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LETTER

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Scrutinizing the impact of policy instruments on adoption of agricultural conservation practices using Bayesian expert models

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Abstract

Policy instruments—such as regulation, financial incentives, and agricultural extension—are commonly applied by governments to promote sustainable agricultural practices and tackle ecosystem degradation. Despite substantial investment, little data are available to gauge the impact of evolving policy mixes. We constructed a Bayesian network model to explore relationships between policy instruments, contextual factors, and adoption. Applying a series of scenarios, we present examples of how different instruments influence adoption and how their effectiveness is shaped by contextual factors. Scenarios highlight that the effect of policy instruments is often modest, and constrained by diverse practice and population characteristics. These findings allow us to reflect on the role of policy instruments, and the conditions necessary to support practice change. For example, our findings raise questions about the role of financial benefits versus financial capacity, and highlight the potential importance of concepts such as mental bandwidth in shaping both motivation and capacity to adopt.

KEYWORDS
agricultural practices, behavior change, extension, livelihoods, practice adoption, regulation

1 | INTRODUCTION

Agricultural expansion and intensification is a major driver of ecosystem degradation (Butler et al., 2007; Norris, 2008), with more than one third of global land area used for livestock and crop production (FAO, 2021). Reducing agriculture's environmental footprint while ensuring global food security is a critical goal (Foley et al., 2011; Ortiz et al., 2021). Policy instruments—the techniques through which governments implement policies—aim to reduce the ecological impact of agricultural practices (Howlett, 2019; Lee et al., 2019). Policy instruments commonly considered in agricultural settings include (i) regulation, for example, formal rules or legislation that mandate adoption, prohibit practices, or require permits/licenses; (ii) financial instruments, for example, incentives to motivate or support capacity to adopt; and (iii) suasive approaches, for example, agricultural extension and training programs, persuasive approaches applying behavioral science, and (iv) procedural (or governance) instruments, comprising activities such as collaborative planning (Howlett, 2019; Kamal et al., 2015; Lee et al., 2019).

Despite significant government investment in developing and implementing policy instruments, it is difficult to quantify effectiveness of specific instruments. Much policy research has focused on policy *inputs*, describing what influences instrument selection (Capano & Lippi, 2017), and how instruments are applied in evolving policy mixes (Schmidt & Sewerin, 2019). However, there are many research gaps related to policy *outputs* (Capano & Howlett, 2020). A key research gap involves assessing the performance and effectiveness of policy instruments and mixes, describing the mechanisms by which tools activate their effects, and the necessary conditions that contribute to success (Capano & Howlett, 2020).

We address these gaps using a participatory modeling approach, incorporating expert knowledge into a Bayesian network model. As our case study, we explore adoption of practices that promote water quality improvements affecting the Great Barrier Reef (GBR), Australia. This provides an informative case study due to sustained government investment, targeted prioritization (of locations and practices), and the use of diverse policy instruments across multiple agricultural industries (Eberhard et al., 2021). While practice data exists for some sectors, the constantly evolving policy mix and socioecological context makes it difficult attribute impact to specific policies, mechanisms, or conditions (Eberhard et al., 2021). In such circumstances, expert-led methods provide an opportunity to scrutinize impact of instruments and the conditions that influence impact. Rather than providing exact estimates of adoption, the project aims to facilitate discussions among decision makers. The current study describes a range of scenarios exploring how the effect of policy instruments varies with practice and population characteristics (Figure 1).

2 | METHODS

2.1 | Case study: Great Barrier Reef water quality targets

The health of the GBR is seriously threatened. While climate change is the most significant threat to the GBR (Hughes et al., 2018), poor water quality is a critical localized threat that undermines resilience in inshore reefs (Brodie et al., 2019; MacNeil et al., 2019). Agricultural runoff—such as sediments from rangeland grazing or nutrients and pesticides from coastal sugarcane lands—is the primary source of water pollutants (Brodie et al., 2017). Reef water quality risk frameworks have identified agricultural practices that reduce downstream water quality risk and set targets (Brodie et al., 2017; Queensland Government, 2018). Despite significant investment in multiple policy instruments, poor water quality persists (Eberhard et al., 2021; Waterhouse et al., 2017).

2.2 | Overall approach

This research is part of a larger project (Figure 2, full detail Supporting Information S1). Modelers facilitated participatory development of a Bayesian network model structure with a multidisciplinary research team (Mayfield et al., 2023). This conceptual model highlighted relationships between policy instruments and adoption, and included practice and population characteristics that may

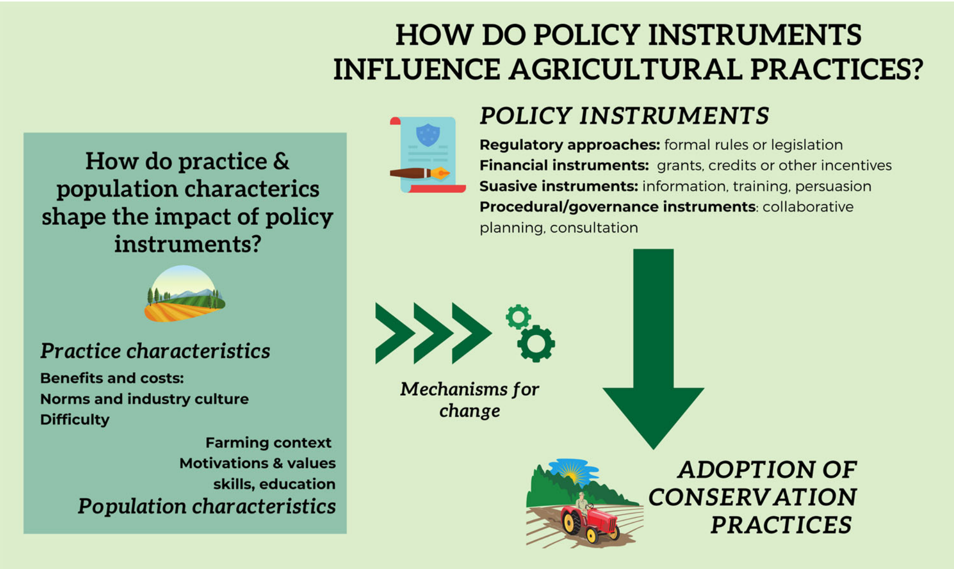

FIGURE 1 Conceptual framework for our study: how do different policy instruments influence adoption of conservation practices, and how is the effect of policy instruments influenced by farming and practice characteristics.

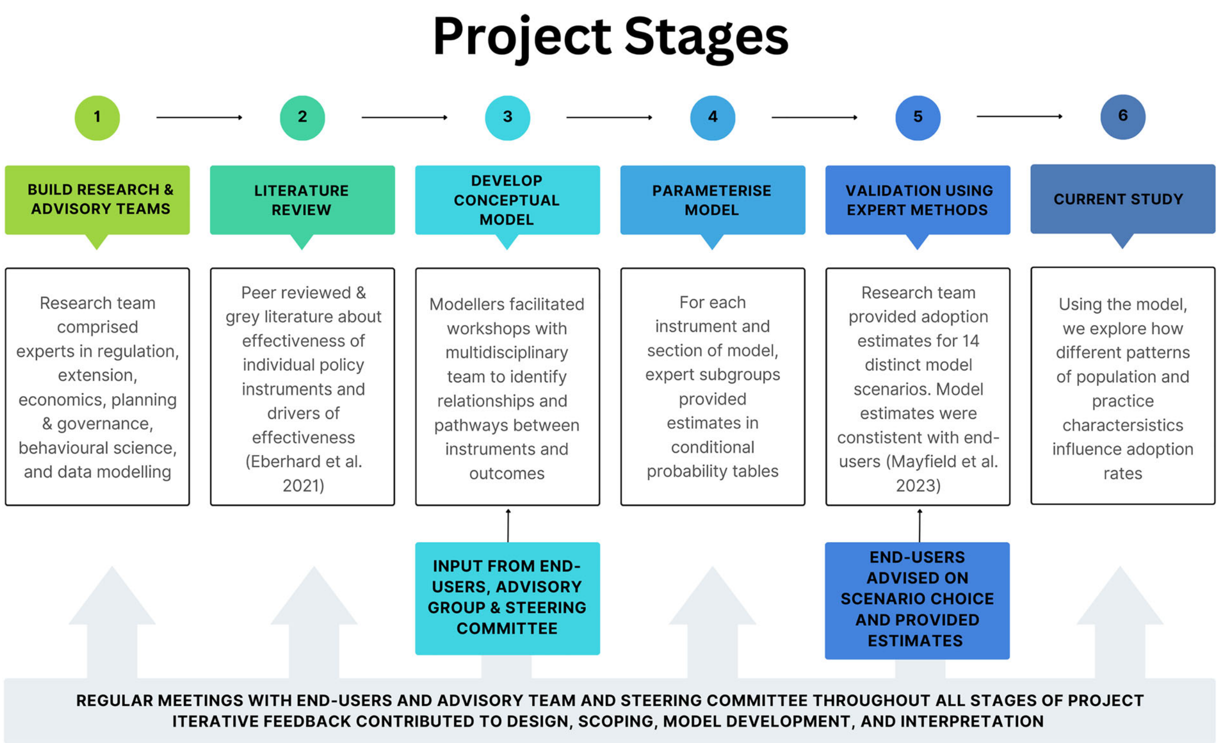

FIGURE 2 Flow chart showing all stages of the project.

influence instrument effectiveness. Input from industry stakeholders was incorporated to ensure that the model comprised all necessary components and reflected their view of the system. The model was then parameterized by the research team using conditional probability tables (Mayfield et al., 2023) (Supporting Information S2). After training, experts estimated the probability of adoption for each possible scenario relating to their area of expertise (e.g., Supporting Information S1). Interdisciplinary nodes representing the mechanisms were completed collaboratively during facilitated workshops. Overall, processes involved in developing and parameterizing the conceptual model involved multiple rounds of structured expert elicitation (Mayfield et al., 2023). Model validation compared estimates from stakeholders with model estimates (Mayfield et al., 2023). To ensure relevance to policy makers, model development focused on sugarcane farmers in the GBR catchments (and grazing to a lesser extent). Industry and enterprise characteristics were included as input nodes, allowing for differences between diverse agricultural industries operating in GBR catchment regions. Ethics approval was provided by Queensland University of Technology (#2020-3150-3559).

2.3 | Model components

2.3.1 | Outcome: "practice adoption"

> The outcome "node" was defined as "*sustained* adoption of a farming practice within five years of policy implementation." An assumption was placed on the model to focus on farmers who had not already adopted the practice, and whose enterprise was potentially suitable for that practice (e.g., target audience for riparian revegetation practices would only include those with unvegetated riparian areas on their land) (Supporting Information S2 provides an example of conditional probability tables).

2.3.2 | Policy instruments

The model included five types of instruments (Table 1, Supporting Information S1). Each instrument had elements that were considered to represent best practice, captured as nodes:

- Regulation (5 nodes)
- Financial instruments (both upfront incentives/grants and ongoing incentives/credits, 5 nodes)
- Extension (7 nodes)
- Behavioral insights (1 node)
- Governance processes that engaged stakeholders (1 node).

When practices were not regulated, the component of the model focusing on regulatory compliance was not activated. In the absence of an "active" instrument, the comparison condition was "limited extension" for nonregulated practices, and "limited regulations and limited extension" for regulated practices (Supporting Information S1).

2.3.3 | Practice and farming characteristics

Using both expert elicitation and peer-reviewed literature, the team then identified characteristics of the practice (e.g., adoption difficulty) and farming population (e.g., farmer motives) that could potentially influence the effectiveness of the instrument (full list in Table 2, Supporting Information S1).

2.4 | Modeling effect of policy instruments and contextual characteristics on adoption

We quantified the estimated impact of each policy instrument on adoption as a range, bounded by upper and lower limits. To assess the upper estimate, all practice/farmer characteristics were set to states, which were considered to be most supportive of adoption (i.e., "most favorable") (Table 2). To assess the lower estimate for each instrument, all practice/farmer characteristics were set to states considered to limit adoption (i.e., least favorable). Estimates for regulated and nonregulated practices were separated (Hamman & Deane, 2018; Verbruggen, 2013).

To further explore the influence of practice and population characteristics, we selected one instrument mix (best-practice extension, plus grant and credit) and assessed the influence of single "step shifts" in practice and population characteristics on adoption. Analyses used three different baselines: (i) *upper limit*: negative influence of each characteristic on adoption, when all other characteristics set to positive; (ii) *lower limit*: positive influence of each characteristic on adoption, when all others were set to negative; and (iii) *average*: positive and negative effect of each single characteristics, with all other characteristics set to "average."

3 | RESULTS

3.1 | Estimates for individual instruments

3.1.1 | Nonregulated practices

When no active instruments were applied (i.e., "limited extension"), our model estimates adoption ranging between 1% and 34% for nonregulated practices (Figure 3a). Applying extension, governance, or behavioral insights as single instruments, yielded minimal increase in estimates. Of the single instruments, upfront financial instruments generated the highest adoption estimates (range

TABLE 1 Policy instruments and instrument characteristics included in the model.

Instrument type	Instrument characteristics (nodes)	Potential node states	Active node state (i.e., when instrument turned "on")	Description
Regulation	Cost of penalty	Significant; insignificant	Significant	Whether the penalty for noncompliance is significant for the population.
	Enforcement approach	Staged; conciliatory; coercive	Staged	Whether enforcement is responsive and proportionate to actual levels of compliance.
	Enforcement frequency	Frequent; infrequent; none	Frequent	Frequency of on ground enforcement.
	Ease of compliance	Easy; moderate; difficult	Easy	Whether complying with regulations involves major costs, time, and resources.
	Regulated Practice	Yes; no	Yes	Whether the practice being modeled is subject to regulation. If triggered, this allows for regulations submodel to be applied. If not, the regulation submodel is not triggered and compliance does not contribute to adoption estimates.
Financial	Adoption grant	Large; small; N/A	Large	A one off, upfront financial contribution to support practice change
	Credits	Large; small; N/A	Large	A future financial payment to landholder for delivering a quantifiable reduction in pollution
	Contracting costs	High; low	Low	Cost of time and resources expended by landholders to manage contracts related to the financial instrument
	Monitoring costs	High; low; N/A	Low	The cost of time and effort in assessing and reporting on activities that are paid for by credits or grants. This may be evidence of compliance (fertilizer records) or evidence of environmental benefit (improved water quality).
Extension	Extension officer capability	Sufficient; insufficient	Sufficient	Whether the extension team has the attributes (skills, knowledge, experience, qualifications, abilities, personality) to successfully deliver extension and meet audience needs.
	Extension officer embeddedness	Sufficient; insufficient	Sufficient	The extent to which the extension team understands and connects with the broader social network.
	Extension approach	Top-down; bottom-up	Bottom-up	Whether approaches to extension design (both content and delivery methods) are top down (limited input or codesign from target audience) or bottom-up a (stronger input and codesign by the target audience).
	Extension coordination	Fragmented; coordinated	Coordinated	Whether extension programs are coordinated (with regard to timing, content, access/engagement options delivery) across a diverse set of providers

(Continues)

TABLE 1 (Continued)

Instrument type	Instrument characteristics (nodes)	Potential node states	Active node state (i.e., when instrument turned "on")	Description
	Extension method	Individual; group; broadcast	Individual	Whether extension delivery is one-on-one to individuals, to multiple end-users (e.g., group work), or to a mass audience
	Learning path	Discrete/one off; pathway	Pathway	Whether the learning comprises one discrete opportunity or constitutes a "pathway" involving different types and/or timing of learning opportunities.
	Provider diversity	High; low	High	Whether a range of institutions are involved (e.g., public, private, NGOs), or the extension effort is via a single agent.
Behavioral insights	Communication for behavior change	Yes; no	Yes	Whether appeals to promote new practices apply insights from behavioral science, such as those used in community-based social marketing.
Governance	Governance	Collaborative; noncollaborative	Collaborative	Whether collaborative governance approaches are applied to instruments.

Note: Estimating the effect of each instrument involved setting its node states to "active" while setting states of other instruments to their nonactive state.

4%–55%). When all instruments were combined, the range was 5%–64%. Differences between upper and lower estimates reflect the influence of practice and farmer characteristics.

3.1.2 | Regulated practices

When no active instruments were applied (i.e., "limited extension/regulations"), adoption estimates for regulated practices ranged from 32% to 64% (Figure 3b). Similar to nonregulated practices, applying extension, governance, or behavioral insights as single instruments produced minimal impacts. Applying regulations generated adoption estimates of 49%–80%. When all instruments were combined, the range was 51%–88%.

3.2 | Influence of practice and population characteristics

We then focused on a specific instrument mix (best practice extension, grant and credit), where adoption estimates ranged from 4% to 58%. The results below describe the influence of step shifts from both upper and lower baselines (analysis using "average" baseline is in Supporting Information S4). Focusing on single practice characteristics (Figure 4a), the strongest negative influence on adoption was implementation costs, where setting implementation costs as high (with all other characterstics set to their most favourable reduced adoption from 58% to 48% (Figure 4a). We then considered the counter scenario (i.e., all characteristics set to *least* favorable). Here, setting individual practice characteristics to their favorable state had minimal benefits on adoption. For example, ensuring implementation costs were low while all other settings were unfavorable only increased adoption to 7% (Figure 4a, Supporting Information S3).

Focusing on population characteristics, the strongest negative influence on adoption was farmers' existing financial resources, which, when limited, reduced estimated adoption from 58% to 24% (Figure 4b). When considering the counter scenario, improving financial resources increased adoption from 4% to 12%. This was followed by mental bandwidth, where limited mental bandwidth reduced adoption from 58% to 28% (Figure 4b, Supporting Information S3).

To consider interactions between practice and population characteristics, we created three scenarios (Table 3). Scenario 1 shows that *Financial settings* have a strong influence on adoption: when all other characteristics were set to most favorable, limited *financial settings* decreased adoption from 58% to 11%. Conversely, when

TABLE 2 Nodes and node states for practice and farmer characteristics included in the model.

Node	Description	Potential node states	Least favorable node states	Most favorable node states
Practice characteristics				
Adoption difficulty	Characteristics of the new practice that make it easier/harder to adopt	Complex; simple	Complex	Simple
Production benefit	Benefits to resource production such as increased yield.	Yes; no	No	Yes
Actual environmental benefit	Water quality benefit of the practice, based on scientific evidence.	High; low	Low	High
Benefit lag	Time lag between the adoption of and the realization of the expected environmental benefits.	Short; long	Long	Short
Profit from credits	How the new practice impacts on-farm profit linked to credits.	Positive; neutral; negative	Negative	Positive
Implementation costs	Upfront costs of time and resources to implement the practice.	High; low	High	Low
Industry support for practice	General culture of the peak industry body in relation to their view on the specific practice.	For; against; neutral	Against	For
Existing practice norm	Existing standards or typical practice within the farming population.	Enabling; against	Against	Enabling
Farmer characteristics				
Audience diversity	Diversity of farmer population (e.g., demographics, farming type) influences tailoring of extension programs	High; low	High	Low
Size of enterprise	Larger enterprises may have greater capacity to engage with new practices.	Large; small	Small	Large
Formal education	Level of formal education completed; may influence literacy and capacity to engage with new information.	Primary; secondary	Primary	Secondary
Existing financial resources	Whether the landholder has sufficient cash resources now to implement and maintain the new practice.	Sufficient; insufficient	Insufficient	Sufficient
Skill set	Whether a farmer has a broad range of skills relevant to enterprise.	Diverse; limited	Limited	Diverse
Farmer commitment to enterprise	The presence of a future-oriented perspective and commitment to active, management of the enterprise.	Yes; no	No	Yes
Mental bandwidth	Whether a farmer has cognitive or emotional capacity to consider new information or new practices.	Yes; no	No	Yes
Problem agreement	Extent target audience agrees that problem being addressed is important and related to their practice.	High; low	Low	High
Farmer motives	Values, or overarching beliefs that shape preferences and decisions with regard to daily choices.	Ecocentric; risk avoider; profit maximizer	Risk avoider	Ecocentric
Farmer postures	Relationship of farmers toward the state with respect to authority and perceptions of regulations.	Commitment; strategizing; capitulation; disengagement resistance	Resistance	Commitment

Note: Most favorable node states are associated with higher adoption rates while least favorable node states are associated with lower adoption rates.

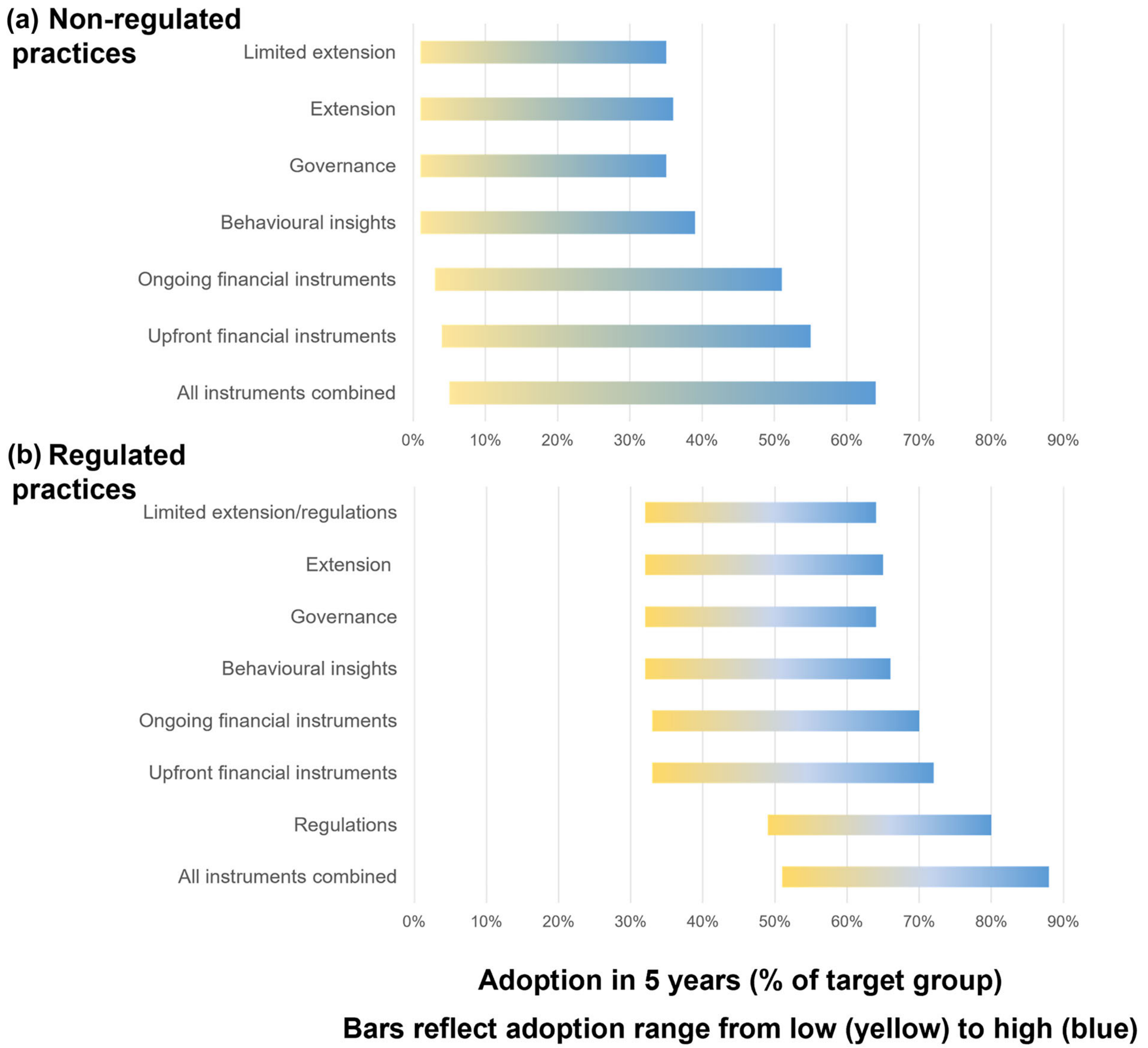

FIGURE 3 Range of model estimates of adoption rates for policy instruments (as single instruments and combined) for both nonregulated practices (a), and regulated practices (b). Upper range estimates (blue) relate to when all practice and farmer characteristics are set to their most favorable state for enabling adoption; lower range estimates (yellow) reflect all practice and farmer characteristics being set to their least favorable state.

all characteristics were set to their least favorable, strong *financial settings* could increase adoption from 4% to 19%. Sensitivity analysis (Supporting information S5) revealed that financial practice characteristics that influenced *capacity* to adopt (e.g., financial capacity) had a stronger influence on adoption that practice characteristics that influenced motivation (e.g., impacts on production). Scenario 2 (*Human settings*) revealed that, when all settings favored adoption, limiting human capital decreased adoption from 58% to 24% (Figure 4c, Supporting Information S2). Scenario 3 (*Pro-environmental settings*) had a more modest influence on adoption (Figure 4c).

4 | DISCUSSION

4.1 | Relative benefits of specific instruments

Of all the instruments, regulations emerged with the strongest relative impact. While this is in line with calls for stronger regulation of land management practices (Brodie et al., 2019; Kroon et al., 2016), we note that our regulatory approach comprised design elements that contribute to impact: ensuring compliance is easy, and applying regular monitoring and staged enforcement with significant penalties. Research suggests that for legislation to

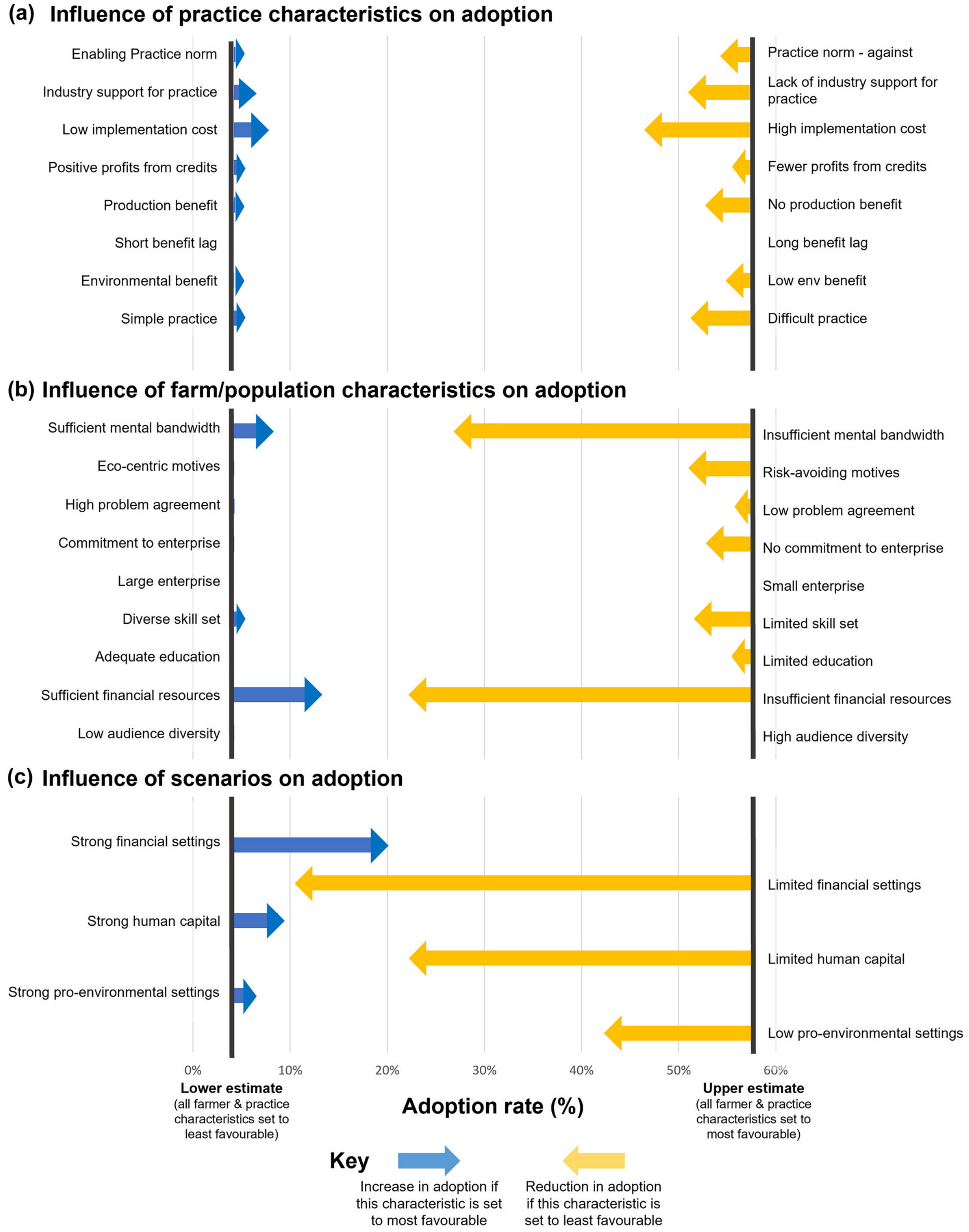

FIGURE 4 The influence of practice characteristics (a), farm and population characteristics (b), and specific scenarios (c) on adoption impact (instrument mix: extension, upfront financial instrument and credits). The vertical line on the right reflects upper adoption estimates (58%, with all farmer and practice characteristics set to their most favorable); each yellow arrow indicates the negative influence of each characteristic when set to least favorable state (all others remaining positive). The vertical line on the left reflects lower adoption estimates (4%, with all farmer and practice characteristics set to their least favorable). The blue bars indicate the positive influence of each characteristic when set to most favorable state (all others remaining least favorable) .

TABLE 3 Description of node settings for each scenario.

Scenario	Nodes	Most favorable node states	Least favorable node states
Scenario 1.	Actual environmental benefit	High	Low
Pro-environmental setting	Benefit lag	Short	Long
	Existing industry culture	For	Against
	Existing practice norms	Enabling	Against
	Audience diversity	Low	High
	Problem agreement	High	Low
	Farmer motives	Ecocentric	Risk-avoiding
Scenario 2.	Profit from credits	Positive	Negative
Financial capital	Production benefit	Yes	No
	Implementation costs	Low	High
	Farmer motives	Profit-maximizing	Risk-avoiding
	Existing financial resources	Sufficient	Insufficient
Scenario 3.	Adoption difficulty	Simple	Complex
Human capital	Skill set	Diverse	Limited
	Formal education	Secondary	Primary
	Mental bandwidth	Yes	No

generate environmental benefits, it must be accompanied by investment in compliance monitoring and enforcement (Mateo-Tomás et al., 2022). In addition to the costly nature of regulation, there are a range of situational factors that might influence its suitability. For example, regulatory approaches have been contested by some industry groups which can result in reactive behaviors (such as increased land clearing) (Simmons et al., 2018), or weakening regulatory standards (Deane et al., 2018). This highlights the need for regulation to consider industry culture and be adaptive to emerging needs (Cosens et al., 2020; Hamman & Deane, 2018). Suitability of regulatory approaches will also vary for different practices. Government regulation tends to set a minimum industry-wide standard, but with no encouragement to go beyond this minimum. In contrast, innovative conservation practices—which may generate significant conservation benefits—would typically begin with a *subset* of engaged farmers. Demonstrating benefits and positive experiences with this subgroup then provides a foundation to promote adoption more broadly. In such situations, nonregulatory approaches—such as novel financial instruments supported by extension-based skills training—may encourage landholders to go beyond the regulated minimum standard.

Model estimates for adoption were lower than expected for many instruments (Supporting Information S6). Regarding extension, reflections with stakeholder groups suggested that extension is necessary but not sufficient to enable practice change. Much extension focuses on building skills and capacity, but importantly, motivation is also an essential element of practice change (Piñeiro et al., 2020). Importantly, for some landholders, barriers to adopting new practices may also act as barriers to engaging with extension services (Morrison et al., 2011; Tamini, 2011). Alternatively, discussions raised the possibility that extension generates benefits that were not captured in our model. For example, potential benefits of extension may occur over extended periods of time, with outcomes not emerging within modeled timeframes. Extension instruments may also have the potential to influence engagement with other instruments or generate other benefits that may support adoption, such as strengthening social networks between landholders.

4.2 | Financial settings

Overall, scenario analysis indicated that financial settings had the strongest influence on adoption. However, when considered in isolation, single practice characteristics such as production benefit and profits from credits had minimal influence on adoption rates. It is recognized that many factors other than profit influence adoption (Emtage & Herbohn, 2012; Knowler & Bradshaw, 2007; Koetse & Bouma, 2022; Pedersen et al., 2012; Weersink & Fulton, 2020). Nonetheless, given other research indicating an important role of profits (Cary & Wilkinson, 1997; Kuehne et al., 2017), we would have expected individual nodes related to profits and yield to exert a stronger influence on effectiveness of policy instruments. Sensitivity analysis revealed that practice characteristics that influenced *capacity* to adopt had a stronger influence compared with practice characteristics that influenced *motivation* to adopt. Given that adoption requires *both* motivation and capacity, the emphasis of our findings on capacity rather than motivation may reflect a limitation of our model. Even in the presence of adequate capacity and resources, farmers will not adopt a practice unless it aligns with their motivations and goals. While we attempted to separate drivers, in practice, perceptions about profit, yield, capacity, and motivation are likely to be intertwined. For example, perceptions about profitability of a practice may motivate a landholder with limited capacity to change an aspect of their financial management to become capable (which would shift this node state). However, in our model, these types of interactions were not able to be captured, which may have constrained the influence of financial settings. Considering these issues, we recommend caution applying model outputs related to financial settings without broader assessment of motivational drivers.

Another issue that may have contributed to the limited effect of individual financial settings relates to how our decision problem was conceptualized. Some agricultural practices have high rates of adoption—for example, adoption of genetically modified cotton in Australia exceeds 90% (Australian Government, 2018). It would be expected that drivers of high adoption would reflect strong relative advantage related to profits, yield, and convenience, all of which would contribute to high rates of uptake (Kuehne et al., 2017). In contrast, many conservation practices are characterized by goal conflicts, where conservation goals may diverge from economic goals (Kirschke & Kosow, 2022; Levy et al., 2018). Many conservation agricultural practices—including those in our case—have the potential to elicit negative effects on profit or yield and involve inconvenience. While efforts have been made to ensure recommended conservation practices deliver potential financial benefits (e.g., by reducing fertilizer costs), these are typically modest compared to commercially oriented practices. Our model was developed to better understand poor ecological outcomes, despite use of numerous policy instruments. Therefore, our model emphasized a system in which there are substantial constraints to effectiveness of policy instruments on adoption. This emphasis may have reduced the model's capacity to predict high adoption rates.

4.3 | Enabling conditions for change

The large variations in estimates of impact speak to the importance of diverse conditions that influence effectiveness of policy instruments. Many authors recommend considering social factors in the design and implementation of policy instruments (Pannell & Zilberman, 2020; Vanclay, 2004), through developing realistic targets, and considering landholder experience and perspectives. One aspect of landholder experience that had a strong influence in our model was mental bandwidth. Research shows that limited financial resources may lead to mental stress, which may deplete cognitive resources available for decision making (Shah et al., 2012). Extending this, many types of personal stress—stemming from on-farm issues such as managing drought, or personal issues linked to poor health—may limit capacity to engage with new information or practices (Weber, 2006). Our scenario findings about human capital rekindle established arguments about the role of governments and organizations in tackling social challenges (Vanclay & Lawrence, 1995). On one hand, it has been argued that substantial investment in human capital—in the form of access to information, skills, and networks as part of Australia's National Landcare Program—has delivered only modest environmental benefits at a national scale (Curtis & Lockwood, 2000; Tennent & Lockie, 2013). Farmer participation in such programs is also influenced by the political landscape (Morrison, 2017; Pini, 2002). However, the concept of human capital extends beyond these elements. For example, research shows that while the Australian agricultural workforce is increasingly educated, workforce capacity to embrace change remains constrained (Wu et al., 2019). For example, as farmers embrace digital agriculture, many still have limited access to the internet. Reduced population growth in regional centers may result in fewer services that are necessary to support farming communities (Wu et al., 2019). Research suggests a broader range of enabling conditions that can influence practice change such as social equity, gender equality, social capital, culture, and identity (Coldwell, 2007; Huber-Stearns et al., 2017), highlighting the importance of understanding how a broader set of enabling conditions evolve to shape the impact of policy instruments.

Our findings suggest that that policy instruments are only one feature of a complex set of enabling conditions. For example, our reference conditions generated adoption estimates resembling some single instruments, which generated much discussion among stakeholders. Rather than supporting a "do nothing" stance, discussions considered the minimal ingredients required to support adoption. For example, in the context of a regulated practice, if a target practice is easy, generates financial benefits, and is supported by industry, these factors may support adoption, even in the absence of well-designed and resourced regulatory instruments.

4.4 | Limitations

One of the limitations of Bayesian networks is that feedback loops are not permitted (Marcot & Penman, 2019). Yet, bidirectional effects and feedback loops are critical components of agricultural systems (Levy et al., 2018). For example, partial adoption or trialing of a new practice creates on-ground experience that may then shape motivation (Montes de Oca Munguia et al., 2021). Elements within the system—such as practice norms or industry culture—may also evolve over time. Emerging methods highlight the opportunity to extend beyond modeling single practice adoption and consider a portfolio of practices, although they do require data from a population who has been exposed to the intervention mixes in the past (Rudnick et al., 2021). Bayesian network models are capable of integrating data, theory, and models from disparate sources, so these data-driven emerging methods offer opportunities to parameterize parts of this model. Given that many people find it difficult to conceptualize feedback loops and interdependencies (Levy et al., 2018), it would be useful for future research to consider how modeling approaches can extend our understanding of farming systems. Another limitation of these types of models is their reliance on expert opinion, and the potential for findings to be biased by the perspectives involved in model development, which are influenced by an individual's disciplinary or professional experience (Guerrero et al., 2021; van Hulst et al., 2020). Our findings rely on a model developed by academic researchers. While we included the perspectives of industry and farming professionals via our advisory groups, it is likely that our model findings were influenced by the make-up of our research team.

4.5 | Conclusions

Overall, our findings show that the impact of instruments on adoption of agricultural practices are modest, and influenced by contextual and social factors, especially financial and human capital. Our findings indicate that there is no single effective instrument or enabling condition. Rather there is a set of conditions needed to enable and legitimize farmers working toward conservation goals (Runhaar, 2016). Policy instrument design and application in agriculture requires us to consider what mix of instruments, their design features, and assumptions about change will work for different audiences within different social and environmental or contexts.

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DATA AVAILABILITY STATEMENT

No data were used for the research described in the article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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