuals choose alternatives based on their beliefs about action-outcome linkages (Gavetti and Levintal 2000). The continuous iteration between past actions and cognition can enable users to develop organizational routines that are derived from constitutive interaction between users, artifacts, and the organizational environment. Based on this understanding, we theorize that algorithmic biases can be perceived through experiential learning and that coping mechanism can be generated through cognitive search processes. This leads to the proposed research questions:

RQ1: How do users perceive algorithmic bias while using algorithmic systems in agricultural practices?

RQ2: How do users cope with algorithmic biases using experiential learning and cognitive search to achieve desired outcomes?

We seek to answer these questions in agricultural settings, where, unpredictable ecological conditions make statistical quantifications difficult. The AI models trained on these statistical data may embed biases. Thus, the complex natural environment combined with the social dynamics of agricultural systems provides a rich context to examine the interaction between users' experiences, actions, cognition, and algorithmic systems in achieving the desired outcomes.

Literature Review

Algorithmic bias

Algorithms play an integral role in computational systems, especially in autonomous systems. Algorithms are used for performing different tasks, such as information retrieval, image recognition and processing, filtering, outlier detection, and recommendation (Kemper and Kolkman 2019). However, algorithmic systems that can enhance the effectiveness of organizational decision making can also, at times, exhibit social and technical biases that negatively impact the organizations (Someh et al. 2019). Algorithmic bias occurs when "the outputs of an algorithm benefit or disadvantage certain individuals or groups more than others without a justified reason for such unequal impacts" (Kordzadeh and Ghasemaghaei 2021, pp.1). Although algorithmic bias is predominantly embedded in unrepresentative datasets (Israeli and Ascarza 2020), they can be reflected in biased methods of data collection or societal biases (Kordzadeh and Ghasemaghaei 2021). The adverse impact of algorithmic bias has been documented in a range of domains from people and employment, healthcare, education, credit markets, and criminal justice (Kordzadeh and Ghasemaghaei 2021), agriculture, and sustainability (Galaz 2021; Jiménez et al. 2019). The negative consequences of algorithmic biases include customers paying higher prices, overpaying welfare recipients, high employee turnover, and high customer churn rates in organizations (Akter et al. 2021; Kordzadeh and Ghasemaghaei 2021). In agricultural settings, the direct impact of algorithmic bias can contribute to productivity loss, environmental pollution, and other allocative risks such as restraining opportunities or resources from certain people or groups (Jiménez et al. 2019). Algorithmic biases can reduce the prospects of digital agriculture (use of advanced technologies to improve agricultural productivity) and may pose a systemic risk to sustainability (Galaz 2021).

Organizational learning

Organizational learning comprises two basic modes: experiential learning and cognitive search (Gavetti and Levinthal 2000; Mao et al. 2020). Experiential learning results from transforming experiences into knowledge, where knowledge structures are formed through the continuous interaction between prior knowledge and new experiences (Kolb 1984). Experiential learning theory describes the individual learning process as a four-stage cycle: concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb 1984). Experiential learning, regarded as a backward-looking process (Gavetti and Levinthal 2000; Mao et al. 2020) has been applied to real-issue problem solving, entrepreneurial learning, innovation, and organizational learning in several domains, including IS and agriculture. Experiential learning provides capabilities that can be integrated into actual situations to find a solution (Bates 2015). The IS discipline has applied the experiential learning perspective to the successful implementation of an IS artifact and pedagogical endeavours (Jewer and Evermann 2014; Monk and Lycett 2011). In the agricultural domain, the use of the experiential learning perspective has centred around using experience to understand the agricultural environment and making decisions to improve agricultural performance (Krupnik et al. 2012, McCown 2012).

In contrast to experiential learning, cognitive search is a forward-looking approach as cognitive representations are used in the creation and selection of alternatives according to their consequences (Gavetti and Levinthal 2000). Individuals' cognitive representations help them choose alternatives based on their beliefs about action-outcome linkages (Gavetti and Levinthal 2000). Through cognitive search, people can experiment with more elements and develop different solutions and outcomes through analogical reasoning. Cognitive search has been found to have a positive role in innovating business models and helping incumbent firms develop novel business models to combat the threat of disruptive business model innovation (Mao et al. 2020; di Toma and Ghinoi 2019).

Algorithmic bias and organizational learning processes

Organizational learning involves iterations between cognition and action (Gavetti and Levinthal 2000). While in cognitive search, action follows cognition, in experiential learning, cognition follows action (Gavetti and Levinthal 2000). Individuals working on farms develop farm processes and routines by evaluating the results of trial-and-error and scaling-up successful routines and discarding unsuccessful actions (Krupnik et al. 2012). For the experiences to be useful, they progress through certain processes of acquiring and assimilating new patterns or routines. Additionally, experiential learning enhances the users' understanding about normal farm practices under given farm conditions. In situations where the algorithmic outputs do not resonate with users' expectations, experiential learning can help in perceiving this dissonance. While experiential learning implies that only one alternative can be explored at a time (as alternatives are explored sequentially), cognitive search invokes a broad set of choices (Mao et al. 2020; Gavetti and Levinthal 2000). Thus, users can use their cognition to choose alternative actions based on their belief about action-outcome linkages, rather than treating algorithmic output as given. Cognitive search can direct users to think about potential solutions through brainstorming and analysing the potential outcomes of the alternative actions. Hence, cognitive search and experiential learning can potentially initiate a mutually beneficial relationship between users and artifacts, where the interaction between the two can augment capabilities for both.

Research Methodology

We propose to employ multiple case studies in this research. Multiple case studies are appropriate for answering how and why questions because these questions deal with operational links that need to be traced over time (Yin 2009). Given that the concept of algorithmic bias in the agricultural context is an emerging and less researched phenomenon, multiple case studies are highly suitable for generating new insights. For the cases, we will select crop farms (as opposed to livestock farms) that deploy AI solutions for agricultural practices because these operations are characterized by a high degree of ecological dynamism, high unpredictability, and differing crop life cycles. We will follow a purposeful sampling strategy to improve the generalizability of the findings (Lyytinen and Rose 2003). Three Canadian farms of different sizes located in different regions of Canada will be recruited. The difference in size will allow us to understand how the deployment of algorithmic systems varies with the number of employees. A convenience sampling method will be adopted in recruiting the three farms. The farms will vary from medium to large because smaller farms are less likely to have deployed algorithmic systems within their operations. The different locations of the selected cases will shed light on the impact of weather on the algorithmic performance and the coping mechanisms developed by organizations. Data collection will primarily take the form of interviews with employees of farming organizations (top management representatives, farmers, and other employees) that use the outputs of algorithmic systems for strategic or operational decision making. The interviews will be conducted in two phases; the first phase will ask the top management team about their experiences using algorithmic systems for farm operations. The second phase will interview the farmers and the other system users to understand their perception of algorithmic outputs and alignment of these outputs with their farm objectives. The study proposes to conduct 10-12 semi-structured interviews for each case; the final number to be determined by theoretical saturation (Saunders et al. 2018). An interview protocol will be developed and pilot-tested with a convenience sample. The interviews will be recorded, transcribed, and coded into higher-order themes (Miles et al. 2020). In addition to interviews, internal documents such as annual reports, and other financial reports of the farms will also be analysed. Open and selective coding of interviews and documents will be followed by development of conceptual model that will be supported by the coded data of evidence.

Expected Research Contributions

This study proposes to explore the role of users' experiential learning and cognitive search in perceiving and coping with algorithmic bias while engaging in agricultural practices. The growing deployment of AI in various sectors aims to improve organizational performance and algorithmic biases could limit this achievement. Despite the growing awareness regarding algorithmic bias in different disciplines, there is no clear framework to prevent this phenomenon (Nelson 2019). This study contributes to scholarship by proposing experiential learning and cognitive search as theoretical lens for bias detection and development of mitigation strategies during the use of algorithmic systems. In addition, this research highlights organizational learning as an important theoretical lens to examine the human-AI interaction and the associated implications. Although the context of this study is agriculture, we expect that results of this research will be generalizable to other contexts and industries that are already using or beginning to implement AI. From a practical standpoint, this study will help developers understand users' needs and problems using algorithmic solutions and, accordingly, help them develop less-biased systems and mechanisms for dealing with bias. Finally, this study motivates IS researchers to use their expertise to address algorithmic bias, considered a socio-technical issue, and bring new insights and innovations to the agricultural sector.

Conclusion

AI solutions are being actively deployed in the organizations to improve decision making and transform operations. Despite the potential of AI to assist in organizational performance, algorithmic biases limit the effectiveness of AI solutions. Examining algorithmic bias in agriculture can be a potentially rich and important research stream for the IS discipline and will have implications for the use and development of AI solutions in other research contexts.

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