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# The adopter versus the technology: their importance as determinants of adoption and their use in research

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# The adopter versus the technology: their importance as determinants of adoption and their use in research


## Abstract

Research on the determinants of adoption of agricultural innovations (technologies and practices) has failed to converge towards a consistent explanation for why farmers do or do not choose to adopt new technologies and practices. This absence of convergence matters because it indicates that agricultural extension and policy are influenced by a body of literature that is often not able to offer clear recommendations on the variables that can be used to design interventions. Our analysis shows that adopter and technology characteristics are important determinants of adoption, but researchers have been mainly focused on researching the adopter and the general farming context, with relatively little attention on understanding the influence on adoption of the characteristics of the technology itself.



## Keywords

Agricultural technology, technology adoption and diffusion, drivers of adoption, variable importance

## JEL classifications

Q160

## AgEcon Search Field

Environmental Economics and Policy


## Highlights

- We analysed the variables that have been used in literature to explain and predict adoption in agriculture.
- Our analysis shows that adopter and innovation characteristics are both important.
- However, we found that existing applied papers in adoption often do not consider innovation characteristics nor their interaction with adopter characteristics and their context.
- We discuss potential solutions to improve the study of adoption in applied papers.

# The adopter versus the technology: their importance as determinants of adoption and their use in research

## Introduction

Extensive research on the determinants of adoption of agricultural innovations has failed to converge towards a consistent explanation for why farmers choose to adopt new technologies and practices. This observation is based on meta-analysis and reviews of agricultural adoption research, including the work of Knowler and Bradshaw (2007), Baumgart-Getz, Prokopy, and Floress (2012), Tey and Brindal (2012), Wauters and Mathijs (2014), Liu, Bruins, and Heberling (2018). This absence of convergence matters for two reasons. Firstly, it means that there is a lack of clarity about the analytical methods and the choice of explanatory variables that we should use to model adoption. Secondly, it means that agricultural extension and policy are influenced by a body of literature that is often not able to offer a clear recommendation on the variables or mechanisms that can be used to design policy interventions.

The green revolution starting in the mid-20th Century resulted in a movement to increase yields and increase productivity of agriculture. Agricultural scholars at the time started producing evidence on the adoption of these technologies based on economics, sociology and psychology. Three studies set the basis for the decision-making models and analytical methods that still dominate the choice of explanatory variables used in adoption studies: Griliches (1957), Rogers (1962) and later Ajzen (1991). Griliches established the practice of using regression modelling to provide evidence of agricultural adoption. In this early study, he used a mix of adopter-related variables (e.g. innovation awareness, innovation 'acceptance'), contextual variables (e.g. farmed area, output prices, level of farm returns, region) and innovation-related variable (e.g. yield, profit advantage) to study the adoption of hybrid corn.

Rogers' diffusion of innovations theory identified five key attributes of innovations that influence diffusion and adoption: relative advantage, compatibility, complexity, trialability and observability. He proposed that the perception of these attributes by individual potential adopters are the main influence on adoption decisions. How potential adopters perceive these attributes has been studied extensively, resulting in dozens of potential explanatory variables (Kapoor, Dwivedi and Williams 2014).

Early studies also showed that not all target populations adopted in the same way, especially in developing countries. The seminal work by Feder, Just and Zilberman (1985) proposed an analytical method that set the scene for a growing adoption literature in agricultural economics, influencing the selection of explanatory variables in subsequent studies. Their framework suggested a dynamic decision-making model to describe the 'time pattern' of parameters that affect farmer's decisions at different stages. In their view, parameters should be able to explain the processes of learning though information gathering, learning by doing and accumulation of resources and the degree of use of the innovation. Under this framework, the decision to adopt or not is derived from a production function aiming at maximising expected utility or profit, subject to a series of constraints and specific characteristics of the technology: packages of technologies including components that can be complementary or independent, technologies that are divisible or apply to the whole farm, etc. This study suggested broad parameters that could be used in modelling the production function determining adoption: farm size, tenure, risk and uncertainty, human capital, labour availability and credit and supply constraints.

Scholars also became interested in the 'behavioural approach' that focuses on the motives, values and attitudes determining the decision-making processes of farmers. Ajzen (1991) proposed the socio-psychological theory of planned behaviour (TPB) as a conceptual framework to account for normative influences, self-identity, and perceived self-efficacy in adoption decisions. This theory became highly influential in adoption studies (Pike 2008), and it continues to be. This influence may have contributed to some scholars moving their attention towards explaining differences in adoption levels based mainly on the characteristics of the adopter.

From the mid 1990s, adoption studies started focusing on the adoption of agricultural practices that are intended to enhance agricultural sustainability. The observed differences of adoption across populations became more acute, especially regarding soil conservation and environmental practices in both developed and developing countries. Scholars responded by looking more into areas of technology and social uncertainty and the role of risk in decision-making (Marra, Pannell and Abadi Ghadim 2003), private and public benefits (Pannell 2008), the role of agricultural extension and policy incentives to increase adoption of sustainable practices (Sunding and Zilberman 2001).

In early 2000s, a new wave of technology surged, enabled by advances in information technology and automation, where technologies were perceived to be more complex, modular and interconnected (Stafford 2000). Scholars responded by focusing attention on complexity and systems theory (Klerkx and van Mierlo 2012), task-technology fitness (Goodhue, Dale, Thompson and Ronald 1995), the role of learning and the social context. (Feder et al. 1982, Sunding and Zilberman 2001, Chavas and Nauges in press).

The advantages or opportunities offered to land owners by new technologies can be studied both from the perspective of the adopter and from the perspective of the innovation. The literature has consistently stressed the importance of considering the interaction between innovation and adopter characteristics to explain adoption (for example Pannell et al. 2006). A recent conceptual framework explicitly accounting for this interaction is the ADOPT model proposed by Kuehne et al. (2017). We have used this conceptual framework as a guideline to interpret the results of our analysis. The ADOPT conceptual framework suggests that adoption can be estimated by pairing innovation-specific factors with measures of how much the potential adopters care about those factors. For example, the impact of a variable like risk aversion is mediated by another variable representing riskiness of the innovation. The actual impact on adoption logically depends on the interaction between those two variables. Despite this, it is common practice that innovation and adopter factors are studied separately and that one or the other may be neglected or omitted. This paper investigates how both groups of variables are used in the existing literature and provides a comparison of their ability in explaining or predicting adoption using three measures: Statistical significance, predictive ability and importance or 'impact'.

**Methods**

Comparing the performance of independent variables in statistical models has been done using several measures, the most common being statistical significance. Most adoption studies produce results by defining statistical models using data from cross-sectional surveys on a sample of farmers. Each regression estimates effect sizes and directions for each independent variable and their statistical significance. However, as noted by McCloskey and Ziliak (1996), and later by Abadi Ghadim et al. (2005), variables of statistical significance do not necessarily correspond with variables of importance or high impact. "A variable may have very little impact on the dependent variable, but still be highly 'significant' in a statistical sense. Conversely, variables that do not meet high standards of statistical significance may still be highly significant in terms of their impact on the dependent variable" (Abadi Ghadim et al. 2005, p. 4). However, establishing the importance or impact of variables in any statistical model is notoriously difficult and cumbersome, especially when covariates and transformations are used. This is further complicated when trying to establish the importance of variables across different types of regression models (OLS, Logit, Multinomial logistic, Probit, Tobit, etc.) and across studies. Another measure to compare the performance of independent variables is their ability to predict the dependent variable. Some authors have noted the differences that exist between choosing independent variables for models aiming at explaining or predicting (Shmueli 2010, Shmueli and Koppius 2011).

In this study, we conducted a descriptive analysis of variables in a sample of adoption studies from 1957 to 2016 to identify patterns in their use over time. We then conducted three quantitative analyses to determine their consistency in statistical significance, their predictive ability and their importance. First, a vote-count method was used to analyse the consistency in statistical significance and direction of variables as reported in a sample of papers. The second analysis consisted of using the Partial Least Squares (PLS) method in data from four studies: Alcon, de Miguel, and Burton (2011), Llewellyn, D'Emden, and Kuehne (2012), Llewellyn and Ouzman (2014), and Brown (2015) to determine the ability of groups of variables (adopter or innovation characteristics) to predict the dependent variable. Lastly, the third analysis consisted of calculating an importance indicator (as defined by Abadi Ghadim et al. 2005) to determine the impact of individual variables on the dependent variable using data from the study by Llewellyn and Ouzman (2014), focusing on the adoption of precision agriculture technologies and practices by a sample of Australian farmers.

*Variable use patterns and statistical significance*

We used a sample of 100 studies from 1957 to 2016 to build a database of explanatory variables grouped into characteristics of the innovation, characteristics of the adopter and characteristics of the environmental context in which adoption takes place (Wejnert 2002). We estimate that the studies on adoption in agricultural economics since Feder, Just and Zilberman's study in 1985 to exceed 5000 papers. A sample of 100 studies can therefore only offers a glimpse of them, but we were satisfied that sample size was representative enough to explore this issue.

To identify candidate studies, we included papers used in previous meta-analysis and reviews by Baumgart-Getz, Prokopy, and Floress (2012), Knowler and Bradshaw (2007), Prokopy et al. (2008), Rubas (2004), Tey and Brindal (2012), and Wauters and Mathijs (2014). These reviews identified mixed results in both the statistical significance and the direction of the effects of variables included in regression models. Our intention was not to duplicate their findings, but to understand potential reasons for the lack of convergence and consistency of results.

We also searched online library databases for papers containing combinations of terms related to our subject (e.g. AGRICUL*, TECHNOLOG*, FARM*, INNOVATION), and concept (e.g.

ADOP*, DIFFUSSION, UPTAKE, LEARN*, FACTOR*). Studies were considered for the database if they were peer–reviewed journal articles on adoption of technology or practices in agriculture containing at least one table of results of a multivariate statistical analysis. Several of the selected papers reported on more than one technology or practice.

Therefore, our database of examples consisted of 175 individual regression analyses using 39 explanatory variables. These are:

- Innovation characteristics (8 variables): Perceived cost of changing to new practice, profit advantage (including profit in years used, cost savings, profit in the future, time for profit to be realised), environmental advantage (including environmental costs and benefits), risk reduction (including potential impacts on yields, risk of trying a new system), ease & convenience (including use of similar, compatible or enabling technologies, easiness to use), ability of the practice to be trialled on a limited basis, practice complexity, and the extent to which the practice adopted by some is observable to other potential adopters.
- Adopter characteristics (12 variables): Profit orientation, environmental orientation, risk orientation, management horizon, level of advisory support, group involvement, innovation awareness, years of experience, relevant existing skills and knowledge, age, level of education and technology orientation (including landholder's innovativeness, and belief in the capacity of technology to solve production and environmental problems).
- Contextual characteristics (11 variables): These included several measures to determine the farm financial, economic and management characteristics, measured in relative terms amongst the population of potential adopters: total farm area, production potential (including farming intensity, level of yields, assessment of land quality), levels of total farm income and revenue, level of diversification, presence of irrigation, off-farm income as percentage of total income, level of capital investment. Contextual characteristics also included external influences on the farm business: market prices of outputs affected by the innovation, degree at which the enterprise affected by the innovation is subject to government regulation and compliance, and the ability to access government's technical assistance and financial support for adoption of the innovation.

For each variable, we used a vote-count method similar to Knowler and Bradshaw (2007) to calculate a frequency chart showing the number of observations found statistically significant, or not significant and the direction of the effect. We coded the statistical significance and the sign of the association of the variable to the dependent variable as "Significant positive", "Significant negative" and "Not significant". We did not record the direction of not statistically significant variables. We included significant variables at 95% confidence level or more.  We did not include effects of specific regions within the studies. When available, we used results presented for all regions included in the study. If results for each region were presented separately, we selected that with the largest sample size. Some studies included several models, the later versions typically eliminating variables found statistically not significant in the first model. In those cases, we selected the first model.

We tested the consistency of the effects of each variable using two-tailed t-tests at the 95% confidence level. We tested the consistency of statistical significance (the ratio of statistically significant vs not statistically significant observations) and the consistency of the direction of the effects (the ratio of positive and negative observations).

We analysed the effects of each variable on adoption at two levels of aggregation. The aggregated level analysis summarised all observations. The disaggregated level consisted of analysing the results by grouping the observations according to five categories of innovations. This was done to identify whether the type of innovation under study determines the mix of variables used and their results. A disaggregated analysis of results is recommended by Wauters and Mathijs (2014). Groups were:

- Automation & information (54 examples): autosteer, computer management systems, information technology, remote sensing, soil testing, variable rate applications.
- Increase yields (26 examples): fertilisers, GM technologies, hormones, machinery, new crops.
- Weed and pest control (21 examples): pest control, weed control.
- Soil conservation (43 examples): minimum or no-tillage, crop rotation, soil conservation practices.
- Environmental practices (32 examples): sustainable management practices, renewable energy, water conservation practices.

*Predictive ability*

It is difficult to make direct comparisons other than a vote-count method across published results in studies. We limited the predictive ability analysis to four existing studies for which data was provided. Furthermore, we analysed predictive ability of variables only as a group because the differences that exist between the four studies, both in terms of the number of variables used and their definition. We excluded contextual variables from this analysis, focusing only on innovation and adopter characteristics.

Partial Least Squares (PLS) was selected because it combines information about the variances of both the predictors and the dependent variables, while also considering the correlations among them. PLS combines multiple linear regression and principal components analysis to conduct variance analysis of complex, correlated, multi-variate predictors (Hair, Ringle, and Sarstedt 2011, Rosipal and Kramer 2005).

PLS is a family of regression-based methods designed for the analysis of high dimensional data, especially suited to social sciences, where “soft models and soft data” are prevalent, with an emphasis on prediction. The mechanics of the process is explained in detail in (Esposito et al. 2011). We used PLS in four of studies, representing a diverse range of adopters, technologies, practices and adoption levels (Table 1).

**Table 1**. Studies used for predictive ability analysis.

| Reference for study | Study Characteristics |
|---|---|
| Alcon, F., de Miguel, M. D. and Burton, M. (2011). Duration analysis of adoption of drip irrigation technology in Southeastern Spain. *Technological Forecasting and Social Change,* 78(6), 991–1001 | Practice: Drip irrigation<br>Type of study: Duration study<br>Method: Survey<br>Population: Spanish farmers<br>Sample size: 326 |
| Llewellyn, R., D’Emden, F. H. and Kuehne, G. (2012). Extensive use of no-tillage in grain growing regions of Australia. *Field Crops Research,* 132, 204–212. | Practice: No-till or zero-till for cropping<br>Type of study: Cross sectional<br>Method: Survey<br>Population: Australia grain growers<br>Sample size: 1170 |
| Llewellyn, R. and Ouzman, J. (2014). Adoption of precision agriculture-related practices: status, opportunities and the role of farm advisers. *Report for Grains Research and Development Corporation,* CSIRO. | Practice: Variable rate fertiliser application and related PA technologies<br>Type of study: Cross sectional<br>Method: Survey<br>Population: Australia grain growers<br>Sample size: 573 |
| Brown, P. (2015). Survey of Rural Decision Makers. Landcare Research NZ Ltd. Available: www.landcareresearch.co.nz/srdm2015 https://doi.org/10.7931/J28913S8 | Practices: A range of environmental practices and novel technologies<br>Type of study: Cross sectional<br>Method: Survey<br>Population: New Zealand landowners<br>Sample size: 4993 |

For consistency purposes, the dependent variable was treated as a dichotomous adoption variable, which is common practice in adoption studies. Accordingly, a generic regression model was used to standardise the analysis across studies. For each adoption example, we defined a logistics regression model (i.e. Logit) using all available variables. The technologies, practices and independent variables analysed for each study were:

Study 1 - Drip irrigation

- Adopter related characteristics (14 variables): age, years of experience, level of studies, risk attitude towards technology, risk attitude towards production, access to credit for irrigation, short-term financial constraints, willingness to borrow money for irrigation, number of sources of information about drip-irrigation, ability to access subsidies, perceived importance of imitation and public image, level of technical knowledge to implement technology, level of technical knowledge to manage technology.
- Innovation related characteristics (15 variables): use of compatible technology and infrastructure, relative advantage (perception of how can drip-irrigation assist in regards to: water scarcity, water savings, increased yields, less work, increase irrigation flexibility, more free time, savings in fertiliser use, conservation of water storage, possibility to use desalinised water, increased crop quality), potential problems (perceptions on the importance of cost, ease and convenience, complexity, and potential soil salinization).

Study 2 – No-till cropping

- Adopter related characteristics (3 variables): age, level of education, use of paid advisory support (consultant, advisor or agronomist).
- Innovation related characteristics (19 variables): use of related technologies and practices (use of cultivation to kill fallow weeds, use of brown/green manure of a sown crop, use of mouldboard ploughing to bury weed seeds, use of delayed seeding with knockdown, use of double knockdown, use of crop topping primarily for weed control purposes, use of pasture spraytopping or hayfreezing), use of harvesting methods for weed control (use of a chaff cart for harvest weed seed control, use of a bale direct system, use of narrow windrow burning, use of chaff tramlining, use of a Harrington Seed Destructor), risk reduction (proportion of land with a herbicide resistant weed population), profit advantage (belief that no-till with stubble retention will lead to less, the same or more levels of crop disease, weed costs, nitrogen fertiliser costs, pest costs, effectiveness of pre-emergent herbicides, and reliability of wheat yields)

Study 3 - Variable rate fertiliser application, auto steer using GPS (on any machinery), yield monitor on a harvester, crop yield map from any paddock, seeding machinery that is equipped with variable rate technology.

- Adopter related characteristics (13 variables): membership to a precision agriculture association or a group, membership to any local farmer group that looks at cropping issues, use of paid consultant, advisor or agronomist for cropping advice, level of computer technology skills, perception of technology self-efficacy, confidence in developing new computer skills, level of data analysis skills, preference to keep operations simple, level of enjoyment in analysing data, availability of skilled labour, age, level of education, gender.

- Innovation related characteristics (13 variables): perceived relative advantage and ease and convenience (reduced input costs, increased crop production, risk reduction, more profitable cropping, potential future benefits, time consuming data analysis, complications due to a wide range of different soil types, cost associated with treating paddocks with gypsum or lime, perception that variable rate technology is complicated, perception that mapping paddock zones is time consuming, ability to identify paddock zones, perception of variability within paddocks to justify using different fertilizer rates, ability to access technical support for precision agriculture technology).

Study 4 – practices to: manage erosion/sediment, reduce pugging, restrict stock from waterways, manage fertiliser, maintain a lower stocking rate, manage effluent storage. Adoption of irrigation systems, electricity generation, automation / robotics, and precision agriculture.

- Adopter related characteristics (15 variables): attitudes (risk aversion, willingness experimenting with new ideas, perceived level of innovativeness, perceived commitment to a tradition of farming, level of affiliation to values similar to those of other farmers in the district, preference for adopting management practices similar to those of other farmers in the district, intention to reduce total output if it is possible to maintain the same long-term profitability, belief that it is important to maintain the recreational use of waterways for activities such as fishing and swimming, belief that private land owners should protect habitat for native plants and animals on private land), level of debt (calculated as debt:equity ratio), perceived level of profitability, sex, marital status, age, years of experience, level of education.
- Innovation related characteristics (4 variables): relative advantage (perception on how has/would the practice impact the farm in terms of profitability, environmental performance, overall management of the farm, and resilience to future climate variability).

*Variable importance*

We conducted the last analysis using data from the third study listed above (Llewellyn and Ouzman 2014) to compare the importance of variables in explaining the adoption of five closely related technologies by the same group of adopters, making a general assumption that the decision to adopt each technology or practice was considered by the farmer under very similar adoption condition and using the same explanatory variables.

We used the approach suggested by Abadi Ghadim et al. (2005) to compare the importance of adopter and innovation related variables. We calculated an 'importance indicator' of independent variables by combining elasticities (i.e. marginal effects) and sample variance to convert marginal effects to total impacts for each independent variable. We calculated the predicted probability of adoption for each technology when each independent variable in turn was set to a value two sample standard deviations above the sample mean and then when was set two sample standard deviations below the mean (all other variables were set to their sample means). The impact indicator for each variable was the difference between the two predicted probabilities. The mechanics of the process is explained in detail in (Abadi Ghadim et al. 2005). We then normalised the impact indicators to compare each variable across technologies.

## Results

### *Variable use patterns in studies*

Disciplines, theories and variables included in adoption studies in agriculture have changed over time. The sample of studies included in our database represents adoption research stretching for more than 4 decades. Over that period, authorship affiliation has changed considerably. While most studies have been published by academics in agricultural and resource economics or sociology faculties and by government officials in agricultural departments, inter-agency papers in our sample (judged by the number of authors and their affiliations) have grown from 10% in the period from 1957 to 1985 to 74% of recent papers (from 2006 onwards) (Figure 1). Most studies in this sample were conducted using an economics-based conceptual framework (64 papers), with the rest of papers using conceptual models based on diffusion theory (11 papers), social psychology/sociology (20 papers) and systems theory (5 papers).

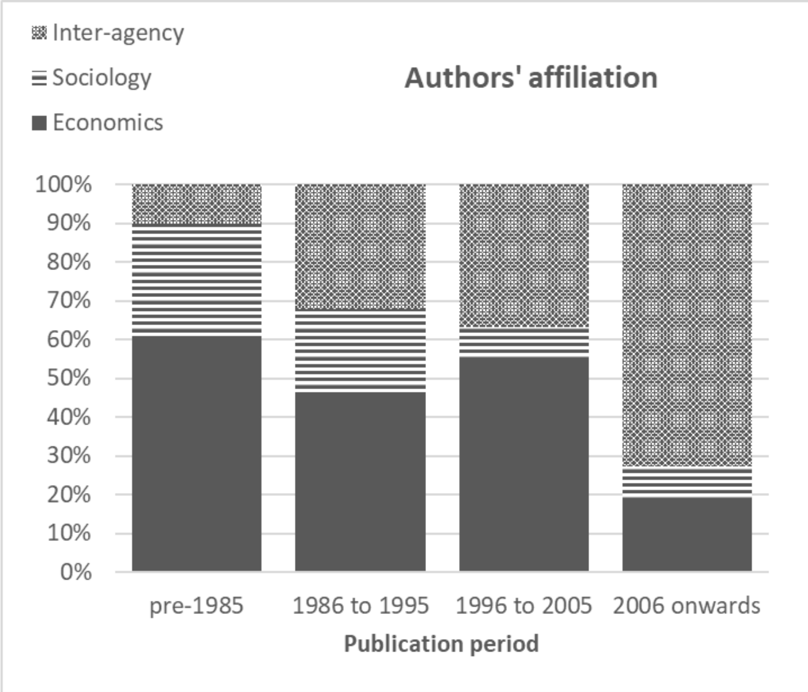


Figure 1. Authorship composition of adoption studies in agriculture over time in our database.

Typically, earlier studies in our sample would include authors from agricultural economics and sociology faculties (for example: Griliches, 1957; Hooks, Napier and Carter, 1983; Lindner, Pardey and Jarret, 1982; Taylor and Miller, 1978), while new studies would typically include a wider range of affiliations (for example: Borchers, Xiarchos and Beckman, 2014; Cary, Webb and Barr, 2001; Schut, Rodenburg, Klerkx, van Ast and Bastiaans, 2014). In these later studies, is it common to find author from different university faculties, research organisations and government agencies.

The average number of variables included in regression models grew steadily from 6.8 variables per case for the 1957 to 1985 period to 9.2 variables per case in the last decade. However, the ratio of not statistically significant variables to significant variables remained relatively constant at around 67%. Figure 2 shows the proportions of variables included in the studies that we assessed as falling into the three categories: variables related to the innovations, the adopters, or the context. Our analysis shows that characteristics of the innovation have consistently been underrepresented in adoption studies. Until the mid 1980s, two thirds of variables chosen related to the adopter, with most of the balance being contextual variables. Contextual variables are often used to supplement adopter characteristics, especially farm financial, economic and management characteristics. Few scholars paid attention to the characteristics of the innovation itself. Until the mid 1990s, we could observe an equal split on adopter and contextual characteristics, with even fewer studies considered innovation-related characteristics. Figure 2 also shows that only from 1996 a modest increase in the number of variables related to the innovation can be observed in our sample.

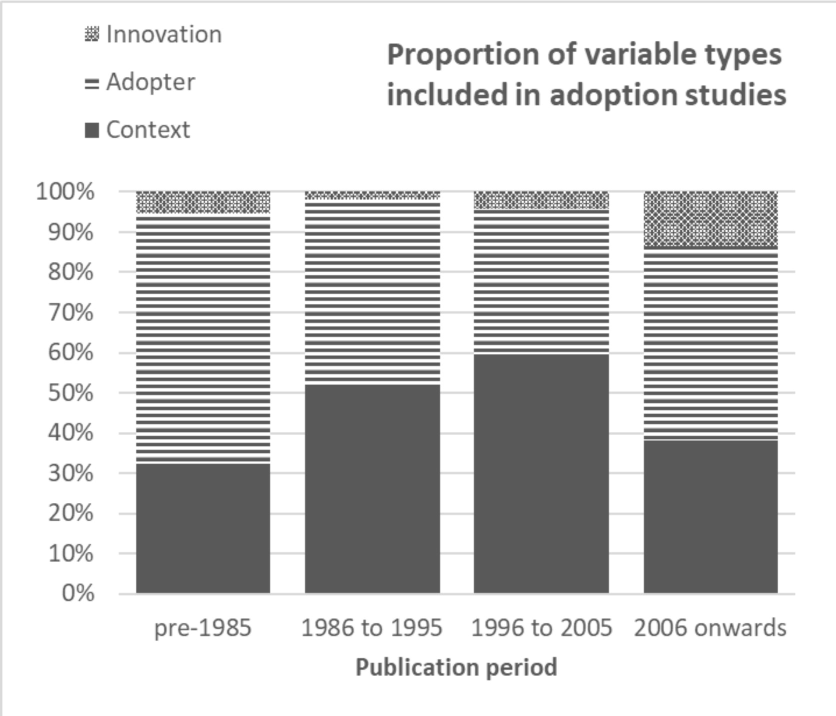


Figure 2. Types of variables included in adoption studies in agriculture over time in our database.

Our analysis suggests that studies have formed distinct functional groups over time, according to their area of application (e.g. behavioural change, rural economics, agricultural extension and precision agriculture). We believe that these application areas have influenced the mix of variables used in statistical models of related, recent studies. We analysed a small sample of papers conducted in the last decade on these different areas of application to illustrate differences on the type of variables used in each group.

We found that applied papers on behavioural change have, in general, focused on variables measuring general attitudes and preferences towards innovativeness, financial, environmental and risk orientation. There were some studies that also considered underlaying values, such as altruism or control. In either case, it was often assumed that an adopter or population of adopters displaying certain preferences would be predisposed to adopt any technology that would deliver to those preferences. Some examples are:

- Zeweld, Van Huylenbroeck, Tesfay and Speelman (2017) used 12 variables to explain the behavioural intentions of farmers of row planting practices and minimum tillage practices. Their model estimates intention, attitude, normative issue and perceived control of farmers. Of the 12 variables uses, 2 variables (perceived usefulness and perceived easiness) where innovation-related characteristics and 10 were adopter characteristics.

- Hamilton-Webb, Manning, Naylor and Conway (2017) studied the relationship between risk experience and risk response in a sample of farmers regarding climate change. They used 6 independent variables to measure direct and indirect flood experiences to estimate the adoption of 11 possible mitigation and adaptation actions on farm. There were no adopter nor innovation related variables included, only contextual variables.

We found that is was common in applied agricultural extension papers to focus solely on the effectiveness of extension interventions on adoption. We found those papers included several demographic characteristics in their regression models and very few innovation specific variables. Some recent examples are:

- Nakano, Tsusaka, Aida and Pede (2018) studied the impact of training on the adoption of 5 technologies in rice production in Tanzania. Their regression model used 20 variables. Of those, 12 were adopter characteristics and 6 were contextual variables. No innovation-related variables were included.
- Kondylis, Mueller and Zhu (2017) studied the evidence of extension on the adoption of 7 sustainable land management practices in Mozambique (mulching, strip-tillage, pit planting, contour farming, crop rotation, row planting and improved fallowing). They defined several regression models using different combination of up to 25 variables. Of those, 13 were farm characteristics and 12 adopter characteristics (mainly demographics). Innovation characteristics were not included in the analysis.

We found that applied papers in precision agriculture tended to include more innovation related characteristics in their regression models than the rest of application areas we analysed. We also found that adopter related variables were more focused on the ability to learn, develop or access technical skills. Precision agriculture papers seemed to use more targeted variables aimed at measuring the technology's relative advantage and ease & convenience. Some examples are:

- Aubert, Schroeder and Grimaudo (2012) studied the adoption of precision agriculture technology by a sample of farmers in Canada. Technologies investigated were: GPS, GIS, yield monitors, remote sensing, variable rate application and guidance and navigation technology. They used 16 variables. Of those, 8 were innovation characteristics, 7 were adopter characteristics and one farm characteristic (farm size).

- Roberts et al. (2004) studied the adoption of site-specific information and variable rate technologies in cotton production in the US. They used 14 variables. Three were adopter characteristics, 3 were innovation characteristics, and the balance were contextual variables.

We found that applied rural economics papers used more innovation related variables when studying the adoption of easily defined, discrete technologies (crop varieties, fertiliser) than when studying the adoption of environmental or conservation practices. We found environmental practices tend to be poorly defined and therefore harder to measure (e.g. sustainable practices, best management practices). Some examples are:

- Borges, Oude Lansink, Marques Ribeiro and Lutke (2014) used the theory of planned behaviour to study the adoption of improved grasslands by a sample of Brazilian farmers. They measured behavioural, normative and control beliefs using 21 variables. Of those, 8 were innovation characteristics and 13 were adopter characteristics.
- Lambrecht, Vanlauwe, Merckx and Maertens (2014) studied the adoption of mineral fertiliser in Eastern DR Congo. They analysed adoption in three stages: awareness, trial and adoption. They used 19 variables to measure social, physical, financial and human capital, location, distance to market and demographics. Thirteen variables were adopter characteristics and 6 were contextual characteristics. They did not include innovation-related variables.

*Variables statistical significance*

Overall results are presented in Figure 3, and the disaggregated results by innovation group are presented in Figure 4. In Figure 3, the frequency table shows the number of observations found to be (statistically) significant negative ("Sig –"), not significant ("Not sig") and significant positive ("Sig +"), and the total number of regression examples in which the variable was included. T-tests were used to determine the consistency of significance (the ratio of statistically significant vs not statistically significant observations) and the consistency of the direction of the effects (the ratio of positive vs negative observations). A "Sig" value in the "T-test sig" column means that the variable, when included, was likely to be found statistical significant in the regression model, while a "Not sig" value means the variable, when included, was likely to be not statistically significant in the regression model. In a similar way, the "T-test direction" column presents the results of the T-test for direction of the effect. Empty cells mean that the consistency of significance or direction could not be established due to either a small number of observations or mixed results.

In Figure 3, the variables listed at the top of the table in each group were consistent in both significance and direction of the effects, followed by variables that showed consistent direction of effects, but mixed significance results. These are followed by poorly researched variables in each category. At the bottom of the list for each category are variables that were likely to be found not significant in regression models.

| Category | Variable | All responses | | | Exam-ples | T-test signifi-cance | T-test direc-tion |
|---|---|---|---|---|---|---|---|
| | | Sig - | Not sig | Sig + | | | |
| Characteristics of the innovation | Ease & convenience | 1 | 10 | 37 | 48 | Sig | Pos |
| | Profit advantage | | 1 | 11 | 12 | Sig | Pos |
| | Environmental advantage | | | 9 | 9 | Sig | Pos |
| | Risk reduction | | 4 | 6 | 10 | | Pos |
| | Trialling ease | 1 | 1 | 2 | 4 | | |
| | Innovation complexity | | 1 | 1 | 2 | | |
| | Observability | | 2 | 3 | 5 | | |
| | Investment cost | 5 | 32 | 8 | 45 | Not sig | |
| Characteristics of the adopter | Level of advisory support | 1 | 18 | 50 | 69 | Sig | Pos |
| | Profit orientation | | 14 | 28 | 42 | Sig | Pos |
| | Orientation towards technology | | 2 | 10 | 12 | Sig | Pos |
| | Level of education | 3 | 50 | 66 | 119 | | Pos |
| | Age | 30 | 49 | 6 | 85 | | Neg |
| | Group involvement | 3 | 39 | 38 | 80 | | Pos |
| | Years of experience | 20 | 33 | 7 | 60 | | Neg |
| | Environmental orientation | | 14 | 24 | 38 | | Pos |
| | Relevant existing skills and knowledge | 2 | 13 | 9 | 24 | | Pos |
| | Risk orientation | 4 | 15 | 11 | 30 | | |
| | Management horizon | 1 | 6 | 6 | 13 | | |
| | Innovation awareness | | 3 | 3 | 6 | | |
| Characteristics of the context | Total farmed area | 10 | 53 | 64 | 127 | Sig | Pos |
| | Level of diversification | 2 | 8 | 27 | 37 | Sig | Pos |
| | Presence of irrigation | 8 | 7 | 20 | 35 | Sig | Pos |
| | Market prices | | 6 | 15 | 21 | Sig | Pos |
| | Governement financial support | | 2 | 11 | 13 | Sig | Pos |
| | Land quality | 13 | 46 | 50 | 109 | | Pos |
| | Level of income and revenue | 14 | 46 | 38 | 98 | | Pos |
| | Production potential | 4 | 20 | 24 | 48 | | Pos |
| | Level of capital investment | 3 | 25 | 15 | 43 | | Pos |
| | Government regulation and compliance | 1 | 10 | 9 | 20 | | Pos |
| | Off-farm income | 12 | 43 | 12 | 67 | Not sig | |

Figure 3. Variable analysis results at the aggregated level for the adoption of agricultural innovations.

Figure 4 shows results of grouping examples by innovation type. T-tests were not run at this level, due to the small number of observations.

| Category | Variable | Automation & Information | | | Increase yield | | | Pest and weed control | | | Soil conservation | | | Environmental practices | | | Exam-ples |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Sig - | Not sig | Sig + | Sig - | Not sig | Sig + | Sig - | Not sig | Sig + | Sig - | Not sig | Sig + | Sig - | Not sig | Sig + | |
| Characteristics of the innovation | Ease & convenience | 1 | 4 | 23 | | 4 | 7 | | 1 | 1 | | | 3 | | 1 | 3 | 48 |
| | Profit advantage | | 1 | 4 | | | 3 | | | 1 | | | 2 | | | 1 | 12 |
| | Environmental advantage | | | 3 | | | | | | 4 | | | 1 | | | 1 | 9 |
| | Risk reduction | | | 2 | | | 1 | | | | | 3 | 2 | | 1 | 1 | 10 |
| | Trialling ease | 1 | 1 | 1 | | | 1 | | | | | | | | | | 4 |
| | Innovation complexity | | 1 | 1 | | | | | | | | | | | | | 2 |
| | Observability | | 2 | 1 | | | 1 | | | | | | | | | 1 | 5 |
| | Investment cost | 3 | 12 | 1 | | | 1 | | | | | 4 | 2 | 2 | 16 | 4 | 45 |
| Characteristics of the adopter | Level of advisory support | 1 | 5 | 18 | | 6 | 5 | | 3 | 8 | | 2 | 12 | | 2 | 7 | 69 |
| | Profit orientation | | 4 | 3 | | 2 | 5 | | | 4 | | 2 | 5 | | 6 | 11 | 42 |
| | Orientation towards technology | | 1 | 3 | | 1 | 2 | | | | | | | | | 5 | 12 |
| | Level of education | 1 | 19 | 23 | | 7 | 16 | 1 | 2 | 14 | 1 | 15 | 10 | | 7 | 3 | 119 |
| | Age | 14 | 12 | 3 | 4 | 5 | 1 | 1 | 4 | 1 | 8 | 11 | | 3 | 17 | 1 | 85 |
| | Group involvement | | 8 | 6 | | 3 | 6 | 1 | 6 | 7 | 1 | 7 | 8 | 1 | 15 | 11 | 80 |
| | Years of experience | 8 | 8 | 2 | 4 | 6 | 3 | 4 | 2 | 1 | 2 | 17 | 1 | 2 | | | 60 |
| | Environmental orientation | | 2 | 3 | | 1 | 2 | | | | | 3 | 8 | | 8 | 11 | 38 |
| | Relevant existing skills and knowledge | | 2 | 3 | | | 3 | | | | 2 | 1 | 1 | | 10 | 2 | 24 |
| | Risk orientation | 1 | 4 | | 1 | 4 | 3 | | 3 | 1 | 2 | 3 | 5 | | 1 | 2 | 30 |
| | Management horizon | 1 | | 2 | | 1 | 2 | | | 1 | | 4 | | | 1 | 1 | 13 |
| | Innovation awareness | | 1 | | | 2 | 2 | | | | | | 1 | | | | 6 |
| Characteristics of the context | Total farmed area | 2 | 14 | 29 | 2 | 4 | 11 | 3 | 5 | 7 | 2 | 17 | 13 | 1 | 13 | 4 | 127 |
| | Level of diversification | | 5 | 10 | | | 1 | 1 | 1 | 8 | | 1 | 7 | 1 | 1 | 1 | 37 |
| | Presence of irrigation | 1 | 1 | 8 | | | 2 | 2 | 2 | 6 | 4 | 4 | 2 | 1 | | 2 | 35 |
| | Market prices | | 3 | 5 | | | 2 | | | | | 3 | 8 | | | | 21 |
| | Government financial support | | 1 | 3 | | | | | | | | | 7 | | 1 | 1 | 13 |
| | Land quality | 5 | 7 | 14 | | 5 | 3 | 2 | 9 | 4 | 6 | 22 | 29 | | 3 | | 109 |
| | Level of income and revenue | 5 | 13 | 15 | 4 | 4 | 4 | | 3 | 5 | 4 | 14 | 9 | 1 | 12 | 5 | 98 |
| | Production potential | 1 | 4 | 9 | | 4 | 8 | 1 | 1 | 2 | 1 | 2 | 2 | 1 | 9 | 3 | 48 |
| | Level of capital investment | | 3 | 5 | | 4 | 5 | | 4 | 1 | 1 | 6 | 1 | 2 | 8 | 3 | 43 |
| | Government regulation and compliance | 1 | 1 | 1 | | 3 | 4 | | | | | 4 | 4 | | 2 | | 20 |
| | Off-farm income | 7 | 17 | 1 | 1 | 3 | 1 | | 5 | 6 | 4 | 12 | 4 | | 6 | | 67 |
| | **Number of observations** | **53** | **156** | **202** | **16** | **69** | **105** | **16** | **51** | **82** | **38** | **157** | **147** | **15** | **140** | **84** | **1331** |

Figure 4. Variable analysis results grouped by innovation types.

Characteristics of the innovation

Innovation characteristics were the least researched group in the sample, accounting for 10% of the total number of variables included in all regression examples (Figure 3). However, our analysis showed that, as a group, they were the most consistent variables used in regression examples. The two most researched variables in this group were ease & convenience (included in 48 examples) and investment cost (included in 45 examples). Interestingly, ease & convenience was the most consistent variable in the group in both direction and significance, while investment cost was the least reliable variable included in regression models.

Ease & convenience, profit advantage and relative advantage showed a high degree of consistency in both direction and significance. Risk reduction showed consistency only on direction. Trialling ease, innovation complexity and observability were the least researched variables in our sample, despite being considered conceptually important (Pannell et al. 2006).

Characteristics of the adopter

Figure 3 shows that adopter characteristics accounted for 46% of the variables used in regression examples. Demographic variables were the most researched variables in the group, but not necessarily the most consistent. Our analysis showed that personality-related variables such as profit orientation, environmental orientation and technology orientation had a consistent positive influence on adoption, while risk orientation showed mixed results.  This is expected in studies that have included risk orientation without it being interacted with the perceived riskiness of the innovation. As a group, adopter characteristics generally showed high consistency in direction, but mixed results in statistical significance.

Figure 3 also shows that level of advisory support, profit orientation and orientation towards technology showed a high degree of consistency in both direction and significance. Level of education, age, degree of group involvement, years of experience, environmental orientation and level of relevant existing skills and knowledge showed consistency only in direction. Management horizon and innovation awareness were the least researched variables.

Figure 4 shows that some variables presented differences in consistency depending on the type of innovation under study. Level of advisory support seemed to be particularly relevant to the automation & information, weed and pest control and the soil conservation groups.

Level of education was the most researched variable in the adopter characteristics group. While its influence on adoption was invariably positive in most cases, it seemed to be more important for some types of innovations: increase yields and pest and weed control innovations, and to a lesser degree in the adoption of automation & information. The adoption of soil conservation and environmental practices was less sensitive to the influence of the level of education (Figure 4).

Age had a negative influence on the adoption of automation & information innovations, and to a lesser extent on soil conservation practices, but it was often found not to be statistically significant in regression examples across all innovation types. Similar results were observed for group involvement, years of experience and relevant existing skills and knowledge.

### Characteristics of the context

Variables related to the context in which adoption takes place accounted for 44% of variables in regression models. Figure 3 shows that all variables in this group showed high consistency of direction, except for off-farm income as percentage of total farm income. Most regression examples included a measure of enterprise scale such as farmed area, production potential, level of capital investment and levels of farm income and revenue. All of these showed a positive influence on adoption but only farmed area was also consistent in terms of significance. Other variables in this group which were highly consistent in significance were level of diversification, presence of irrigation, market prices of outputs affected by the innovation, and the ability to access government's technical assistance and financial support for adoption of the innovation.

Figure 4 shows that some variables in this group presented differences according to innovation type. Total farmed area was mostly statistically not significant in studies relating to soil conservation and environmental practices. Other measures of enterprise size had mixed results across all innovation types. The presence of irrigation had a positive effect on adoption of all innovation types except for soil conservation practices, for which it showed a negative effect.

*Variables predictive ability*

Table 2 shows the results of the PSL analysis of four studies. The table shows, for each technology or practice, the study, sample size, level of adoption, and the total level of variance explained in the dependent variable by the characteristics of the adopter and the characteristics of the innovation. Within studies, the technologies and practices have been sorted according to their level of adoption.

**Table 2**. Statistical ability of adopter and innovation characteristics to explain variance in adoption in four studies.

| Study | Sample size | Technology or practice | Adoption rate % | Total variance in adoption (%) that can be explained by: | |
|---|---|---|---|---|---|
| | | | | Characteristics of the adopter | Characteristics of the innovation |
| Alcon 2011 | 347 | Drip irrigation | 98% | 4.6 | 7.7 |
| Llewellyn 2012 | 602 | No-tillage | 92% | 1.9 | 3.4 |
| Llewellyn 2014 | 571 | Autosteer using GPS | 77% | 19.4 | 4.6 |
| Llewellyn 2014 | 571 | Yield monitor on a harvester | 59% | 12.9 | 3.5 |
| Llewellyn 2014 | 571 | Variable fertiliser rates | 49% | 7.5 | 26.3 |
| Llewellyn 2014 | 571 | Variable seeding machinery | 35% | 9.9 | 11.9 |
| Llewellyn 2014 | 571 | Crop yield maps | 33% | 23.0 | 7.3 |
| Brown 2015 | 544 | Effluent management system | 90% | 5.7 | 1.4 |
| Brown 2015 | 123 | Soil fertility tests | 78% | 15.9 | 3.2 |
| Brown 2015 | 98 | Variable fertiliser rates | 66% | 7.3 | 4.1 |
| Brown 2015 | 1373 | Excluding stock from waterways | 64% | 4.8 | 5.9 |
| Brown 2015 | 1823 | Maintaining a lower stocking rate | 42% | 5.2 | 22.5 |
| Brown 2015 | 519 | Reduce pugging by using feed pads | 40% | 2.3 | 9.8 |
| Brown 2015 | 1281 | Manage erosion by planting trees on slopes | 32% | 4.3 | 1.2 |
| Brown 2015 | 1078 | Irrigation | 20% | 4.4 | 23.3 |
| Brown 2015 | 2214 | Precision agriculture | 10% | 4.4 | 1.0 |
| Brown 2015 | 2214 | Electricity generation (e.g. windmills, solar) | 7% | 2.1 | 1.1 |
| Brown 2015 | 2214 | Automation (e.g. robotic milking) | 3% | 2.6 | 2.2 |

Eighteen technologies and practices were analysed using PLS, showing mixed results on the predictive ability of variable groups. We did not find discernible patterns both within or across studies, levels of adoption, types of innovation, or the number of variables included in each group. For example, Brown (2015) data included 4 innovation-related variables and 15 adopter-related variables. In two instances those four innovation-related variables were able to explain more than 20% of the variance in adoption of irrigation and maintaining a lower stocking rate. On the other hand, the analysis using Llewellyn and Ouzman (2014) data showed, using an even number of variables in each category, that innovation-related variables were better predictors of the adoption of variable rate fertiliser rates, but adopted-related variables were better predictors of the adoption of autosteer and the use of crop yield maps. Incidentally, autosteer had the highest adoption rate amongst that particular sample of farmers (77%), while the use of crop yield maps had the lowest adoption rate (33%) amongst them.

*Importance of variables*

Results of the analysis of importance of variables on the adoption of precision agriculture practices and technology by a sample of Australian farmers are presented in Table 3.

**Table 3**. Relative importance of variables in explaining the adoption of precision agriculture technologies and practices by a sample of Australian farmers.

| | **Variables** | **Auto steer using GPS (on any machinery)** 77% adoption | **Yield monitor on a harvester** 59% adoption | **Variable fertiliser rate application** 49% adoption | **Variable rate seeding machine** 35% adoption | **Crop yield map from any paddock** 33% adoption |
|---|---|---|---|---|---|---|
| **Characteristics of the adopter** | Use of paid consultants or advisors for cropping advice | 1.00 | 0.96 | 0.04 | 1.00 | 0.76 |
| | Membership to producers group | 1.00 | 1.00 | 0.09 | 1.00 | 0.13 |
| | Membership to PA group | 0.22 | 0.06 | 1.00 | 0.05 | 1.00 |
| | Level of computer technology skills | 0.49 | 0.45 | 0.40 | 0.26 | 0.38 |
| | Preference to keep operations simple | 0.04 | 0.60 | 0.02 | 0.04 | 0.45 |
| | Technology self-efficacy | 0.07 | 0.02 | 0.40 | 0.50 | 0.09 |
| | Confidence in developing new computer skills | 0.46 | 0.01 | 0.02 | 0.12 | 0.35 |
| | Level of education | 0.03 | 0.07 | 0.10 | 0.06 | 0.70 |
| | Level of data analysis skills | 0.04 | 0.03 | 0.41 | 0.03 | 0.39 |
| | Enjoyment in analysing data | 0.06 | 0.03 | 0.23 | 0.53 | 0.02 |
| | Sex | 0.18 | 0.31 | 0.19 | 0.04 | 0.08 |
| | Lack of skilled labour | 0.02 | 0.02 | 0.06 | 0.01 | 0.34 |
| | Age | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 |
| **Characteristics of the innovation** | No justification for using different fertilizer rates | 0.48 | 0.43 | 0.35 | 0.43 | 0.34 |
| | Benefit in increased crop production | 0.63 | 0.03 | 0.52 | 0.02 | 0.48 |
| | Mapping paddock zones is very time consuming | 0.03 | 0.02 | 0.45 | 0.58 | 0.45 |
| | Using variable rate technology is very complicated | 0.39 | 0.02 | 0.44 | 0.55 | 0.02 |
| | Benefit in more profitable cropping | 0.09 | 0.02 | 0.53 | 0.17 | 0.21 |
| | Potential future benefits | 0.01 | 0.26 | 0.04 | 0.40 | 0.31 |
| | Treating paddocks with gypsum or lime is a major cost | 0.02 | 0.43 | 0.35 | 0.16 | 0.06 |
| | Lack of technical support for PA | 0.08 | 0.04 | 0.11 | 0.48 | 0.02 |
| | Managing PA data is very time consuming | 0.05 | 0.57 | 0.03 | 0.03 | 0.01 |
| | Benefit in reduced risk | 0.11 | 0.02 | 0.02 | 0.02 | 0.48 |
| | It is not obvious how to identify paddock zones | 0.01 | 0.21 | 0.39 | 0.03 | 0.01 |
| | Wide range of different soil types | 0.48 | 0.04 | 0.04 | 0.02 | 0.02 |
| | Benefit in reduced input costs | 0.03 | 0.02 | 0.04 | 0.13 | 0.07 |

These results show that even when analysing closely related technologies normalising regression models, the number of independent variables in both groups, farmer sample size, and contextual variables, there was still a great diversity on the influences on adoption for each technology. However, the importance indicator for three adopter variables was consistently higher in every case: The use of paid consultants or advisors for cropping advice, membership to producer groups and membership to precision agriculture groups.

Across technologies, the importance indicator analysis was consistent with our predictive ability analysis: Adopter variables were clearly better predictors in the adoption of autosteer, yield monitors in harvesters and the use of crop yield maps, while innovation variables were better predictors of the adoption of variable rate fertiliser application.

## Discussion

It may be the case that every adoption case is unique, in which case inconsistency of results would reflect reality. However, we found that omitted variables seem likely to be contributing to the observed lack of convergence between adoption studies. We also found that both adopter and innovation variables are important in determining adoption across three measures: statistical significance, predictive ability and an importance indicator. Furthermore, we found no evidence to support that either an adopter-perspective or an innovation-perspective lead to better results in explaining adoption in regression models.

Although different studies omitted different variables, there is a clear tendency for variables related to the technologies or practices to be under-represented in adoption studies. Perhaps it is time to re-balance the research to better understand the technology or practice itself. The under-representation of innovation-related variables in our sample suggests that the innovation under study itself is poorly defined, poorly understood or its advantage over alternatives is taken for granted. This issue is particularly noticeable in the study of environmental practices, where is common to find studies researching the adoption of generic categories (e.g. sustainable practices, best management practices) rather than specific practices. Under these circumstances, it would be very difficult to ascertain the advantage or opportunity of adopting the innovation in relation to alternative or existing practices.

We found that variables related to behaviour change in adoption have, in general, focused on general attitudes and preferences towards innovativeness, financial, environmental and risk orientation. There are some studies that also consider values, such as altruism or control. In either case, it is often assumed that an adopter or population of adopters displaying certain preferences would be predisposed to adopt any technology that would deliver to those preferences.

We also found that variables in extension studies comprise mainly innovator-related variables focusing on attitudes, skills and ability to learn in general and demographics. In this group of studies, it is interesting to note the differences in the consistency of education levels across innovation types (Figure 4). This inconsistency may be explicable. For instance, a complex innovation that has high relative advantage may be more readily adopted by farmers with high education, whereas a complex innovation with negative relative advantage may be more rejected by farmers with high education.

Our results highlight common weaknesses in the research methods in studies of agricultural adoption. We found relatively few studies pairing adopters' preferences, attitudes, intentions and beliefs with corresponding aspects of relative advantage of the innovation (profit advantage, environmental advantage, risk reduction) as suggested by the ADOPT conceptual model (Kuehne et al. 2017). If they include both aspects (i.e., a variable related to the benefits of a practice and a matching variable representing farmers' preferences for that benefit), they were often included as independent variables in a linear model structure, not as an interaction. Authors like Andersson and D'Souza (2014), Brown, Nuberg, and Llewellyn (2017), Pannell and Claassen (in press) and Weersink and Fulton (in press) have also noted the need for a better understanding of adoption to define meaningful dependent variables in regression studies. They have emphasized the inadequacy of regression studies where adoption is measured as a binary variable. Part of a potential solution to improve adoption studies could be an effort by researchers in the field to jointly define a set of best-practice guidelines to statistical adoption studies, including a definition of adoption that could go beyond a binary decision.

In this paper, we have explored which types of variables are commonly included in studies that aim to explain the adoption or non-adoption of particular innovations in agriculture. We found that an imbalance exists in the variables commonly included in research studies, with a relative neglect of the performance of the innovation or practice, and of its interaction with farmer attitudes and preferences. We propose that researchers should in future address this neglect in order to better inform extension and policy efforts to improve uptake of beneficial agricultural innovations.

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