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Review

Adoption of Improved Rice Varieties in the Global South: A Review

Julia CHECCO[1], Fathin Ayuni AZIZAN[1, 2], Jaquie MITCHELL[1], Ammar Abdul AZIZ[1]

(*[1]School of Agriculture and Food Sciences, The University of Queensland, Gatton 4343, Queensland, Australia; [2]Department of Agrotechnology, Faculty of Mechanical Engineering and Technology, Universiti Malaysia Perlis, Arau 02600, Perlis, Malaysia*)

Abstract: Improved rice varieties (IRVs) play a significant role in establishing food security and improving livelihood in the Global South since its introduction in the 1960s. However, the adoption of new IRVs has remained relatively low. This low adoption poses a challenge to rice-producing and consuming countries as they are increasingly threatened by production shortages, malnutrition, and poor rice quality. Many empirical studies have attempted to identify the determinants influencing the adoption of IRVs by distinguishing the characteristics between adopters and non-adopters. This review showed a consensus on the important determinants influencing the adoption of IRVs in the Global South. Findings synthesized from 99 studies suggested that variables (farm size, education, information access and farm location) examined extensively are not necessarily the most important determinants of adoption when undertaking a weighted analysis. Terrain, source of seed and technology-related attributes (perceived yield, maturity, ease of use, marketability and technical efficiency) are more important determinants of adoption, with determinants changing according to adoption type (probability or intensity of adoption), variety type and region. The recommendations for future adoption studies include: incorporating more technology-specific variables, increasing research for overlooked regions and variety types, shifting away from predominant static analysis by capturing the dynamics of the adoption process, and considering the potential biases in analyses. This review will facilitate the development of targeted interventions and policies that promote IRV adoption in the Global South.

Key words: technology adoption; improved rice variety; systematic literature review; the Global South

Rice is arguably the most important staple food for nearly four billion people in the Global South. Almost all the milled rice produced globally is consumed in these regions, contributing up to 70% of calories for millions living in poverty (Zeigler and Barclay, 2008). The majority of this demand is met by production in the Global South, which consists of 97% of the total global harvested land area (1.62×10^8 hm^2) and 96% of total global milled rice production (5.55×10^8 t) in 2019 (FAO, 2021). Primarily grown on farms less than 2 hm^2 per household (Zeigler and Barclay, 2008; Samberg et al, 2016), this extensive rice production system contributes to the employment of more than 200 million smallholder farmers, most of which rely on rice as a primary source of income (Muthayya et al, 2014; Samberg et al, 2016). However, there are rising concerns over the rice sector's ability to provide food security, social stability and improved livelihood in the Global South (Seck et al, 2012).

Fueled by population growth and urbanization, growing demands for staple food in the Global South will require an increase of 5.90×10^7 t in production from 2020 to 2035, posing a challenge to an industry already facing production deficits (Seck et al, 2012).

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Corresponding author: Julia CHECCO (j.checco@uq.edu.au)

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Major rice producers, such as the Philippines and Indonesia, increasingly depend on imported rice to meet local demands (Redfern et al, 2012). These production shortages will likely worsen, with declining growth rates in production levels and harvested areas in the Global South in recent years due to climate change and urban development (Lu et al, 2017; Barthel et al, 2019; FAO, 2021).

Additionally, food security and farmer livelihood continue to be an issue for the Global South with the continued production of less nutritious and inferior quality rice. Rice-eating populations in these regions struggle with micronutrient deficiency due to the lack of dietary diversity, particularly among poorer communities (Majumder et al, 2019). Poor quality rice production in the Global South also fails to meet the quality standards required for higher market prices, making it challenging to absorb rising production costs (Demont and Rutsaert, 2017; Ba et al, 2019). To secure food security and social stability in the Global South, the rice system in these regions need to shift towards improving rice production efficiency, nutrition, and quality by adopting sustainable technologies, such as improved rice varieties (IRVs).

First introduced during the Green Revolution, IRVs have since helped double the mean yield of rice and increased rice production by almost 140% (FAO, 2021). The growing challenges in production have led to the development of IRVs that are high-yielding, stress-tolerant, climate-smart, nutritious, and high-quality, with new varieties released annually (IRRI, 2020). However, the adoption of IRVs in the Global South is still lagging, especially in Africa, Latin America and the Caribbean (LAC), and Pacific Islands, where many farmers continue to grow traditional rice varieties (Abebrese and Yeboah, 2020). Despite high adoption rates of IRVs in Asia, farmers in large areas in Cambodia and Myanmar continue to grow traditional rice varieties (Laborte et al, 2017). Varietal replacement in Asia also remains slow, with some countries still growing older IRVs introduced 40 years ago (Laborte et al, 2017). These varieties are no longer suited for the changing environments (Peng et al, 2010).

Extensive research has been undertaken to understand the low adoption of IRVs in the Global South by examining the determinants influencing IRV adoption (Wu et al, 2010; Mottaleb et al, 2015; Paltasingh et al, 2017; Devkota et al, 2018; Nguyen, 2020). However, there have been limited attempts to synthesize these findings. Previous reviews in the Global South have provided a general understanding of technology adoption for multiple technologies across various crops without specifically analyzing the determinants of the adoption of IRVs (Acevedo et al, 2020; Ruzzante et al, 2021). With adoption varying according to technology type and cropping system, the failure to capture important rice varietal determinants of adoption can make it challenging to develop tailored adoption policies.

This review aimed to effectively identify and understand the determinants of adopting IRVs in the Global South at an individual level. Compared with a diffusion perspective where adoption considers the population, this individual unit of analysis will provide a better understanding of the internal process of an adopter's decision-making (Montes de Oca Mungula et al, 2021). This review evaluated the limitations of current adoption studies and provided areas for improvement. It will help facilitate the development of targeted policies that can influence adoption, provide valuable information for future adoption studies, and ultimately improve the adoption of IRVs.

Method for literature review

This review adopted the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method to explore the literature on IRV adoption (Moher et al, 2009), which has been widely adopted in the field of agricultural and food science research (Koutsos et al, 2019; Kiloes et al, 2022; Yadav et al, 2022) and is also increasingly used to understand technology adoption in agriculture (Acevedo et al, 2020; Olum et al, 2020; Lee et al, 2021; Begho et al, 2022; Fadeyi et al, 2022). A systematic literature review can provide merits over conventional approaches, such as an unbiased robust conclusion and identification of possible gaps, and it is also replicable, methodical and transparent (Siddaway et al, 2019).

The review covered peer-reviewed journals from 1966 (when International Rice Research Institute first introduced an IRV) to 2021. The research question was dissected into concept domains to generate keywords for the search (Xiao and Watson, 2019). Alternative spellings, related terms and synonyms of the keywords were included, which were gathered from a general search using 'adopt*' AND 'rice variet*'. A detailed search was finally performed using the search string 'rice OR paddy' AND 'farmer* OR household* OR smallholder*' AND 'adopt*' AND 'variet* OR cultivar* OR seed*' in five well-established economic and scientific databases, including Google Scholar, Web of Science, Scopus, ScienceDirect and AgEcon.

Google Scholar was particularly selected for its comprehensive set of published materials and to avoid selection and publication bias by including manuscripts published in less popular journals from the Global South (Norris et al, 2008). The primary search in all the databases yielded 22 510 papers (Fig. 1), most of which were not included in the subsequent screening process as the papers were duplicates or unavailable due to access restrictions.

Titles were first screened for eligibility, and irrelevant papers were removed. The resulting abstracts were then screened using the following eligibility criteria: (1) papers were published in English and peer-reviewed; (2) a quantitative analysis was undertaken to statistically identify significant determinants of adoption to allow for the generalization of patterns across entire farming systems or study area; (3) studies were conducted in the Global South with results provided for individual countries; (4) data were collected at a plot, farmer or household level to provide influencing drivers of adoption at an individual level; (5) studies empirically estimated the variables of adoption of IRVs (adopters), versus traditional varieties or older IRVs (non-adopters). IRVs included varieties bred to increase current levels of yield (i.e. hybrid, inbred, high-yielding, certified or climate-friendly), capture higher prices (i.e. premium), or enhance nutrition (i.e. biofortified). Studies on

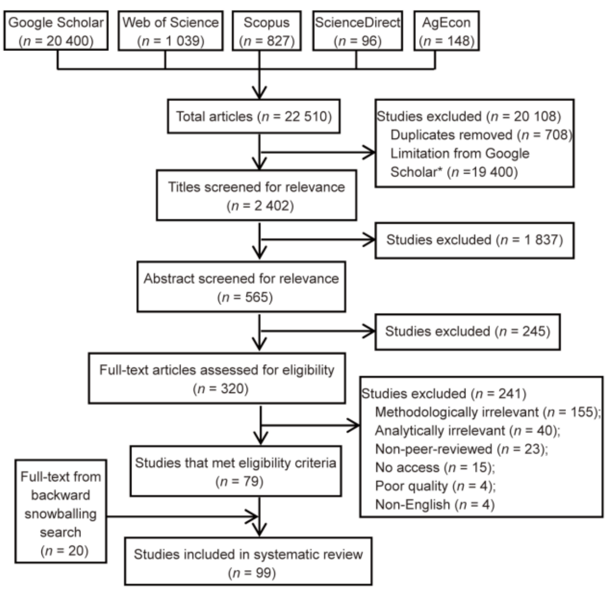

Fig. 1. Selection process using Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow diagram.

Ineligible studies were excluded at each stage of the selection process. Google Scholar only exhibited the results for the first 1 000 relevant papers. Despite this limitation, 15% of unique papers were found in the search engine.

using IRVs as an adaptation strategy to climate change or as a precursor to an impact assessment were also included. Manuscripts which were methodologically or analytically irrelevant and manuscripts without full-text access were further rejected. A backward snowballing search was then undertaken, which involved exploring the reference list of the eligible papers to identify studies that may not have emerged during the initial screening process. Finally, 99 manuscripts were included in this systematic review.

Relevant information included publication year, country, variety type (e.g. hybrid and climate-smart), adoption rate, sample size, data collection (e.g. focus group and survey), study level (i.e. farm and plot), research design (e.g. cross-sectional and longitudinal), adoption type (e.g. probability and intensity), econometric models performed (e.g. Tobit and Logit), determining variables and their significance were collected. The significant level 0.10 or lower was used as a criterion to determine whether a variable was considered statistically significant. If a study adopted multiple econometric models to determine a superior model in explaining adoption decisions, only variables and their significance from the identified superior model were included.

The same determining variables with a different unit of measurement were conceptually clustered to form descriptive concepts. For example, fertilizer use as a dummy variable (i.e. use of fertilizer = 1, otherwise = 0) or continuous variable (i.e. quantity of fertilizer applied) was combined to form a single conceptual variable. Similar conceptual variables were further grouped to simplify the descriptive analysis. A weight analysis method proposed by Jeyaraj et al (2006) was adopted to identify important adoption determinants of IRVs in the Global South. According to Jeyaraj et al (2006), the significant weight for the best predictors of adoption can vary depending on the stringency of the analysis. For this study, a significant weight of 0.75 was selected to provide an adequate analysis of adoption. Mektel and Mohammed (2021) also used this method in their systematic literature review to determine the factors of adoption of IRVs in Ethiopia. Best predictors of adoption will be referred to as important determinants of adoption henceforward.

To further aid in the analysis, grouped variables were then characterized into four characteristics commonly cited in agriculture technology adoption studies: (1) household and farmer, (2) farm biophysical, (3) institutional and access related, and (4) technology-specific attributes (Ghimire and Huang, 2016; Massresha et al, 2021; Fadeyi et al, 2022). These themes are in line with existing adoption theories, where shared views across theories demonstrate that individual characteristics (traits that predispose individuals to seek change), contextual characteristics (surroundings and environment) and innovation characteristics (specific to particular technologies) influence adoption (Straub, 2009). This grouping aimed to understand whether specific characteristics were more important than others in adoption and if all characteristics were equally studied (Table S1). A summary of the extracted information is listed in Table S2.

Descriptive analysis

Exponential increase in published studies

Only 6 out of the 99 studies on IRV adoption were published before the 2000s, with the most being conducted in Asia (Fig. 2-A). The success of the Green Revolution in increasing rice yields through the adoption of IRVs may have alleviated the importance of undertaking adoption studies, and researchers believed that variables related to innovation adoption have been already answered (Dalrymple, 1979; Valente and Rogers, 1995).

However, there is a renewed interest in adoption research in the Global South, with published papers increasing more than 3-fold in the last decade (Fig. 2-A). The increased investment in research on IRV adoption can be explained by rising production deficits (Muthayya et al, 2014), lagging varietal adoption and replacement (Laborte et al, 2017), and an increase in pressure in agriculture investment triggered by new challenges since the mid-2000s (Pingali, 2012; Arouna et al, 2017). The number of papers released reached its peak in 2021, with the increasing trend being consistent for Asia and Africa. This upward trend is expected to increase in the next few years as breeders release higher-yielding, nutritious, and quality varieties to meet growing challenges (IRRI, 2020).

Insufficient studies across regions

The adoption studies were concentrated in Asia and Africa (Fig. 2-B). The high focus in Asia can be attributed to the vital implication of rice towards food security and improved livelihood in the region, prompting investment in adoption research. Bangladesh, Vietnam and India published the highest number of adoption studies in Asia. These countries consist of the top five consumers and producers of rice

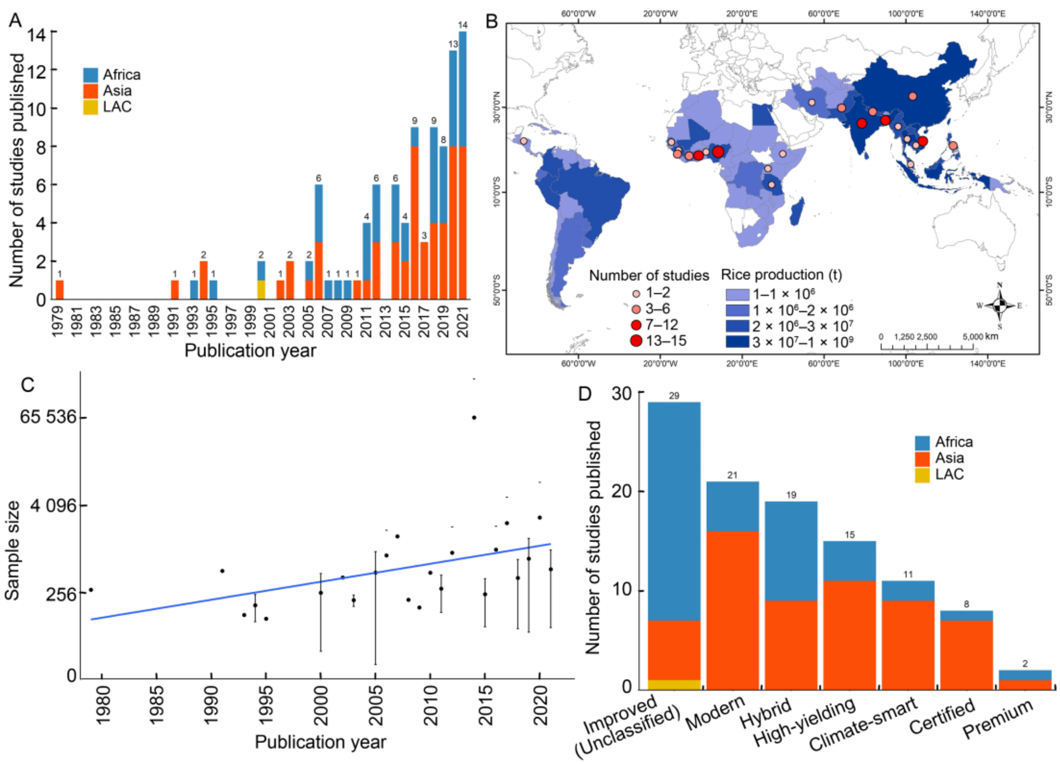

Fig. 2. Characteristics of reviewed adoption studies.

A, Publication number in Africa, Asia and LAC (Latin America and the Caribbean). **B**, Publication number by countries and paddy rice production. The number of observations is 100 (One study studied two countries). **C**, Mean sample size (number of households) across the years, including trend line in time and standard error of mean sample size. **D**, Publication number for each rice variety type.

globally. In Africa, the high number of studies is likely a consequence of continued low yields per unit and an increased dependence on imported rice (Arouna et al, 2017). This dependence may explain the focus of studies on Nigeria and Ghana, the two top rice importers in Africa (Lancon and David-Benz, 2007). Rice shortages in these countries may have prompted the need to increase rice production by developing and disseminating IRVs.

Despite the high number of studies in Asia and Africa, a lack of study persists in countries most vulnerable to food security. Malaysia, the Philippines and Indonesia (Fig. 2-B) rely on escalating volumes of imported rice to ensure sufficient national stocks (Redfern et al, 2012), but continue to grow older varieties (14–17 years on average) (Laborte et al, 2017). Senegal is a top rice importer in Africa, depending on rice as a core staple and consuming three times more rice per capita than Nigeria and Ghana (Lancon and David-Benz, 2007). A perceivable gap in the number of adoption studies also exists in LAC and Pacific Islands. These two regions have already started importing rice to meet local demand (Muthayya et al, 2014).

Additionally, only 5 out of the 23 countries had 10 or more studies published per country (Fig. 2-B). With several reviewed studies being conducted at a micro-level (Adesina and Zinnah, 1993; Mabe et al, 2018; Ashoori et al, 2019), a lack of understanding of adoption levels persists as there is insufficient variation (e.g. agro-ecological, infrastructure and market access) in the sample to provide a representation of adoption at a national level for many countries in the Global South (Doss, 2006).

Increasing sample size

By analyzing the investment in rice adoption research in the Global South in recent years, we can find an increase in sample size from an average of 224 observations before the 2000s to an average of 1 621 ones from 2020 to 2021 (Fig. 2-C). One reason for the considerably larger sample size is the shift from area-specific micro-level adoption studies (Asaduzzaman, 1979; Sarap and Vashist, 1994) toward a more representative sample of rice-growing populations (Mansaray and Jin, 2020; Paik et al, 2020), including variations across agro-ecological (Zhou et al, 2018; Kumar et al, 2020) or social and cultural variables (Addison et al, 2018). This larger and more representative sample provides opportunities to generalize observations to a higher degree of aggregation (Doss, 2006). Several studies have used national-level agricultural censuses for data collection (Mottaleb et al, 2015; Duong and Thanh, 2019). Although this method restricts the inclusion of additional variables suitable for the area studied and is solely based on the availability of variables by the census, this provides a more representative understanding of adoption levels and their impacts on the determinants examined.

Skewed concentration on specific varieties

Many studies have not classified IRVs (Fig. 2-D), either combining a few variety types in their analysis or failing to define the variety type examined. Only two studies examined the adoption of high-quality rice to capture higher market prices (premium seeds), while none examined biofortified seed adoption. Most other studies revolved around varieties that improve yield, including modern, hybrid, high-yielding, climate-smart and certified varieties.

Modern varieties are cultivars that have been recently released; hybrid varieties are derived from two different parent varieties being crossbred; high-yielding varieties (HYVs) have higher yield potential; climate-smart varieties withstand abiotic or biotic stressors; and certified varieties consist of genetically pure seeds. The high varietal concentration of studies focused on improving yield can result from pressure faced by increasing production deficits due to growing demands and, more recently, climate change (Redfern et al, 2012). In fact, adoption studies on climate-smart varieties have experienced significant growth, with an average of 1.6 papers per year since the first paper was published in 2014.

While varieties have been generally classified according to these variety types, it is essential to note that they often overlap. For example, climate-smart varieties are usually high-yielding in a specific region, while modern varieties often consist of other variety types. Nonetheless, addressing these variety types according to their classifications can provide essential insights as some determinants examined are more specific to the individual variety type (e.g. effects of abiotic stressors on climate-smart varietal adoption). A few studies have separately analyzed multiple variety types or multiple varieties within a variety type, providing a clearer understanding of determinants for individual variety adoption within a study area.

Higher focus on probability of adoption

Three adoption types were used as measures to assess the determinants of IRV adoption in the Global South:

probability, intensity and adoption speed. Fourteen studies investigated more than one facet of adoption (Adesina and Zinnah, 1993; Thanh and Duong, 2021), which provided a better understanding of the adoption behavior of farmers.

Probability studies are often used as a precursor to evaluate the productivity or impact of IRVs and can result from insufficient present knowledge of who has or has not adopted IRVs in many rice-producing countries. Understanding who adopted IRVs is the first step in understanding the adoption environment before proceeding to other adoption types. This has been demonstrated by a few studies where the Cragg's Double Hurdle model (Cuevas, 2016; Bannor et al, 2020; Kumar et al, 2020; Nonvide, 2020; Thanh and Duong, 2021) and the Heckman model (Oladeji et al, 2015) are used to model the probability and intensity of adoption decisions as separate entities in a two-step process, potentially allowing for a different set of explanatory variables to be observed (García, 2013).

The higher proportion of probability studies explains the predominant utilization of Probit or Logit regression model in adoption studies. Out of the 124 models used in the 99 reviewed studies, 63% have assessed adoption using binary outcome variables (e.g. yes = 1, no = 0), a univariate object or jointly with other improved technologies, managerial decisions or crops (e.g. bivariate or multivariate Probit), or categorical outcome variables to examine the adoption of varieties or technologies (e.g., multinomial and ordered Logit) (Fig. S1 for econometric models employed).

Instead, studies examining the adoption intensity still lag that of the adoption probability, with the determinants that influence the area of IRV remaining poorly understood. This comes despite previous calls for more studies on the adoption intensity (Doss, 2006; Feder et al, 1985). However, there is a rise in the number of studies on the adoption intensity in the last 10 years. The adoption intensity has gained importance and interest recently, with policymakers looking at determinants that can increase planting area of IRVs. Additionally, only one study attempted to capture the temporal dimension of adoption by looking at the adoption speed.

When looking across regions, the number of probability studies was more prevalent in Asia than in Africa (Fig. 3). The number of intensity studies was also skewed towards Asia, compared with Africa and LAC. Unlike Africa, where the adoption of IRVs is still lagging, the high adoption rate in Asia following the Green Revolution has led to a shift towards more intensity studies. Diagne et al (2012) explained that as adoption increases, other adoption studies, such as intensity, become more relevant. As for individual variety type, the intensity of adoption was studied proportionately the most for HYV (28%) and modern (28%) varieties, followed by unclassified (24%), hybrid (16%), and certified (4%) varieties. Intensity adoption studies for climate-smart and premium varieties have not been conducted. This could be explained by the limited number of studies for these specific variety types where researchers are still discovering the basic descriptive information from probability studies.

Determinants of rice variety adoption

This section describes and discusses the top determinants examined in the adoption studies and determines the important determinants of adoption, including differences between adoption types, region, and variety types. The single study on LAC and speed of adoption does not have sufficient data to evaluate this region and adoption type individually. Still, their results are included when evaluating determinants for overall adoption.

Top determinants examined

There was a wide variation in the number of times that the variables were examined, from one observation (i.e. record keeping) to a variable with more than 140 observations (i.e. education). Four variables were examined more than 100 times, demonstrating their perceived importance as determinants of adoption. These are education, farm size, information access and farm location (Fig. 4).

When consolidating results from all adoption types,

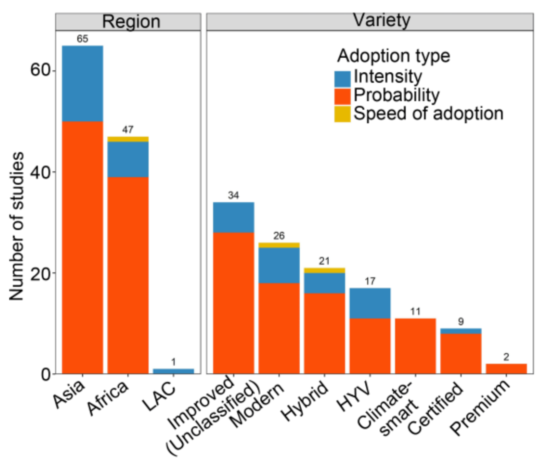

Fig. 3. Number of studies examined for probability, intensity and speed of adoption, classified into region and variety type.
HYV, High-yielding variety; LAC, Latin America and the Caribbean.

the proportions of significant observations for education, farm size, information access and farm location are 48%, 57%, 51% and 65%, respectively, with these variables also having the highest frequency of significant observations (Fig. 4). There is also a shift in influence in these top four variables examined when observing individual regions and variety types. Education, farm size and information access have greater effects on adoption in Asia, whilst farm location has a greater effect on adoption in Africa, especially the adoption of climate-smart and modern varieties. These results demonstrate that the influence of these top examined variables in adopting IRVs varies according to adoption, region and variety type.

Jones-Garcia and Krishna (2021) reviewed the improved technology adoption in maize systems in the Global South, and the findings in this study agree with the published results. They found that farm location appeared statistically significant more than 100 times, with information access, farm size and education being statistically significant variables in 64%, 55% and 51% of the studies, respectively. Ruzzante et al (2021) further confirmed the latter three variables in a meta-analysis on agricultural technology adoption in developing countries. Feyisa (2020) and Mektel and Mohammed (2021) also discovered that farm size, extension contact and education are important variables in adopting improved agricultural technology in Ethiopia. The subsequent sections aim to explain the implications of these heavily examined variables on adoption.

Education

Education plays a significant positive role in adopting IRVs, consisting of more than 40% of total observations compared with only 8% being negatively significant. An additional year of education can increase the adoption probability by an average of 2% (Mazoyer, 2008; Udoh and Omonona, 2008; Ologbon et al, 2012; Hagos and Zemedu, 2015; Villano et al, 2015; Ghimire and Huang, 2016; Addison et al, 2018; Chandio and Jiang, 2018; Mabe et al, 2018; Bello et al, 2020; Onyeneke, 2021). Education can improve a farmer’s ability to collect information and obtain technologies to address production constraints (Villano et al, 2015). Godoy et al (2000) discovered that

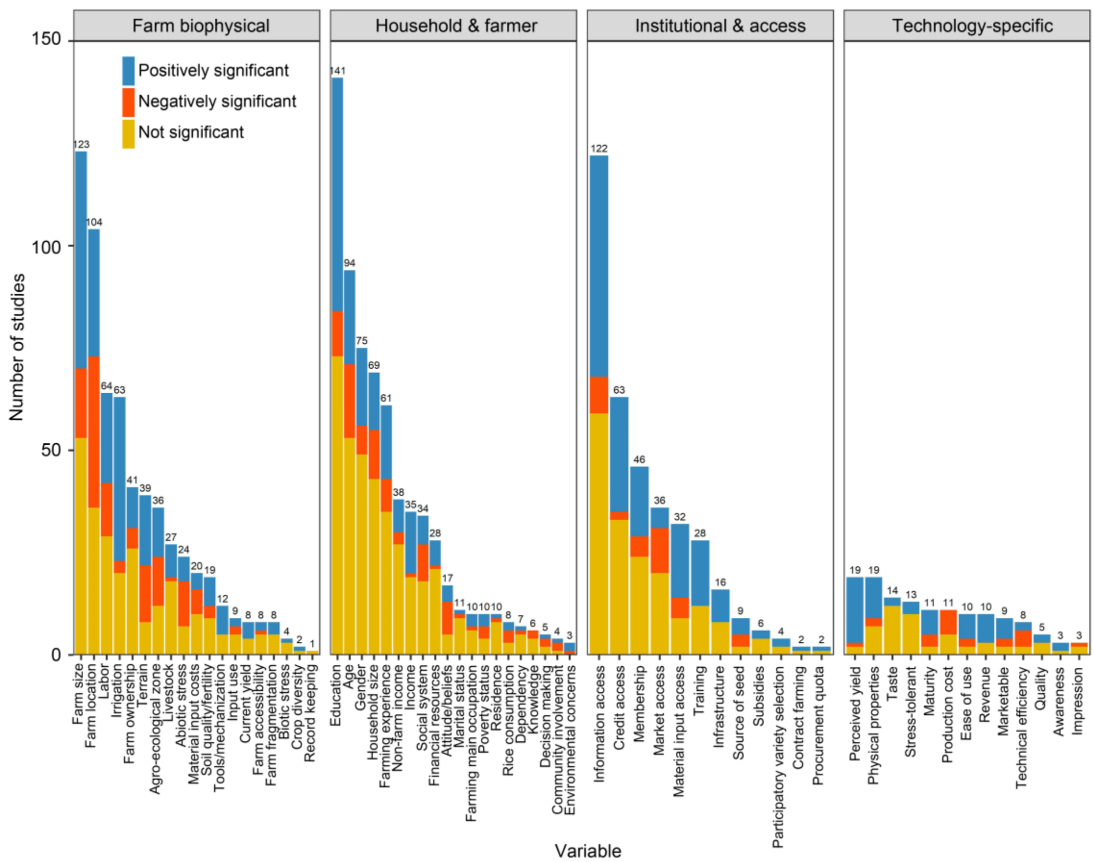

Fig. 4. Number of observations that are positively significant, negatively significant, and not significant for each variable, grouped into farm biophysical, household and farmer, institutional and access-related, and technology-specific characteristics.

education promotes the adoption of IRVs by boosting interpersonal skills and confidence of farmers towards approaching extension agents to obtain information and buy seeds. Farmers with higher levels of education are also more aware of climate change and are more likely to adopt strategies to address climate risks (Ali and Erenstein, 2017).

Additionally, education can enhance the utilization of information to respond to new and potentially risky agriculture technologies, such as IRVs (Schultz, 1982). Education increases a farmer's risk tolerance by improving their capacity to apply agricultural technologies more efficiently throughout the adoption process, facilitating their understanding of the long-term benefits of productivity growth (Feder et al, 1985). This increased risk tolerance may explain the greater importance of education on the adoption intensity compared with the adoption probability, where farmers take on more risk when investing a more significant proportion of land to IRVs.

However, understanding the precise impacts of education requires the correction of endogeneity bias created by family wealth (Jones-Garcia and Krishna, 2021), which most studies failed to address. Educated farmers tend to be wealthier, increasing their capacity to invest in new varieties. Awotide et al (2012) even suggest that wealth plays a more significant role in adoption than education after discovering that education significantly and negatively affects the adoption intensity of wealthy households. Nonetheless, the reviewed results demonstrated that only 25% of the financial resource variable is significant compared with 48% for education, proving the effect of education on adopting IRVs regardless of the potential effects of wealth.

Farm size

Landholding size or cultivated area generally influences adoption positively, representing 43% of total observations, and has increased the probability and intensity of adoption by up to 25% and 95% for every hectare increase, respectively (Oladeji et al, 2015; Ghimire and Huang, 2016). Only 14% of total observations for farm size are significantly negative. Farm size is often a proxy for a household's economic power, input access, economies of scale, and risk-bearing capacity (Jones-Garcia and Krishna, 2021). Larger farmers generally have higher financial resources and preferential access to credit, providing greater capacity to absorb higher input material costs associated with IRVs. These costs can sometimes exceed the output earnings of smaller and marginalized farmers (Tripathy et al, 2006). This may further explain the greater prominence of landholding size as a positive determinant for the adoption intensity (60% of observations) when compared with the adoption probability (39% of observations), because improved economies of scale can be achieved as the area under IRVs increases.

The risk of technology failure is also reduced in larger farms, because farmers can allocate a portion of land to IRVs and have greater access to crop insurance schemes, an option not as readily available to smaller farmers (Mariano et al, 2012). Additionally, farm size is also associated with improved information availability. Firstly, more significant absolute gains experienced by larger farms motivate farmers to invest in search efforts to discover new and improved technologies (Feder et al, 1985). Extension officers will also concentrate on larger and wealthier farm-sized farmers who are more likely to adopt IRVs to demonstrate immediate and visible results (Feder and Slade, 1986). This demonstrates the importance of policy and institutional interventions to reduce adoption barriers for smallholder farmers by diminishing the risks involved in adopting IRVs (e.g. provision of input subsidies and increasing credit access), and ensuring farmers receive the appropriate information on new rice seeds regardless of farm size.

Information access

Awareness of IRVs is the first stage of the adoption process, and is a component, together with technology access, required for adoption to occur (Nguezet et al, 2013). Information disseminated via extension officers (Saka et al, 2005), media (Nonvide, 2020), and fellow farmers can improve awareness (Paik et al, 2020), ultimately increasing the adoption rate. The reviewed studies demonstrated that information availability, frequency of information contact, and reduced distance to information sources positively affect adoption. Nearly 44% of total observations found a significant positive relationship between information access and the adoption of IRVs. In contrast, only 7% are negatively significant.

Extension access, sometimes considered a primary source of information for farmers (Akinnagbe and Akinbobola, 2022), is examined the most significant number of times (n = 83) and is positively significant in 47% of the total observations. Extension agents are known to provide technical advice and training on IRV production methods and benefits (Mabe et al, 2018), reducing the uncertainty of non-adopters and inducing more risk-averse households to adopt this technology (Hiebert, 1974). Providing access to extension agents can improve adoption by an average of 14% (Ghimire and Huang, 2016; Bello et al, 2020; Onyeneke, 2021), with adoption increasing by up to 29% with every additional extension visit (Mabe et al, 2018), and 11% with every 1 km decrease in distance from an agricultural extension office (Hagos and Zemedu, 2015). Although Paik et al (2020) have found that other fellow farmers are one of the least likely sources of information to farmers on IRVs, the reviewed studies suggested potentially strong influences of friends, family and the community on adoption.

However, information access can potentially be endogenous. Abdul-Rahaman et al (2021) addressed the possible biases derived from farmers that could have adopted IRVs before any extension visit, where visits were conducted to improve production methods instead of adoption. Purposive selection of likely adopters by extension officers, or farmer characteristics such as age, education, motivation and farm size, can further create biases in the relationship between information access and adoption (Jones-Garcia and Krishna, 2021). Despite this, the effects of information in promoting and enabling an environment for the effective adoption of IRVs cannot be overlooked. Unlike variables such as gender and age, information access is an external intervention that can be modified in the short-term. Policies that develop information and communication technologies and promote strong institutional support, may obtain higher adoption rates in the short run compared with other interventions addressing more complex internal variables, such as attitude and culture.

Farm location

Location-included variables from a village level (Kumar et al, 2016) up to a state level (Mehar et al, 2017) are often used to understand the existence of characteristic differences between locations in explaining the adoption of individual farmers. With sufficient agro-ecological variation in the sample, location variables can distinguish production potential, rainfall and soil characteristics (Doss, 2006; Anang, 2018), and influence the adoption of IRVs (Ali and Erenstein, 2017).

Location variables can also disentangle institutional, access-related, and even socio-economic variables, possibly identifying market failures. Adoption, for example, is associated with improved information access via government-targeted agriculture development programs (Budhathoki and Bhatta, 2016) or private companies (Mehar et al, 2017) in specific locations. A lack of market access for inputs (Wu et al, 2010; Beke, 2011; Budhathoki and Bhatta, 2016; Ali and Erenstein, 2017; Thanh and Duong, 2021) or outputs (Beke, 2011), high material costs (Hossain et al, 2003), poor infrastructure (Thanh and Duong, 2021), inability to access credit (Thanh and Duong, 2021), poverty (Mehar et al, 2017; Addison et al, 2018), subsistence pressure (Hossain et al, 2003) and gender-related issues (Addison et al, 2018), are also as constraints to adoption at a location level.

However, many of these explanations are based on perception or observation, which may not depict an accurate understanding of specific location differences that influence adoption. Location can be a highly endogenous variable and is potentially influenced by an intrinsic web of variables. Understanding the reason behind the differences in the determinants of adoption between locations may require examining specific explanatory variables for the individual locations at a farm level and some variables (e.g. terrain and soil quality) at a plot level. Additionally, there may be limitations when examining locations at a broader level (e.g. state or province). The clustering of farmers at a higher administrative level may provide overgeneralized results and ignore characteristics that constrain adoption at a more micro-level (e.g. village), making it difficult for targeted policymaking. Kumar et al (2016) examined location variables at a village level, providing a more precise understanding of adoption differences between villages.

Important determinants of adoption

The highest number of significant observations demonstrates that farm location, farm size, education and information access can greatly influence adoption. However, these most frequently observed variables fail to meet the requirement of important determinants of adoption after undertaking a weight analysis proposed by Jeyaraj et al (2006).

Overall important determinants

Seven variables are important determinants of adoption in the Global South: terrain, source of seed, technical efficiency, perceived yield, maturity, ease of use and marketable (Fig. 5).

Terrain

Terrain type is an important adoption determinant for IRVs, particularly for adoption intensity. Land type (e.g. slope or terrace) (Wu et al, 2010; Nguyen, 2020;

Wang et al, 2020) and land position (e.g. lowland, medium-land or upland) (Diagne, 2006; Samal et al, 2011; Ghimire et al, 2015) can affect adoption at farm and plot levels. Sloped land has shown a generally negative effect on adopting IRVs, potentially attributes to the less productive environment often associated with this land type (Wang et al, 2020). The suitability of new rice varieties for a specific land position also plays a vital role in adoption, suggesting the importance of developing farmland location-appropriate varieties to encourage adoption (Napasinuwong and Pray, 2014; Mansaray et al, 2019).

Source of seed

The distribution of seeds from government agencies, Non-governmental Organizations (NGOs) and private companies can improve the adoption of IRVs (Joshi and Bauer, 2006; Kumar et al, 2020). Joshi and Bauer (2006) found an increase in demand for cultivating three of the four modern varieties examined if varieties were distributed to farmers from existing extension services or NGOs in the western Terai region of Nepal. However, compared with government agencies, Kumar et al (2020) found that adopters in India are more likely to source modern varieties from private sources due to the greater accessibility and availability of seeds from these sources. Households in India receive information on modern varieties mostly from other progressive farmers (60.9%) and input dealers (23.1%), compared with extension officials (6.6%) (Kumar et al, 2020). This finding suggests that private sources are more efficient in distributing IRVs than government outlets in India. Examining the influence of the seed sources on the adoption of IRVs can help uncover inefficiencies in the distribution of IRVs in a study area. This can aid in the policy development towards establishing an efficient delivery of extension services in these farming communities to improve the distribution and adoption of improved seeds.

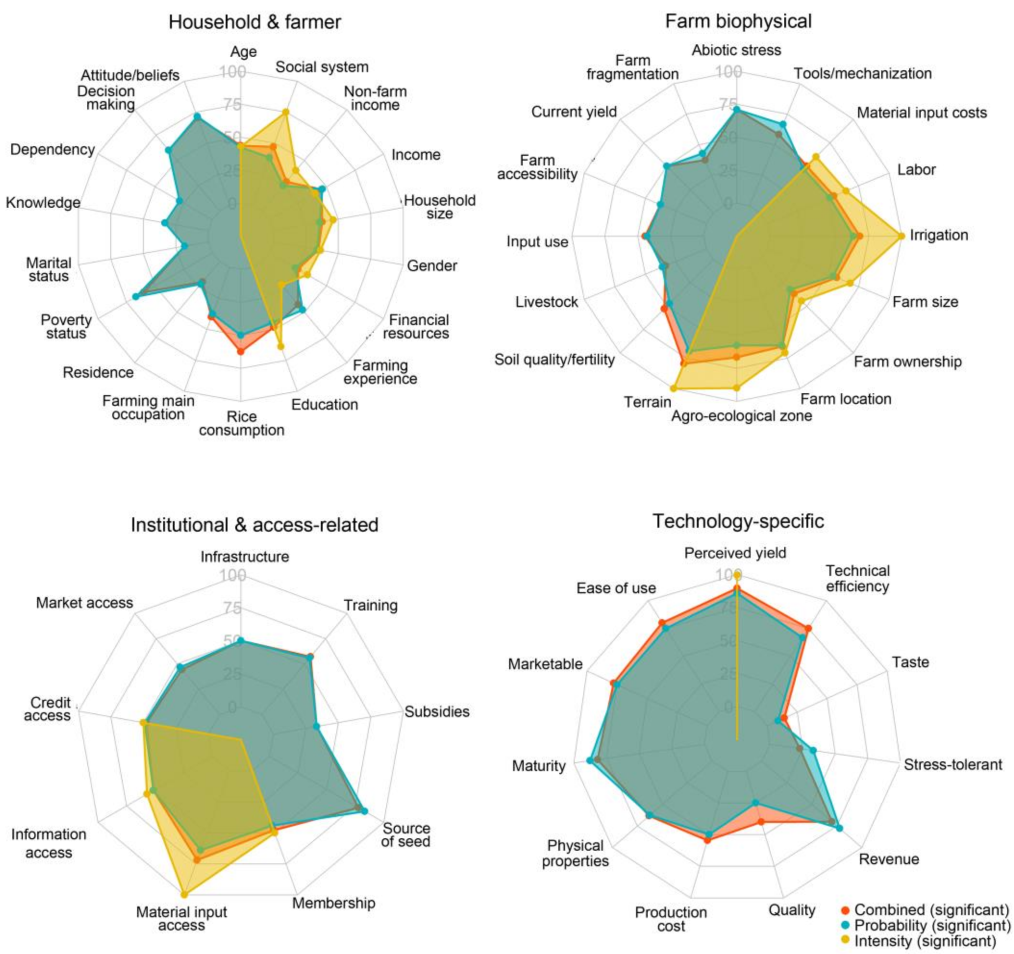

Fig. 5. Proportion of variables that are statistically significant for adoption probability, adoption intensity, and combination of all adoption types (probability, intensity and speed).

Only variables examined at least five times for each category (i.e. combined, probability and intensity) are included.

Technology-specific variables

Besides terrain and source of seed, other important determinants of adoption are associated with the characteristics of IRVs. Perceived yield is the most important determinant out of all variables studied. Farmers prefer rice varieties that produce higher yields (84% of observations) (Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995; Saka et al, 2005; Saka and Lawal, 2009; Oladele and Wakatsuki, 2011; Ghimire et al, 2015; Islam, 2018; Paltasingh, 2018; Bannor et al, 2020). Perceived yield can play a fundamental role in the decision to plant IRVs regardless of whether rice is produced for subsistence or commercially, as it can directly affect food security and improve farmer livelihood (Diagne, 2006; Napasinuwong and Pray, 2014). Other agronomic characteristics that concern farmers based on the reviewed results are maturity, technical efficiency and the ease of use of IRVs. Shorter maturity cycles are often preferred by farmers (55% of observations) (Sall et al, 2000; Joshi and Bauer, 2006; Beke, 2011; Paltasingh et al, 2017; Paltasingh and Goyari, 2018), possibly explained by the lower water requirements, less exposure to abiotic and biotic stresses, and improved availability of land for subsequent plantings with the use of shorter duration rice varieties (Vergara et al, 1966). Farmers also opt for varieties that have a higher level of technical efficiency, preferring varieties that require fewer inputs such as irrigation and labor, which allow for significant cost savings for the farmer (Joshi and Bauer, 2006; Addison et al, 2018; Islam, 2018; Kumar et al, 2020). Adoption of IRVs is further driven by the perceived ease of implementation, with the suitability and adaptability of an IRV to a particular farm ecosystem affecting farmer adoption decisions (Oladele and Wakatsuki, 2011; Paltasingh et al, 2017; Ashoori et al, 2019; Connor and San, 2020). Varieties that are more tailored to a farmer's need or farm ecosystem are more likely to be accepted by farmers, as they can be easier to grow, and productivity can be improved.

Non-agronomic traits also influence varietal adoption. Better marketability of rice, such as market acceptability or preference, can improve the adoption of IRVs in the Global South. Incorporating traits demanded by the market can increase adoption by providing farmers with opportunities beyond home consumption, allowing them to sell to markets at a higher price (Ghimire et al, 2015; Ghimire and Huang, 2016). Additionally, adoption can be enhanced if IRVs provide opportunities to export due to the higher prices offered by importing countries (Myint and Napasintuwong, 2016). This important determinant suggests the importance of including food quality characteristics and consumer preferences when developing rice technologies beyond the conventional approach of focusing on enhanced agronomic characteristics (Adesina and Baidu-Forson, 1995).

Although these patterns of adoption are identified when results across empirical studies are combined, the most important determinants of adoption vary depending on adoption type, region and variety type. This was similarly found by Ruzzante et al (2021) and Jones-Garcia and Krishna (2021), where adoption determinants of agricultural technology in the Global South vary widely by cultural context, geography and technology, with determinants of adoption varying between adoption intensity and adoption probability.

Important determinants based on adoption type

Important determinants that affect the adoption probability of IRVs in the Global South are source of seed and technology-specific variables such as maturity, perceived yield, perceived revenue, marketable and ease of use (Fig. 5). Important determinants that influence the adoption intensity are irrigation facility, terrain, material input access, perceived yield, agro-ecological zone and social system (Fig. 5).

The lesser importance of terrain type on the adoption probability compared with the adoption intensity suggests that farmers are willing to explore and at least partially adopt IRVs before determining the suitability for the farmer or farm ecosystem. Perceived revenue is another important determinant for the adoption probability, with farmers encouraged to adopt varieties that capture higher market prices or are more profitable (Oladele and Wakatsuki, 2011; Napasinuwong and Pray, 2014; Rahman and Chima, 2015; Ashoori et al, 2019).

As for the adoption intensity, irrigation can encourage farmers to allocate more land to IRVs (Wang et al, 2012; Islam, 2018; Paltasingh, 2018; Kumar et al, 2020; Thanh and Duong, 2021), with irrigated conditions improving the productivity of rice production (Ut and Kajisa, 2006; Mendola, 2007). The importance of terrain type and agro-ecological zone on the adoption intensity further indicates the necessity for new varieties to be adaptable to an environment to encourage farmers to increase the area planted with IRVs. Additionally, access to seeds and fertilizers can also improve the availability of inputs for farmers to expand the area planted with IRVs (Paltasingh et al, 2017; Paltasingh, 2018; Bannor et al, 2020).

Social systems such as ethnicities and castes can further affect the area planted with IRVs (Godoy et al, 2000; Beke, 2011; Kumar et al, 2020; Thanh and Duong, 2021). Non-native and lower-caste farmers are less likely to own land, reducing the access and use of improved agricultural inputs due to being resource-poor and experiencing higher credit constraints (Beke, 2011; Kumar et al, 2020). Apart from perceived yield (Adesina and Zinnah, 1993; Saka et al, 2005; Islam et al, 2012; Paltasingh et al, 2017; Bannor et al, 2020), it is difficult to conclude whether other technology-specific attributes are essential for adoption intensity due to insufficient observations.

Important determinants based on region

Apart from perceived yield, important determinants differ between Asia and Africa (Fig. 6). Important determinants for adoption in Asia are perceived yield, terrain, seed source, marketable, abiotic stress, material input access and maturity. In Africa, important determinants of adoption are ease of use, perceived yield, physical properties and farm location. These important variables may indicate the reasons behind the poor adoption levels found in the adoption studies by interpreting these determinants as potential constraints to adoption (Jones-Garcia and Krishna, 2021).

The probability of adopting IRVs in Asia (17%), particularly in South Asia (14%), is substantially lower than that in African countries (36%) (Table 1). However, these adoption levels should be used with caution. Firstly, adoption levels could have changed since the year of data collection. Several studies have also selected their sample purposively, and findings cannot be extrapolated to represent an entire region or a variety type. Additionally, the definition of 'adopters' differs across studies. Some studies look at multiple IRVs combined (Saka and Lawal, 2009) or as a single IRV (Akinnagbe and Akinbobola, 2022), whereas others examine recently released varieties (Ghimire and Huang, 2016) or IRVs as a whole (Nonvide, 2020). Nonetheless, these adoption rates still demonstrate low levels of general adoption at the time of study and further confirm low varietal replacement as the region continues to grow older IRVs.

One constraint in adopting IRVs in Asia could be the increased abiotic stress faced by farmers. Climate change and abiotic stress generally negatively influence (52% of observations) the adoption of IRVs in Asia (Mariano et al, 2012; Villano et al, 2015; Mehar et al, 2017; Begho, 2021). Mariano et al (2012) and Villano

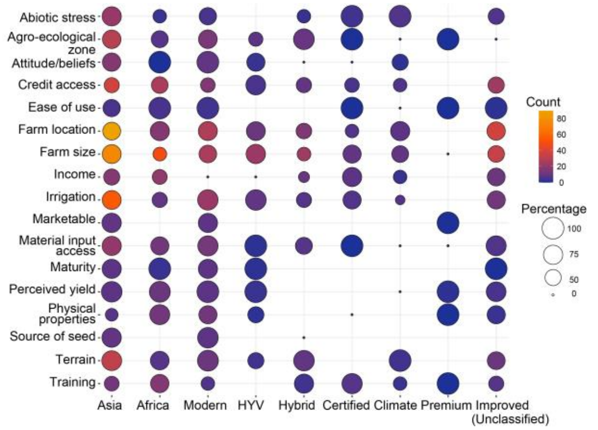

Fig. 6. Number of total observations and proportion of significant observations for each variable, grouped into region and variety type.

et al (2015) suggested that farmers exposed to floods and droughts are discouraged from adopting certified rice by up to 8% due to the higher risks of crop failure costs, effort and time involved in mitigating these adverse conditions. Begho (2021) further explained that the losses incurred during natural disasters can limit the ability of farmers to purchase new rice varieties due to the constraint in resources in the short term. The effects of this variable in impeding adoption in Africa remain unknown due to insufficient observations. Additionally, the poor suitability of new seeds to a

Table 1. Adoption probability and intensity levels based on region or variety type.

Region/variety type [a]	Adoption probability [b]	Adoption intensity [b]	Studies for area [c] (%)	Studies for farmer [d] (%)
Region				
Asia (50p, 13i)	17 (16)	61 (21)	53	81
South Asia (27p, 11i)	14 (10)	64 (21)	57	85
South East Asia (17p, 1i)	62 (48)	47 (0)	60	80
East Asia (5p, 1i)	52 (26)	34 (0)	0	100
Africa (33p, 2i)	36 (30)	19 (28)	50	90
West Africa (30p, 1i)	45 (28)	22 (0)	54	92
East Africa (35p, 1i)	40 (16)	18 (0)	25	75
Total (85p, 16i)	17 (16)	34 (23)	50	83
Variety type				
Modern (17p, 9i)	43 (22)	66 (19)	55	90
Hybrid (15p, 2i)	12 (7)	21 (4)	25	85
High-yielding (13p ,3i)	67 (22)	26 (10)	15	58
Climate-smart (8p, 1i)	36 (16)	47 (0)	63	75
Certified (5p)	35 (17)	–	75	67
Premium (2p)	60 (7)	–	50	100
Unclassified (25p, 1i)	50 (25)	55(0)	63	87

[a] Numbers of available probability (p) and adoption intensity levels (i) in reviewed studies in the parentheses. [b] Calculated based on available adoption levels from individual studies using sample size as analytical weight. Mean values are shown and the SD is shown in the parentheses. [c] Percentage of studies in which researchers randomly selected the study area. [d] Percentage of studies in which researchers randomly selected the farmers from the study area.

farm's terrain may explain the low adoption and varietal replacement in Asia (Wu et al, 2010; Mottaleb et al, 2015; Paltasingh et al, 2017; Devkota et al, 2018; Nguyen, 2020).

The low adoption level in Asia may also relate to the poor perception or knowledge of the technological characteristics of IRVs. Newer IRVs may lack the varietal attributes desired by Asian farmers. They may be perceived as having insufficient improvements in terms of yields, growing cycles and marketability compared with existing varieties used. Similarly, the barriers to adoption in Africa mainly consist of technology-related variables, with farmers not desiring or seeing much improvement in the varietal traits of newer varieties. The desired traits in Africa include ease of use, higher-yielding and improved physical properties (e.g. tillering capacity), threshing, height, and proneness to lodging (Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995; Oladele and Wakatsuki, 2011). This makes it important to involve farmers in designing new IRVs, as demand of farmers and evaluation of varietal attributes may differ from what is currently understood and developed by rice breeders.

Possible poor distribution of seeds from private companies or government agencies may also explain the low varietal replacement in Asia, as farmers continue to rely on farm-saved or older IRVs despite the introduction of newer ones (Joshi and Bauer, 2006; Kumar et al, 2020). Seed access and availability play essential roles in adopting IRVs in Asia, confirming the inefficiencies in the current distribution of improved seeds. Understanding the effect of seed sources on adoption is particularly important in Africa, where introduced IRVs are mostly hybrid (e.g. NERICA), and seeds cannot be saved. The current absence of studies in Africa examining the effect of seed sources on adoption makes it difficult to conclude the effectiveness and influence of different stakeholders in distributing seeds.

Additionally, despite the higher adoption levels of IRVs in Africa than in Asia, the share of farm areas under IRVs is much lower in Africa (19%) compared with Asia (61%). This lower adoption intensity suggests that farmers in Africa are less willing to commit a larger share of land to IRVs once adopted. However, the lack of observations on the adoption intensity in Africa makes it difficult to determine factors contributing to this phenomenon.

Important determinants based on variety type

Modern varieties have the highest number of important determinants: attitude, perceived yield, terrain, source of seed, irrigation, material input access, marketable and maturity (Fig. 6). Appearing significant in all observations, attitude, particularly risk-taking attitude, is an important determinant in the adoption of modern varieties (Mehar et al, 2017; Bannor et al, 2020; Begho, 2021). Surprisingly, more risk-averse farmers are more likely to adopt modern varieties. Begho (2021) suggested that more salient attributes (e.g. stress tolerance) may mask other important attributes (e.g. cooking quality and yield) considered by farmers in modern varieties, creating fewer incentives for risk-tolerant farmers to adopt them.

Abiotic stress positively influences the adoption of climate-smart varieties (Zhou et al, 2018; Al-Amin et al, 2019). The effects of abiotic stress on adoption can be influenced by variety, with farmers more likely to adopt varieties specifically designed to address the current abiotic stress they face. This further explains the importance of the location variable for this variety type, where adoption is potentially influenced by areas that experience abiotic stress. Additionally, important determinants for HYV are irrigation, farm size and credit access, while those for certified seeds are training and income. Many rice varieties developed require irrigated conditions to generate improved productivity and profit (Ut and Kajisa, 2006; Mendola, 2007) and reduce crop failure (Mariano et al, 2012), making irrigation access important in the adoption of HYV. Higher water and labor requirements also make income essential, with farmers needing to afford higher input costs for production. As for certified varieties, greater risks associated with this variety type due to higher seed costs can also be reduced through higher income and training.

When it comes to hybrid varieties, important determinants are terrain and agro-ecological zones. The mixed polarity in the significance of these variables on adoption suggests that current hybrid seeds may not be suitable for certain environments that the variety is introduced into, possibly explaining the lowest adoption and intensity levels for this variety type (Table 1). Perceived yield and material input access are important determinants of adoption for unclassified improved varieties.

Insufficient observations make it difficult to conclude important determinants for premium seeds. There is also a lack of technology-related determinants for climate-smart, hybrid, HYV, certified, and premium rice. One would expect that technological characteristics of IRVs will likely influence adoption, as traits of this technology are specifically altered during breeding to meet a certain requirement (e.g. climate-smart and stress-tolerant). The omission of technology-related variables may have created biases when determining important determinants of adoption. A limitation of the reviewed studies is the large discrepancies in technology-specific attributes that can be observed when categorizing all examined variables into characteristics. This aspect will be discussed further in the next subsection.

Areas of improvement

Inclusion of technology-specific variables

Examining household and farm characteristics is critical in providing policymakers with basic information on farmer adoption of IRVs. Contextualizing farmer adoption within institutional and access-related characteristics, variables that are beyond the control of farmers or individuals, can also help determine the role of institutions, policies, and infrastructures in creating a favorable environment for adoption. However, most studies continue to undervalue the importance of technology-specific characteristics when understanding adoption. Fig. 4 graphically displays the total number of observations for 64 variables revealed from the reviewed studies, assigned into four categories: household and farmer, farm biophysical, institutional and access-related, and technology-specific characteristics.

The inclusion of technology traits in the adoption of rice was first raised by Adesina and Zinnah (1993), who discovered that technology attributes are more significant determinants for both the intensity and probability of adoption than farm and farmer characteristics. The failure to include technology-specific characteristics in adoption studies may be attributed to various reasons. Firstly, the shift toward secondary data (18% of reviewed studies) may prevent examining technology-specific variables. Although secondary data, such as censuses, can provide larger and more representative samples, data on technology traits are often unavailable (Thanh and Duong, 2021). Additionally, researchers usually select variables based on previous studies. The unpopularity of technology traits in current studies may have led to the exclusion of technology-related variables, as researchers may have overlooked the importance of examining such variables. Determining technology-related variables may also be difficult, where particular awareness and understanding of rice attributes and farmers' preferences are required. This can be particularly problematic for studies that combine multiple variety types in these analyses (29% of reviewed studies) instead of analyzing individual variety types or even specific varieties, where researchers can select relevant technological traits based on variety.

However, excluding technology-specific variables can create bias when concluding the determinants influencing adoption. The most critical determinants in the reviewed studies fall in the technology-specific category, with it being significant (61% of the total observations) compared with farm biophysical (58%), institutional and access-related (52%), and household and farmer (42%) characteristics. Future research needs to include technological-specific variables that address perceived usefulness and ease of use, which can help identify key agronomic and non-agronomic characteristics that influence the attitude and intention of adoption (Davis, 1989). This will allow targeted research and development programs to introduce better suitable varieties or traits that meet preferences of farmers. As production and technology systems become more complex with time, increasing this degree of technology fitness becomes even more crucial (Douthwaite et al, 2001).

Increasing research in overlooked regions and varieties

The absence of studies in LAC and the Pacific Islands limits the ability to form a basic understanding of adoption in these regions. Increasing rice production in these regions through the adoption of IRVs is vital, as current domestic production fails to meet demand, with LAC and the Pacific Islands increasingly relying on imports (Muthayya et al, 2014). Adoption studies in the Philippines, Malaysia, Indonesia and Senegal, which rely on increasing volumes of imported rice, will also need to be increased to better understand the adoption behavior in these countries to boost productivity (Lancon and David-Benz, 2007; Redfern et al, 2012). Furthermore, the lagging number of intensity studies in Africa makes it difficult to understand constraints of farmers when deciding the proportion of land cultivated with improved varieties.

It is also important to understand adoption for variety types that have not been sufficiently examined (particularly premium and biofortified varieties), indicating the need for more probability and intensity studies. The potential to improve the livelihood of farmers from adopting high-quality rice should not be overlooked. Urban consumers are more likely to buy and pay a premium for high-quality rice, and can also provide high-valued export opportunities (Diagne et al, 2016). Additionally, there are currently no studies on the adoption of biofortified seeds.

Capturing dynamics of adoption process

Glover et al (2016) described current adoption research as ‘too linear in both spatial and temporal terms, too binary, too focused on individual decisions, and blind to many important aspects of technology change’. Most studies on IRV adoption also failed to capture the dynamics of the adoption process. Future research should shift towards considering this dynamic process by examining the interdependence of adoption between technologies, involving the series of adoption decisions over a period of time, and including duration analyses when examining adoption.

Most reviewed studies assume that farmers only adopt one form of improved technology or variety and continue to adopt static individual adoption models (e.g. univariate Probit or Logit). Feder et al (1985) first raised this issue, stating that modern agricultural technology is usually introduced in a package and that farmers choose between combinations of components. Only a few studies have attempted to capture this dynamic by examining the interdependence of adopting different IRVs (Mehar et al, 2017; Mesfin and Zemedu, 2018), different technologies (Ali and Erenstein, 2017; Anang, 2018; Khan et al, 2021; Onyeneke, 2021; Ho et al, 2022), and improved seeds for different food crops (Rahman and Chima, 2015), using either a bivariate or multivariate Probit or Logit. Future studies should capture this interdependence of adoption decisions between technologies to understand the determinants of adoption of an individual technology in a system.

The reliance on cross-sectional data prevents the dynamic analysis of adoption (Doss, 2006). Although this type of data collection is suitable for obtaining useful information on technology adoption by understanding farmers’ decision-making processes at a single point in time, this static description further fails to address the dynamic adoption process. Adoption involves a series of decisions, where decision-making critically depends on previous decisions. Studies may need to include longitudinal data to capture this dynamic nature by understanding the series of farmer’s decisions, which can even help control heterogeneity across households (Doss, 2006). Despite this importance, only 11 studies adopted longitudinal or panel data when analyzing adoption, possibly explained by the time and resource commitment of this data collection method.

Additionally, it is essential to consider other adoption types beyond whether farmers have adopted a particular technology and the extent of adoption. The high focus on the probability and intensity of adoption provides a static analysis, which further fails to accurately reflect the dynamic process of adoption, where explanatory variables can change during the observed period (Feder et al, 1985; Alcon et al, 2011). Undertaking a duration analysis approach can provide information beyond the fundamental reasons why farmers adopt IRVs by including adoption timing and the determinants influencing the observed time patterns (Sánchez-Toledano et al, 2018). Only one study employed duration analysis by looking at the speed of adoption of two IRVs in Sierra Leone using the Accelerate Failure Time model, and discovered that the adoption rate depends on farmland location and variety type (Mansaray et al, 2019). Adopting IRVs can occur at different speeds for various reasons (Burton et al, 2003), making it essential to identify drivers of early seed adoption. Timing of adoption provides an understanding of farmers’ perception of benefits and receptiveness towards IRVs and can outline potential barriers affecting adoption speed (Dadi et al, 2004). It can provide policymakers with opportunities to explore interventions encouraging and accelerating the adoption of IRVs.

Apart from adoption speed, other types of duration analyses remain largely ignored. Adoption duration of IRVs, another adoption outcome relevant to agriculture, which allows policymakers to understand the determinants that affect the time that IRVs are used before being replaced (Montes de Oca Mungula et al, 2021), has not been examined in the reviewed studies. The difficulties in modelling duration analyses in technology adoption may explain why researchers continue to opt for static analyses due to its simplicity and establishment of this type of method in adoption studies in this field (Diagne et al, 2012).

Correcting bias in adoption analyses

Most reviewed studies were subjected to several limitations, which may have led to biased regression estimates or potential inaccuracies in the adoption analyses. Firstly, most reviewed studies (93%) ignored plot characteristics by relying on household and farm-level data when analyzing adoption. Farms in the Global South are usually characterized by small and scattered plots, where characteristics of different plots can have different farm biophysical conditions such as soil quality, terrain, irrigation, and even ownership (Noltze et al, 2012; Nguyen, 2020). Ignoring these differences at the plot level can create biases in the analysis. Using plot-level data allows the examination of within-household adoption decisions for the various plots owned by a farmer.

Additionally, only 15% of studies have utilized qualitative insights to support quantitative data, including mixed method research. Most qualitative data were conducted before quantitative data collection. This absence of qualitative data collection can prevent the exploration of new variables that may be more relevant to a study area, creating bias in determining important determinants of adoption. Additionally, only Godoy et al (2000) collected qualitative data (in-depth interview) after preliminary quantitative results to explain initial quantitative data; the remaining studies used adoption theories, perceptions or explanations from similar studies. However, there are limitations when relying on the latter to explain results, which may provide inaccuracies in the analysis of adoption behavior. These limitations include the failure for conclusions and interpretations to be modified according to a particular context (Johnson and Onwuegbuzie, 2004), the inability to interpret poorly understood results or outliers (Morse, 1991), and the difficulty for results to be enhanced, clarified or elaborated (Greene et al, 1989). Thus, incorporating qualitative data collection using a mixed method can minimize the weaknesses as it can include potentially overlooked key variables and provide a context-specific explanation.

Diagne (2006) also raised potential weaknesses in current adoption method by highlighting the issue of selection or non-exposure bias. Farmers unaware of improved technologies cannot make adoption decisions. This bias can only be removed if awareness is randomly distributed in a population or if the whole population is aware of the technology (Nguezet et al, 2013). Due to this non-exposure bias, simple Logit, Probit and Tobit models cannot accurately estimate adoption determinants (Diagne, 2006). Instead, Diagne and Demont (2007) proposed an Average Treatment Effect methodological approach to manage this bias. Future adoption surveys need to understand farmers' exposure to IRVs to provide more reliable determinants of adoption.

Further adding to this bias is the potential for some variables to be highly endogenous. For example, the effects of education on adoption can be influenced by family wealth and information access by age, farm size and motivation. Endogeneity bias needs to be rectified to obtain precise impacts of the effects of specific variables on adoption, and failure to do so may result in drawing the wrong inferences of determinants of adoption (Abdallah et al, 2015). To provide a consistent and unbiased estimation of these variables, Abdul-Rahaman et al (2021) corrected the potential endogenous nature of extension visits, farm group memberships and credit access by employing Wooldridge's control function.

The neighboring effect influence can add to the potential endogeneity of variables in adoption studies. The observed performance of adoption by neighboring farmers can encourage or discourage farmers from committing larger land areas to improved seeds. Feder et al (1985) describe this as Bayesian learning, where the influence of neighbors can allow analysis of the evaluation stage of the adoption process before the adopter actually uses the new innovation. In turn, this effect of neighbors can cause initial investments to result in copy or secondary adoption, which can create inconsistencies and bias in examined estimators in standard adoption models (Case, 1992). Holloway et al (2002), Miguel et al (2021), and Ward and Pede (2014) tried to capture this neighboring effect on the adoption of HYV in Bangladesh by using a Bayesian spatial Probit model or a spatial two-stage least square, where the inclusion of spatial relations prevented bias on conventional estimators created by the influence of neighbors.

Nonetheless, the absence of studies that attempt to correct endogeneity bias demonstrates the importance of developing the right methodological toolkit that addresses different types of endogeneity in adoption studies (Abdallah et al, 2015). With the potential influence of friends, family and the community on adoption, future studies may consider undertaking a social networking analysis to understand the social phenomena better. This analysis technique can depict the relations between actors, including their connectivity and closeness, and the network of information exchange on IRVs (Filippini et al, 2020). The potential endogeneity of variables also affirms that adoption behavior is likely to be non-linear and complex, and oversimplified econometric analysis may provide inaccurate conclusions for policymakers. Viewing adoption from a system perspective may be more appropriate when understanding the determinants of adoption. The use of system dynamics can capture the interactions between multiple causal factors (endogenous and exogenous), and can also allow the quantitative simulation of multiple effects of feedback interactions amongst the complex dynamic causal factors (Fisher et al, 2000; Muflikh et al, 2021). System dynamics can provide a better understanding of the interactions of variables on adoption in a system compared with the use of econometric analysis. The use of the latter often leads to oversimplifying research problems in adoption studies, leading to inaccuracies and potentially misleading researchers and policymakers (Glover et al, 2016).

Perspective

Most studies have extensively examined four variables (farm location, farm size, education and information access). However, other variables that have not been prioritized have resulted in more important adoption determinants based on the weight analysis method. These crucial determinants include mainly technology-related variables (perceived yield, maturity, ease of use, marketability, and technical efficiency of rice varieties) as well as terrain type and source of seed, and they vary depending on adoption type, region and variety.

Low adoption levels in Asia are possibly affected by abiotic stress exposure, terrain, ineffective sources of seed, poor material input access and low perceived benefits of technology (i.e. perceived yield, maturity and marketability). Potential adoption constraints in Africa are the location of the farm and low perceived benefits of technology (i.e. ease of use, perceived yield and physical properties). Hybrid rice varieties have the lowest probability and intensity of adoption with important determinants, suggesting that hybrid seeds introduced are potentially unsuitable for certain agro-ecological zones and terrain types.

Despite the potential of technology-specific variables impacting adoption, this group of characteristics are examined the least compared with household and farmer characteristics, farm biophysical, and institutional and access-related characteristics. Future research must incorporate relevant agronomic and non-agronomic technological traits to prevent bias in determining the determinants that affect adoption. More research should be undertaken in countries/regions currently facing production deficits. Furthermore, premium and biofortified rice will also require more research, with the absence of studies making it challenging to conclude important determinants of adoption.

There is a need for adoption studies to shift towards capturing the dynamics of the adoption process. This includes examining the interdependence of improved technologies, incorporating the series of adoption decisions by using longitudinal data, and undertaking duration analyses to explore adoption beyond the current predominant static analyses. Lastly, correcting inaccuracies and bias prevalent in current adoption studies are essential. The collection of data at a plot level can capture the effects of differences in plot characteristics on adoption. Including qualitative data using a mixed method research design can allow the exploration of new site-specific variables and provide a more accurate explanation of adoption behavior. Studies will also need to rectify the problem of non-exposure, neighboring effect, and endogeneity bias to obtain a more precise understanding of the impacts of the variables on adoption. The limited number of studies that attempt to correct endogeneity bias suggests the need to develop a methodological toolkit to address the various types of endogeneity prevalent in adoption studies. The endogenous nature of variables also suggests the need to view adoption from a system perspective.

Policymakers can combine this better understanding of the critical potential determinants of adoption recognized in this review and the proposed improvement areas to capture adoption behavior and patterns of farmers in the Global South. By identifying salient determinants of adoption, policymakers can target future funds and efforts to improve adoption effectively, ultimately food security, farmer livelihood and social sustainability.

This study is limited by the various problems existing in current adoption studies. The sample is not representative due to the wide variation between the number of time variables and the distribution of studies across regions and variety types. This study has used a weighted method to address this significant variation in data available to determine important determinants of adoption instead of the frequency count commonly used in existing adoption studies (Acevedo et al, 2020; Jones-Garcia and Krishna, 2021). However, the insufficient number of time variables examined in some regions and variety types still make it difficult to conclude whether certain variables are important and will require further study. Additionally, there is often a preference to publish studies demonstrating statistically significant results (Owens, 2021), with studies sometimes opting to discuss results from econometric models that provide the greatest number of significant variables. Therefore, it is essential to note that the results presented in this study are a collection of findings available in the scientific community and cannot be strictly generalized to all contexts.

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SUPPLEMENTAL DATA

The following materials are available in the online version of this article at http://www.sciencedirect.com/journal/rice-science; http://www.ricescience.org.

Fig. S1. Econometric models employed and adoption type.

Table S1. Definition of variables.

Table S2. Table of included studies on adoption of improved rice varieties.

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