Agricultural Innovations, Diffusions and Adoptions: 2009-2021

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Introduction

American Association for Agricultural Education National Research Agenda: 2016-2020 listed *New Technologies, Practice, and Products Adoption Decisions* as the second research priority (Roberts et al., 2016). Within the research agenda, Lindner et al. (2016) stressed Rogers's diffusion of innovations as an early social science theory still needs more contextual sophistication considering the heterogeneity of individuals' or organizations' decision-making processes.

Rogers's theory has inspired multidisciplinary diffusion studies. Understanding the impact of those studies is of the utmost importance to influence both research and adoption practice. The Altmetric Explorer (AE) is a data platform launched in 2012. AE is a real-time, researcher-friendly academic database where subject keywords for classification make relevant research outputs possible. AE research outputs provide details on authors' affiliations, published journals, and study locations from innovations to adoptions. Innovations varied by farm inputs, machinery, and precision agriculture in North America, Western Europe, Australia, and India respectively. Moreover, individual publications have unique Altmetric Attention Scores that inform academic contributions and receive the number of Social Networking Service (SNS) mentions to deliver the highlights of each study.

Machine Learning (ML) is ideal for finding causality, matching innovation-diffusion-adoption cases, and exploring predictors that facilitate diffusions and adoptions. In this research, no human work better matches the complete and exact process from innovations to adoption in a short period like ML does. Neither is it easy for researchers to identify those per innovation. Instead, ML extensively and exhaustively searches every possible diffusion and adoption factor. These methods helped determine whether more public, social, and academic mentions increased the course of diffusing an innovation. Through publication titles and abstracts, ML approaches assisted intricate and gradual systematic reviews in improving the quality and increasing predictive performance (Hempel et., 2019).

Methodology

According to Google Scholar, as of October 25, 2021, Rogers (2010) had nearly 135,000 citations, and of those, 1,250 have been in agriculture. The literature was divided into agricultural innovations, diffusion, and adoption stages, and matched to a complete diffusion research tradition set. Two issues arose: time and complete cases. In this 12-year period, one cannot make a direct connection between a citation in Google Scholar and the adoption and diffusion on an innovation. Thus, the primary research conducted an extensive search of innovations, research and development, technology/technologies, and techniques using AE in four subjects, i.e., *Agriculture, Land, and Farm Management*, *Agricultural Biotechnology*, *Agricultural and Veterinary Sciences*, and *Other Agricultural and Veterinary Sciences*. As a result, 1,780 publications between 2009 and 2021 were identified; the number exceeded 1,250 articles which cited Rogers (2010) publications, including the *Journal of Agricultural Education* articles (King et al., 2019; Rumble et al., 2016; Ruth et al., 2017; Smith et al., 2018; Warner et al., 2019). To determine factors that lead to likely innovation adoption, ML was used.

ML is a machine-assisted technique that artificial intelligence (AI) learns from the original raw data, trains itself, and predicts cases. Test data emerge from AI predictions. The foremost post-estimation is to compare misclassifications between training and test data. For predictive accuracy, researchers should consider minimizing overfitting. Overfitting means possible erroneous predictions when new information comes in, despite given training and test data accuracy (Song & Ying, 2015). To reduce overfitting, a random forest structures test data randomly. By selection of the number of trees built, random test data and subsample proportions, predictive accuracy and statistical power are determined. Ideally, ML assists to gather transparent, interpretable, and reliable results (Storm et al., 2020).

Statistica (Version 13.5) software is a package designed for ML (IBM, n.d.). Researchers select Random Forests in Data Mining. Before conducting the analysis, researchers must decide and provide information on target and predictor variables, proportions for random test data and subsamples. AI returns predictor variable importance to the target, the overall data structure, and classification matrix to researchers for the results.

Results to Date

The Random Forests analysis revealed that there were 452 innovation-diffusion-adoption cases, 625 innovation-diffusion cases, and 703 innovations only cases. The four major areas were smart, organic, conservation, and precision agriculture. The first finding was that more SNS mentions led to likely innovation diffusion. However, few connected to adoptions. Altmetric Attention Scores counted innovations more in research and development.

From 452 innovation-diffusion-adoption cases, AI found explanatory factors leading to diffusion of adoptions. The most robust predictor was needs. That is, the more innovative ideas, devices, or technologies came out after needs assessments, the more clients adopted. Compatibility was the next most important predictor. Over 75% of the total cases, innovations that are familiar with current use and past experiences, were adopted by end-users. Subsequently, low barriers to the complexity of innovations ascertained if diffusions ended up with adoptions.

Four more considerations were: costs of adoptions, related policies, number of early adopters, and cultural norms. There was evidence that more policies to induce such innovations advanced diffusion of adoptions. However, lower costs did not necessarily connect innovations to adoptions. Instead, the more peers who can facilitate adoptions adopted such innovations, the faster diffusions and adoptions were.

Future Plans

There should be more tests to ascertain whether cultural norms affect adoptions. Also, more statistical evidence is needed that relative or absolute advantages cause more adoptions. These two are the most pressing for further study. Because AE updates research outputs daily, more cases could be considered as time progresses.

Costs/Resources Needed

The researchers' affiliated libraries should subscribe to AE. If not, there is a subscription cost. The researchers can use Statistica Data Miner (Version 13.5) for Machine Learning which has an annual subscription.

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