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FARMING AT THE EDGE

THEORY OF REASONED ACTION AND ITS INTEGRATION WITH ECONOMIC MODELLING IN LINKING FARMERS' ATTITUDES AND ADOPTION BEHAVIOUR – AN ILLUSTRATION FROM THE ANALYSIS OF THE UPTAKE OF LIVESTOCK TECHNOLOGIES IN THE SOUTH WEST OF ENGLAND

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Abstract

The behavioural intentions of a sample of livestock farmers in the south-west of England towards new technologies were analysed within a Theory of Reasoned Action (TORA) framework, in order to explore reasons for the apparently low rate at which research-based knowledge is being transferred to the livestock industry. Correlations between components of attitudes (outcome beliefs and evaluations), subjective norms (normative beliefs and motivation to comply) and behavioural intentions were integrated with Positivistic Mathematical Programming (PosMP) to create a set of farm type models, which can predict the potential rate and equilibrium level of uptake of different kinds of technologies. Data relating to techniques for oestrus detection in dairy cows are used to illustrate the analysis and to show how this approach can help improve the targeting of knowledge and technology transfer strategies. Linking the Theory of Reasoned Action findings with the Positivistic Mathematical Programming approach identified where there is a realistic prospect for increasing or accelerating the uptake of a technology, thus helping an agency charged with knowledge and technology transfer to decide where investment in communication is likely to pay off. In the case of MDC observation times, even a 20% change in attitude score among hill and upland dairy farmers would have minimal impact on the numbers adopting; while a similar change among mixed farms would lead to a greater increase. Targeting mixed farms with this particular technology would make more sense than promoting it among upland farmers. The overall findings reinforce the importance of understanding and addressing the prevailing beliefs and values within the objective population

Introduction

The examples of innovations and practices emerging from national and international research and development systems that have not been taken up by farmers, despite their economic advantages, are numerous. The research that explains such behaviour tends to emphasise the characteristics of innovations and those of the adopters and non-adopters along with profit motive (Ruttan, 1996) rather than uncover the complex interaction of the variety of motives and attitudes of likely adopters as related to the adoption process. Over the last two decades or so, several farm management studies have used the social psychology theory, Theory of Reasoned Action (TORA), where attitudes (positive or negative dispositions) and intentions of decision-makers, as influenced by beliefs, norms and the expectations of significant others, are central drivers of behaviour rather than profit alone. These studies are concerned primarily with understanding and predicting decision-making behaviours that are not amenable to straight forward explanations and such research falls into four broad categories: (a) environmental conservation management (Batchelor *et al*., 1999; Beedell, 1996; Beedell and Rehman, 1999 &2000; Bennett *et al*., 1999; Carr and Tait, 1991; Kiely-Brocato *et al*., 1980; Korsching and Hoban, 1990; McKemey, 1996; Willock, *et al*., 1999; Zubair, 2000); (b) soil conservation issues (Duff *et al*., 1991; Lynne and Rola, 1988; Lynne, *et al*., 1988; Napier *et al*., 1984); (c) pest management problems (Fernandez-Cornejo *et al*., 1994; Hassan, 2002; Heong and Escalada, 1999; Tait, 1983); and, (d) knowledge and technology transfer for subsumption into farmer practice (Batchelor *et al*., 1999; McKemey and Sakyi-Dawson, 2000; McKemey *et al*. 2002; Rehman *et al*., 2003).

This paper presents a recently completed research project at The University of Reading on knowledge and technology transfer, where TORA has been combined with a formal economic modelling approach in a novel way to understand and to predict farmers' behaviour towards the adoption of technologies that have stayed 'on shelf' for quite sometime, despite being otherwise promising. The Department for Environment, Food and Rural Affairs (DEFRA), the Environment Agency, the Meat and Livestock Commission and the Milk Development Council (MDC) have sponsored this project. Three specific livestock technology adoption behavioural domains have been targeted: oestrus detection, fertiliser and slurry management, and white clover inclusion in pastures among farmers in South West England. The process of technology adoption is explored in two main steps: first, TORA is used to identify barriers to and drivers for technology uptake; second, the results from TORA analysis are integrated with farm type economic models to project likely rates of adoption.

The paper is divided into the following sections: introduction to TORA; application in South West England; survey on heat detection; results from TORA application; farm type models and their results; and, implications for knowledge and technology transfer.

Theory of Reasoned Action

TORA is essentially a series of linked concepts and hypotheses postulated and developed by social psychologists to understand and to predict human behaviour (McKemey and Sakyi-Dawson, 2000). The theory is one of the "expectancy-value" models of human behaviour and its terminology is not very different from that of the well-established subjective expected utility model used by economists (Lynne, 1995). It has developed from the long-standing collaborative research by eminent psychologists Fishbein and Ajzen (see Fishbein and Ajzen (1975) and Ajzen and Fishbein (1980)). Since its introduction to behavioural research, it has been applied to study a wide variety of situations and is now regarded as one of the most influential theories about volitional human behaviour (Trafimow and Finlay, 2002). As the name of the theory implies, it " ... is based on the assumption that human beings usually behave in a sensible manner; that is, they take account of available information and implicitly or explicitly consider the implications of their actions ... the theory postulates that a person's intention to perform (or not perform) a behavior [sic] is the immediate determinant of that action; barring unforeseen events, people are expected to act in accordance with their intentions" (Ajzen 1988, p.117).

The immediate antecedent of any behaviour is the intent to perform it. The stronger the intention, the more the person is expected to try and therefore the greater the possibility that the behaviour will actually be performed, and thus the primary concern is with identifying the factors underlying the formation and change of behavioural intent (Fishbein & Manfredo, 1992). A person's intention to behave in a certain way is based on: their 'attitude' toward the behaviour in question and their perception of the social pressures on them to behave in this way, that is, 'subjective norms'. The relative contribution of attitudes and subjective norms varies according to the behavioural context and individual involved. Attitudes are determined by the beliefs about the outcomes of performing the behaviour and the evaluation of these expected outcomes. The subjective norm is dependent on beliefs about how others feel the individual should behave and their motivation to comply with these 'others' (Ajzen & Fishbein, 1980). These relationships are summarised in Figure 1.

The strength of the relationships between the variable constructs within the theory is measured using correlation coefficient analysis. The multiple-correlation coefficient (R) serves as an index of the extent to which behavioural intention can be predicted from the simultaneous

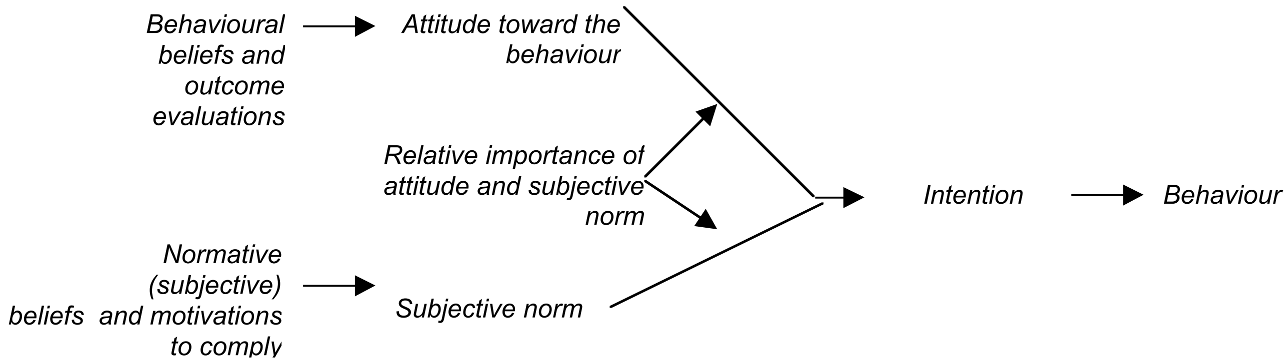

***Figure 1: Causal relationship links among the components of TORA* (Ajzen and Fishbein, 1980)**

consideration of attitude and subjective norm. In computing (R), weights (w) representing the contributions of attitude and subjective norm towards the prediction of the behavioural intention are obtained. These weights are indicative of the relative importance of the variables' contribution to the prediction of intention (Ajzen & Fishbein, 1980; DeBarr 1993, pp.6-7) and therefore the relationship between attitudes and behaviour becomes:

$$A = \sum_{i=1}^{n} b_i e_i \text{ and } SN = \sum_{j=1}^{n} sb_j m_j \text{ so that } B \cong BI = Aw_1 + SNw_2$$

Where **A** is attitude toward the behaviour, $\mathbf{b_i}$ is a belief about the likelihood of outcome **i**, $\mathbf{e_i}$ is the evaluation of outcome **i**, **n** is the number of salient beliefs, **SN** is the subjective norm, $\mathbf{sb_j}$ is a normative belief (that the reference group or individual, **j**, thinks the person should or should not perform the behaviour), $\mathbf{m_j}$ is the motivation to comply with referent **j**, **B** is the behaviour, **BI** is the behavioural intention and w_1 and w_2 are the empirically determined weights.

Application of TORA

Context
Three different types of livestock technology adoption behaviour were studied. For each behaviour around 500 farmers were surveyed from a random sample drawn by DEFRA from the June Census records for the South West of England. The results presented here relate to only one specific oestrus detection behaviour; 'the use of MDC recommended observation times'.

Applying TORA would typically consist of at least 4 distinct stages:

i. Identification of behaviour or set of behaviours to be studied;
ii. Identification of salient outcome beliefs and social referents with respect to the selected behaviour/s;
iii. Development and application of the structured interview schedule; and,
iv. Analysis of data and implications for future communication strategies.

Identification of behaviour or set of behaviours to be studied
The incidence of an actual behaviour (action) is distinct from its impact (outcome) and for any behaviour to be congruent with its determinants, it must be defined by its four constituent elements: action, target, context and time. Sets of specific behaviours form a behavioural category or domain. For example, the oestrus detection behavioural domain consists of the following specific behaviours:

_ Relying on knowing the cows and being around them constantly
_ Use of a bull only
_ Keeping a bull in close proximity to cows to help trigger heats
_ Use of kamars
_ Using the MDC recommended observation times
_ Using milk progesterone testing kits
_ Using a computer-based pedometer system
_ Using ultrasound scanning at 28 days plus post-calving
_ Seeking routine vet visits

Identification of salient outcome beliefs and social referents with respect to the selected behaviour(s)
A salient outcome belief is what the subject expects to happen by engaging in a particular behaviour. A salient referent is a person, or social entity, in the subject's social environment that is influential in establishing the normative component. Several methods can be used to identify the salient beliefs and referents. For this project the following two approaches were used:

i. The 'structured' elicitation of positive and negative responses to the particular behaviour in a pilot survey (with individuals and / or groups)
ii. The elicitation of beliefs through open interviews (individuals and /or groups)

Development and application of the instrument for belief and social referent elicitation
The main instrument is a structured questionnaire, designed specifically to elicit information on TORA's components. The responses are measured most commonly along semantic-differential interval bi-polar scales e.g., 'very strong = (+2) to very weak = (-2)' and 'very good = (+2) to very bad = (-2)'

Intention was measured by asking the subjects "How strong is your intention to strictly follow the MDC recommended observation times on your farm during the next year?"

Attitude. Two measures are usually used: the emotive response (affective) and the calculated or reasoned (evaluative). The emotive measure was the response to "In your opinion how good or bad would it be to strictly follow the MDC recommended observation times on your farm during the next year?" The calculated or reasoned attitude measure was the sum of the products of belief strength and value attributed to each salient outcome, expressed as $A = \Sigma b_i{*}e_i$ where A = calculated attitude, b_i = strength of agreement with outcome statement i, e_i = the value attributed to the outcome i.

The strength of belief (b) was solicited by asking the degree to which the subject agreed or disagreed with the statement "What do you think of the statement?" followed by the relevant statement itself. The attributed value (e) was obtained by the subjects' evaluation of the outcome, "How important is the issue (outcome) to you?"
The product (b*e) for each 'outcome belief' gives the attitude measure for each salient outcome. The possible range for this product (b*e) is -4 to +4.

The sum of these outcome attitudes provides the measure of attitude toward the particular behaviour in question. There were 9 salient outcomes for the MDC recommended observation times and thus the possible range for A is (-36 to +36).

The subjective norm. Two measures of the subjective norm are usually taken: (i) the stated subjective norm was measured by asking "Would people who you respect in the farming industry be supportive if you adopted the MDC recommended observation times as a heat detection method on your farm over the next year?" and (ii) the calculated subjective norm is measured as the sum of the products of the subjective or normative belief strength and the motivation to comply related to the salient referents, that is,

$SN = \Sigma sb_i * m_i$

where SN = subjective norm, sb_i = subjective belief regarding referent i, and m_i = the motivation to comply with referent i.

The subjective belief (sb) was identified by asking "How strongly do you feel (the specific referent) would agree with you adopting one of the heat detection methods mentioned on your farm during the next year?" along the 'strongly agree (+2) to strongly disagree (-2)' scale.
The motivation to comply (m) with regard to a particular referent was measured in a similar way by asking "How motivated would you be to follow the advice of (specific referent) regarding the use of one of the three heat detection methods on your farm during the next year?" Next, the product (sb*m) for each salient referent is calculated to give a normative measure regarding each referent. For the MDC recommended times behaviour there were 8 referents; thus, using a 5 point semantically differentiated scale for both measurements, the range for the SN score is (-32 to +32).

Survey on heat detection behaviour

Design and administration of the questionnaire.
The scales used to measure the outcome beliefs, attitudes and subjective norms can be rather repetitive, which could be off putting for the respondents; therefore, for a questionnaire administrated through the post, several steps were taken to minimise the impact of such a possibility.

Sample for the heat detection behavioural domain

Of the 500 questionnaires sent to farmers, 29% returned usable responses. Table 1 shows their crop and livestock details. The high standard deviations relative to the means show that a broad range of dairy farms were covered. The average farm size and grassland areas were 96 ha and 75 ha respectively, and the average herd size was 91 milking cows and 50 replacements. Table 2 shows the distribution of farms by farm type as defined by DEFRA's Farm Business Survey (FBS). The majority of farms (41%) are medium sized specialist dairy with 17% being small specialist dairy farms. Although the sample contains few large farms and few severely disadvantaged area farms it shows a good distribution over other farm types and between small and medium farms, which are the focus of this study.

Only 9% of the farms were organic. The majority of farms (68%) were all lowland farms, with a further 13% 'mostly lowland'. Upland farms accounted for 2% of the sample, with another 7% being 'mostly upland'. The remaining farms (10%) were a combination of lowland and upland. Almost 67% of the respondents were owner-occupiers, 22% were tenants, and 3% had both tenures. The remainder had another role on the farm. A total of 87% of respondents were the main decision takers and some 60% belonged to a farming or countryside organisation; 92% were male.

The respondents were predominantly middle-aged as almost 80% of them were over 40; and around 60% were aged between 41 and 60 years old. Around 19% of the respondents had definitely identified a successor whilst 30% thought that they probably had done so. Those who don't yet know accounted for 18% of the sample; the remaining 21% had definitely not or probably not identified a successor. Whilst over half the respondents had received no education beyond school, a total of 38% had attended college with 8% going on to university. Of those who had received further education, 50% stated that this was specifically in agriculture.

Over half of the respondents rely entirely on farming as their source of income; a further quarter receive 75% of their income from farming; some 13% claimed that 25% or less of their total income came from the farm business.

Results from survey analysis

An overview of the TORA analysis of the observation times behaviour is presented in order:

a) to identify current levels of behaviour and behavioural intent;
b) to identify the differential influence of the attitudinal and normative components on the behavioural intent;
c) to identify the cognitive drivers and barriers to the uptake of the particular behaviour; and,
d) to identify the rationale supporting the identified influential barriers and drivers.

The findings for the whole sample are given in Figure 2. The correlations between the different variables are non-parametric Spearman type and the significance of differences between the mean scores has been tested using the Mann Whitney 'U' test.

Behaviour and behavioural intent
The MDC observation times are being used by only 10% of the respondents and the intention to adopt the MDC times is generally negative, though not strongly so (mean = -0.66, cf. Figure 2 and Table 3). The projected increase in taking up the MDC observation times is just 9%. This is calculated by comparing the proportion of actual use with the proportion intending to use the MDC times.

Differential influence of the attitudinal or normative components
This is determined by comparing the strength of the correlation between attitude (A) and the stated behavioural intent (I) and between subjective norm (SN) and the stated behavioural intent (I). In the case of dairy farmers following the MDC recommended times, both A and SN correlate significantly with the farmers' intention and therefore are both influential (cf. Figure 2 and Table 3). However, the SN versus I is the stronger correlation implying that farmers are also sensitive to the opinions of their salient referents regarding MDC times.

Identification of cognitive 'barriers' and 'drivers'
The barriers and drivers can be identified by observing the correlations between the different outcome attitudes and the behavioural intent, that is (b_i*e_i) versus I. For the MDC observation times no 'barriers' were observed (see Figure 2 and Tables 5 and 6) and the main 'drivers' in order of their respective influence are (a) cost effectiveness; (b) improved heat detection rates; (c) improved conception rates; and, (d) effective silent heat detection. This analysis provides a strong inference that any promotional messages regarding the MDC observation times should seek to reinforce these issues when targeting dairy farmers in the South West.

Differences between subject categories
Table 6 shows the differences observed between some of the categories of farmers compared; for example, in the case of organic farmers two 'barriers' are observed (Figure 3) that is 'would fit the system' and 'ease of management'

For farmers under 40 years of age, the suggestion that following the MDC recommended times is relevant for their untrained staff is a barrier, although it is not the dominant influential outcome belief (Table 6). It is worth noting that female respondents are most influenced by the issue of reduction in demand for labour; this is a topic that did not register any effect on other categories of subjects (Table 6). This difference in attitude appears to underpin an observation made in the preliminary studies that the female members of the farming households tended to be responsible for heat detection.
Rationale supporting the identified 'barriers and drivers'
The differences between the influential outcome beliefs (b) and attributed values (e) can provide insights into the underlying rationale regarding the particular barrier or driver as the example of expected appropriateness for untrained staff regarding the MDC times indicates (Table 4). This is just one instance where TORA analysis has brought out latent differences among different categories of subjects.

Table 4 presents the mean scores regarding the outcome beliefs (b), attributed values (e) and attitudes (b*e). Surprisingly, the attributed value regarding 'MDC times being appropriate for untrained staff' is negative. This seems counter-intuitive and suggests underlying issues regarding this outcome expectation; that is, some farmers may find the concept of a method being appropriate for untrained staff demeaning to their own herd knowledge and skill. Thus the messages that stress the appropriateness of a heat detection method for untrained staff may be reinforcing an existing barrier: undervaluing the farmer's skill and knowledge for heat detection.

Example Subjective Norm construct
Table 7 presents the mean scores for the different social referents regarding the adoption of one of the heat detection methods addressed. The referents that correlate most closely with farmers' intention to use MDC times are: veterinarians; other farmers; and the MDC. However, when the motivational scores are examined, the value attributed to the MDC is slightly negative. Thus any strategy to promote a change in general heat detection practice will need to address farmers in the context of their referents and seek the endorsement of local vets in order to combat the negative motivation to comply with the MDC.

Combining TORA and Economic Modelling

TORA identifies the barriers and drivers to the adoption of oestrus detection technologies. This information in itself, however, does not provide quantitative estimates of the possible rates of adoption of any technology. To obtain these estimates, results from TORA analysis are linked to an economic modelling framework based on mathematical programming (MP). In this section, only the essential features of this framework are mentioned, the complete details are given in Rehman *et al.* (2003).

Farm level MP models have been constructed using South West regional data from the Farm Business Survey, whilst a randomly selected sample of farms in the South West was used to apply TORA. As both data sets are derived from the same population, it is feasible to integrate them notwithstanding any survey bias. The TORA survey has been used to identify specific farm types (consistent with DEFRA's FBS types) ensuring that it contains sufficient data to be representative of a particular farm type. The TORA survey also provides data on the current use of a given technology on each farm making up each type.

In linking TORA analysis with the MP models, a basic assumption is being made about how the attitude score for a technology and the proportion of farms using that technology are related. It is a monotonically increasing relationship, implying that a negative score of -36 means no adoption and a score of +36 corresponds to complete adoption. The two key parameters that are taken from the TORA analysis results to drive the MP models are the attitude score with regard to a technology and the social norm associated with it. MP methods have endured the test of time and remain popular for examining decision-making situations. Recently Howitt (1995) has proposed a version of MP, known as Positive Mathematical Programming (PMP) that allows modellers to construct an objective function to replicate the observed decisions for a given period. PMP is very popular in policy modelling (Heckelei et al. 2001).

The current project has used a modification of PMP, called Positivistic Mathematical Programming (PosMP), which is conceptually and theoretically more rigorous than PMP. The basic concept is that farmers (or for that matter any economic agent) make decisions based upon whatever information they have available at the time. PosMP seeks to estimate a farmer's utility function, based upon expectations and information at the time of taking a decision. For instance, although gross margins may not be known, the farmer may have an expectation of the likely gross margin and also of the associated risk (the variance in profits or yields). It is these expectations, and facts such as changes in subsidies, together with beliefs and attitudes that influence a farmer's decision. This approach is similar to the TORA in that it seeks to provide estimates of the likelihood of a given decision being taken. However, it does not take into account the belief and attitude structure generated by TORA analysis. On the other hand being an economic model, PosMP considers the actual physical farm constraints.

The Farm Type Models

The PosMP has been used to simulate the cropping and livestock decisions on a range of farm types in the South West of England derived from the Farm Business Survey and June Census data, over 1993 to 2002 for: Specialist dairy; Mainly dairy; Mixed; Hill and Upland

Each model consists of three sets of distinct activities: cash crops; pasture and fodder; and, livestock. For each of these types of activity, a Behavioural Response Function (BFR) has been estimated statistically. For instance, on the Specialist Dairy farms, the key drivers for cropping decisions are the expected gross margins (higher the gross margin of an activity, higher its contribution to the BFR), financial risk (higher the risk, lesser the incentive) and labour (higher the labour requirement, lesser the incentive). All BRFs include a term representing the preceding year, which is always the most significant indicator of behaviour as it represents 'unwillingness to change'.

Importing results from TORA to farm type models

Unlike PMP, PosMP can include new activities that were not present at the calibration and estimation phases in the model. Assuming that the decision maker knows perfectly how the use of a new technology will contribute to the BRF, then that activity can be included. In our example the use of MDC observation times improves heat detection but also increases labour; therefore, the effect of increased heat detection should translate into a lower replacement rate and hence an increase in gross margin. But if labour is a significant factor, then the use of the new technology will also lower the contribution to the BRF because of the greater need for labour; so, two activities are considered: cows without the use of MDC observation times; and, cows with the use of observation times. Because the two activities have different gross margins and labour requirements, the contributions to BRF will be different (also the effect of previous behaviour is a severe deterrent to the adoption of a new technology). Thus the model is able to replicate the proportions of animals with and without the use of the technology.

However, in reality technology adoption is not as simple as above. The assumption of 'perfect knowledge' can hardly be sustained; thus making it necessary to estimate empirically how farmers perceive the performance of a technology in relation to their BRFs, by importing the results of the TORA survey into the PosMP models.

In the survey, a set of nine questions was related to the use of MDC observation times for heat detection. Using a five-point Likert scale, these questions measure both the strength of a belief held by a decision maker to various belief statements and their importance in decision-making. Take the following statement:

"*The MDC recommended observation times are an effective method of identifying silent heats*"

On the five-point scale, -2 corresponds to disagree strongly, 0 to no opinion and +2 to agree strongly; that is, positive beliefs are measured in a positive sense. Likewise importance of a belief is also measured on a five-point scale, where -2 corresponds to unimportant, 0 to no opinion and +2 to very important. Hence an effective measure of the perceived benefit of a technology can be given by summing the product of the belief and importance statements. If a farmer records +2 for his belief in the above statement but scores 0 for the importance of this statement, the overall contribution to the proposed measure is therefore 0. By summing these measures an attitude score ranging from -36 to +36 is obtained.

In the next stage these results are calibrated with the observed level of technology use. In the survey, 11% of farmers were already using the MDC observation times. The PosMP model can therefore be used to determine the additional contribution to the BRF, above that of cows without use of the technology, required in order that 11% of farmers would adopt the technology. It is also necessary to calculate the minimum addition to the BRF required to obtain a 100% adoption.

It is now necessary to make an assumption. If farmers' attitude scores towards a technology are very strongly negative (e.g. corresponding to a score of -36 given above) then no farmers would adopt the technology. On the other hand, if attitude scores are extremely positive (+36) then adoption would be 100%.

Suppose a particular attitude score is B, the difference in the BRF is D_{obs} under 11% adoption (or A_{obs}) and D_{max} is the difference in the BRF for maximum adoption, three points can be calibrated to each other. Hence:

	Difference in BRF	Percent adopted	Belief and attitude
Zero adoption	0	0	-36
Current adoption	D_{obs}	A_{obs}	B
Maximum adoption	D_{max}	100	+36

It is now possible to fit a curve through these points. This curve is used to calculate the additional contribution to the BRF under different levels of attitude score, and through the use of the PosMP model the level of adoption.

Next the effect of social norm (SN) is accounted for to measure the influence of referents. This measure is also composed of two parts. The first attribute, scored on a five-point Likert scale, measures the motivation of the decision maker to following the advice from various sources (local colleges and universities, veterinary surgeons, other farmers, etc.). The second attribute, similarly measured, records the degree to which each social referent would support a decision to adopt a technology. The sum of the product of these scores for all referents gives a quantitative measure of the SN, scaled along a –32 to 32 range (re-scaled from -1 to 1). Therefore, if 11% of farmers have adopted the technology and the social norm is 0.1 then the difference to the BRF is increased by 0.11*0.1 expressed as a percentage (that is, an increase of 1.1%). This mechanism simulates the effect of those farmers who use the technology and other social referents on all farmers. The higher the social norm the greater influence adopters will have on the non-adopters.

It is necessary to make a final assumption about farmers who use a technology currently but would not use it in the following year. If the current system is assumed to be in equilibrium (that is 11% of farms will be using the technology in the following year *ceteris paribus*), then the positive/negative effect of SN on adoption must be cancelled out. Therefore, a correction factor representing the proportion of farmers using the technology in the current year who will not use it in the subsequent year is set equal to the effect of the SN under current conditions.

Finally, predictions for successive periods are updated. The farmers who use a technology would receive the benefits (if any) as the new technology adds to the value of the BRF through changes in expected gross margins, labour use and risk, which can then be fed back into the models to predict adoption in subsequent periods.

Assessing the prospects for the adoption of MDC recommended observation times

Table 8 shows the distribution of the study farms currently using MDC recommended observation times. Clearly in some cases the sample sizes were very small and hence the errors associated with these estimates are large. However, it is interesting to note that none of the hill or upland farmers use this technique. The BRF for hill and upland farmers shows that increasing labour requirement has a detrimental effect on it and thus activities requiring more labour are less attractive to these farmers. The use of MDC recommended time heat detection method does increase labour by requiring farmers to observe their cows at certain times.

To avoid difficulties with small sample sizes on some farm types, differences in farm size have been disregarded. The models simulate farm production patterns over the period modelled accurately. Further analyses in which successive years are omitted from the estimation procedure before providing forecasts for these years showed that the models do perform equally well, the average percentage deviation increasing nominally from 7.7% to 8.1%. Under current conditions the models predicted no change in percentage of farms using MDC recommended observation times, not a surprising result as the current adoption is assumed to be in equilibrium.

Figures 4 to 7 show the adoption process over a 10-year horizon by modelling arbitrary changes to the attitude score of -10%, 0%, 10% and 20%. The results show an initial effect of either increasing or reducing the attitude score. With an increase in attitude score the results show a sharp rise in the numbers of farmers using the technology; whereas a decrease in positive attitude towards the technology reduces the numbers of farmers using it. The hill and upland farmers, where there was no record of this technology being used, were the least responsive to change. This effect is also compounded by the nature of the BRF of this farm type, showing a reluctance to adopt a technology that increases labour demands. Following an initial change in technology use the results converge towards equilibrium over a number of years. This result is due to the influence of the social norm. However, this effect is relatively small and hence the equilibrium is quickly reached and is only slightly greater than (or less than) the initial change.

Figure 8 shows the effect of social norm for the specialist dairy farms assuming a 10% increase in attitude score and a 100% increase in social norm. Although this increase in social norm appears high, in reality the social norm is very small and thus a 100% increase is also small. The results show that the initial adoption is the same as previously (it is assumed that social norm increases in year 2 and that year 1 is subject to the current social norm) but it increases marginally more rapidly than before. However, equilibrium is reached in approximately the same time frame as for changes in attitude scores.

Implications for knowledge and technology transfer

The combination of TORA's ability to decompose behavioural intent into quite specific components of attitudes and subjective norms, and the predictive ability of PosMP models, offers a useful tool for the improved targeting of knowledge and technology transfer in the agricultural sector. The model outputs also remind us that attitudes are not static: they can change and therefore they can be influenced through communication. A knowledge transfer strategy is essentially a communication strategy for a specific purpose. Three key decisions in designing such a strategy relate to the audience, the appeal and the channel through which information reaches the intended audience. Before exploring these, however, we touch on an important ethical concern.

Social psychology models have been widely used in commercial advertising to identify "appeals" and sources, based on an analysis of attitude and subjective norm components respectively, that are likely to reinforce or change the behavioural intent of distinct audiences towards particular products. The motivation here is to boost company profits by increasing the amount of the product that consumers buy. Advertisers try to influence what consumers believe about the product: that there is a strong incentive to exaggerate or mislead is shown by the fact that governments find it necessary to introduce regulations governing what can and cannot be claimed in commercial advertising. With agricultural R&D funded by industry levy or the public purse, the underlying objective of technology transfer is to benefit the farmer and/or the population at large. A TORA analysis may show that farmers disagree with researchers' perceptions about the merits of a particular technology. If, for example, farmers do not believe that the technology will be labour saving, researchers should revisit their earlier conclusions relating to labour requirements, from the perspective of the reality of farm businesses, before trying to devise clever advertising or demonstrations to convince farmers otherwise.

The farm type models can show where there is a realistic prospect for increasing or accelerating the uptake of a technology, thus helping an agency charged with knowledge and technology transfer to decide where investment in communication is likely to pay off. In the case of MDC observation times, even a 20% change in attitude score among hill and upland dairy farmers would have minimal impact on the numbers adopting; while a similar change among mixed farms would lead to a greater increase. Targeting mixed farms with this particular technology would make more sense than promoting it among upland farmers.

The second area of decision concerns what one says about the technology in order to influence the audience's decisions. The relative influence of attitude and subjective norm on behavioural intention is one consideration. If the TORA analysis shows that intention is more strongly influenced by attitudes than by subjective norms, promotion of the technology should focus on reinforcing those beliefs that are identified as drivers and combating those which are barriers. For example, the suggestion that MDC observation times allow farmers to substitute unskilled labour for their own herd management expertise is not one that is likely to appeal to farmers. More sensible would be to provide data, which demonstrate the relative cost-effectiveness of the method. Where subjective norms are the more significant determinant, then promotion should portray the views of those referents whom the analysis shows to be particularly influential, or seek their endorsement of the proposed technology. It can however be effective only if the views of referents are supportive of the proposed technology.

How to channel information for knowledge and technology transfer to the audience is the third area of decision. This is where the TORA analysis of salient referents and motivation to comply is most useful. Veterinary surgeons – not coming to the farm specifically to advise on heat detection, but in the normal course of their work – are seen, together with other experienced farmers, to have the greatest potential to influence farmers' decisions on whether to use the recommended observation times. Placing stories in the farming press about how experienced farmers have found the observation times to complement their own expertise, and circulating to vets in dairying areas well-designed briefing documents on the research evidence relating to observation times, should therefore be part of any strategy to promote this technology.

The research reported here had its origins in concerns about the slow uptake of technologies that seemed to offer potential benefit to farmers. The analysis suggests that combining TORA with PosMP modelling can help R&D agencies target their knowledge and technology transfer more effectively. Further research will be needed to show whether communication strategies informed by this analysis do in fact result in an increase in the rate and equilibrium level of uptake.

Acknowledgements

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Table 1: Sample study farm statistics

	N	Mean	Stand. Dev.	Min	Max
Farm size (ha)	134	96.4	66.9	5	400
Permanent pasture (ha)	134	45.8	48.2	0	324
Temporary pasture (ha)	134	29.0	28.2	0	135
Forage maize (ha)	134	7.5	14.2	0	100
Other forage crops (ha)	134	1.5	5.3	0	50
Other arable crops (ha)	134	9.1	18.2	0	100
Dairy cows	134	90.9	62.5	0	280
Beef cows	134	43.3	59.6	0	400
Sheep	23	173.1	152.6	1	700
Dairy replacements	134	49.5	50.5	0	400

Table 2: Distribution of study farm types as defined by DEFRA's Farm Business Survey

	Total	Small	Medium	Large
Specialist Dairy	79	23	55	1
Dairy and arable	15	3	12	0
Mixed	18	6	10	2
Disadvantaged area	20	5	13	2
Severely disadvantaged area	3	0	3	0
Total	135	37	93	5

Table 3: Mean, median and IQR readings of TORA variables for the whole sample re MDC observation times and correlations of these variables with stated intent

n	131			I vs. Correlations
Main TORA variables (possible range)	mean	median	IQR	r_s
Strength of intention (1) (range -2 to +2)	-0.66	-1	(-2/0)	
Stated attitude (SA) (range -2 to +2)	0.36	0	(0/1)	0.607
(CA) Calculated Attitude $\Sigma b_i * e_i$ (range -36 to +36)	3.78	2	(0/5)	0.208
Stated (SN) (range -2 to +2)	0.36	0	(0/1)	0.343

IQR: Inter Quartile Range
The Spearman correlation coefficients are shown which are significant at a p = <O.050

Table 4: Outcome (OA) and calculated attitudes (CA), mean, median and Inter Quartile Range readings re MDC observation times

Outcomes n = 131	Outcome belief (b)			Value attributed (e)			Outcome attitudes (OA) (b*e)		
	mean	median	IQR	Mean	median	IQR	Mean	median	IQR
(5) Improve HD rates	0.22	0	(0/1)	0.32	1	(-1/1)	**0.80**	1	(0/1)
(4) Cost effective	0.18	0	(-1/1)	0.19	0	(-1/1)	**0.69**	0	(0/1)
(8) Improve conception rates	0.23	0	(0/1)	0.44	1	(0/1)	**0.67**	0	(0/1)

(1) Effective for silent heats	0.30	0	(0/1)	0.28	1	(-1/1)	**0.54**	0	(0/1)
(3) Would fit system	-0.33	0	(-1/0)	0.07	0	(-1/1)	**0.39**	0	(0/1)
(6) Appropriate untrained staff	-0.09	0	(-1/1)	-0.01	0	(-1/1)	**0.31**	0	(0/1)
(9) Used all year round	0.12	0	(-1/1)	0.17	0	(-1/1)	**0.29**	0	(0/1)
(2) Easy to manage	-0.27	0	(-1/1)	0.21	0	(-1/1)	**0.24**	0	(0/1)
(7) Reduce labour demand	-0.77	-1	(-1/0)	0.11	0	(-1/1)	**-0.17**	0	(-1/1)
Calculated attitude $\Sigma b_i * e_i$ (range -36 to +36)							**3.78**	2	(0/5)
Alpha coefficient re scale reliability[14]							**0.823**		

***Table 5:* Outcome attitudes (b*e) vs. intention (I) correlations re MDC observation times (whole sample)**

Outcomes n = 131	Attitudes (b*e) r_s
(1) Effective for silent heats	0.231
(2) Easy to manage	
(3) Would fit system	
(4) Cost effective	0.381
(5) Improve HD rates	0.282
(6) Appropriate for untrained staff	
(7) Reduce labour demand	
(8) Improve conception rates	0.276
(9) Can be used all year round	
(CA)Calculate Attitude $\Sigma b_i * e_i$ re MDC times	0.208

The Spearman correlation coefficients are shown which are significant at a p = <O.050

[14] The reliability test of the CA scale made, up of the different outcome attitudes, produced an Alpha (Cronbach) coefficient of 0.8. For a scale to be considered reliable the coefficient should be 0.6>.

***Table 6:* Intention vs. outcome attitude correlations (r_s) re use of MDC observation times (whole sample, age, experience, farm type, organic?)**

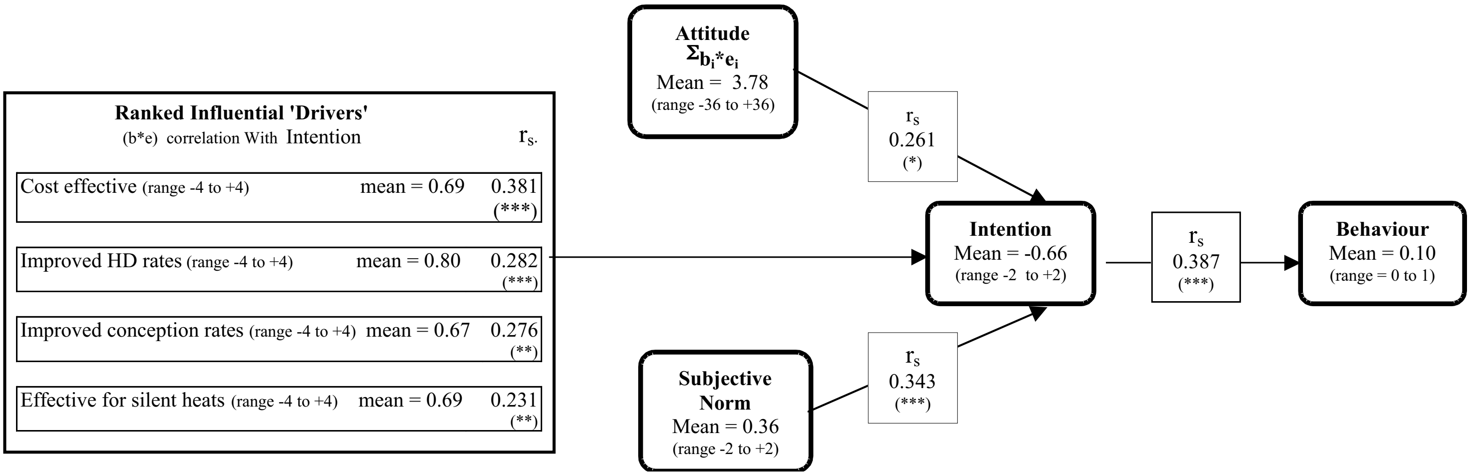
Outcome belief statements re MDC observation times	**All**	**Gender**		**Age**			**Used MDC times**		**Type of enterprise**			**Organic**	
		Male	Female	< 41	41 - 60	> 60	no	yes	dairy	dairy / arable	mixed	yes	no
	n = 131	n=121	n=10	n = 30	N =81	n = 20	n=117	n=14	n=89	n=16	n = 26	n=11	n=119
(att1) Effective for silent heats	0.231		0.652		0.249				0.226	0.525			0.235
(att2) Easy to manage			0.774					0.580				-0.632	
(att3) Would fit system								0.718				-0.760	
(att4) Cost effective	0.381	0.370		0.423	0.396		0.279	0.542	0.452				0.402
(att5) Improve HD rates	0.282	0.275			0.371		0.251		0.319	0.550			0.301
(att6) Appropriate for untrained staff				-0.373									
(att7) Reduce labour demand			0.852										
(att8) Improve conception rates	0.276	0.313			0.294		0.256		0.311	0.592			0.300
(att9) Can be used all year round					0.243								

***Table 7:* Individual referent and calculated subjective norm, mean, median and IQR readings re heat detection practice change in general**

Referent n = 134	Motivation			Strength of normative belief			Subjective Norm		
	mean	median	IQR	Mean	median	IQR	Mean	median	IQR
Vet	0.86	1	(0 to 1)	0.87	1	(0 to 1)	**1.14**	1	(0 to 2)
Other farmers	0.72	1	(0 to 1)	0.53	0	(0 to 1)	**0.76**	0	(0 to 1)
AI service	0.43	1	(0 to 1)	0.60	1	(0 to 1)	**0.53**	0	(0 to 1)
Farming press	0.32	1	(0 to 1)	0.49	0	(0 to 1)	**0.45**	0	(0 to 1)
ADAS	-0.34	0	(-1 to 1)	0.28	0	(0 to 1)	**0.43**	0	(0 to 1)
MDC	-0.09	0	(-1 to 1)	0.50	0	(0 to 1)	**0.42**	0	(0 to 1)
Agric college or UNI	-0.04	0	(-1 to 1)	0.46	0	(0 to 1)	**0.39**	0	(0 to 1)
Internet	-0.56	-1	(-2 to 0)	0.10	0	(0 to 0)	**0.38**	0	(0 to 0)
(CSN) Subjective norm (range -36 to +36)							**4.66**	3	(0 to 8)

Table 8: Percentage Distribution of FBS Farm Types in the TORA survey currently using MDC recommended observation times

	Total	Small	Medium
Specialist Dairy	10.3	17.4	7.3
Dairy and arable	20.0	0.0	25.0
Mixed	16.7	16.7	20.0
Hill and Upland	0.0	0.0	0.0
Total	11.9	13.5	9.7



Notes

1. Only the Spearman correlation coefficients (r_s) are shown that are significant at ≤0.050. (*, **, *** denote significance (p) at the 0.05, 0.01 and 0.001levels respectively).
2. In the case of MDC observation times only 4 cognitive 'drivers' and no cognitive 'barriers' are observed when the whole sample is considered.
3. The possible range and the mean score registered regarding each of the variables considered are presented.
4. The Subjective Norm presented is the stated rather than calculated measure.

Figure 2: TORA nalysis of the MDC observation time findings (whole sample)

Notes

1. Only the Spearman correlation coefficients (r_s) are shown that are significant at ≤0.050. (*, **, *** denote significance (p) at the 0.05, 0.01 and 0.001levels respectively).
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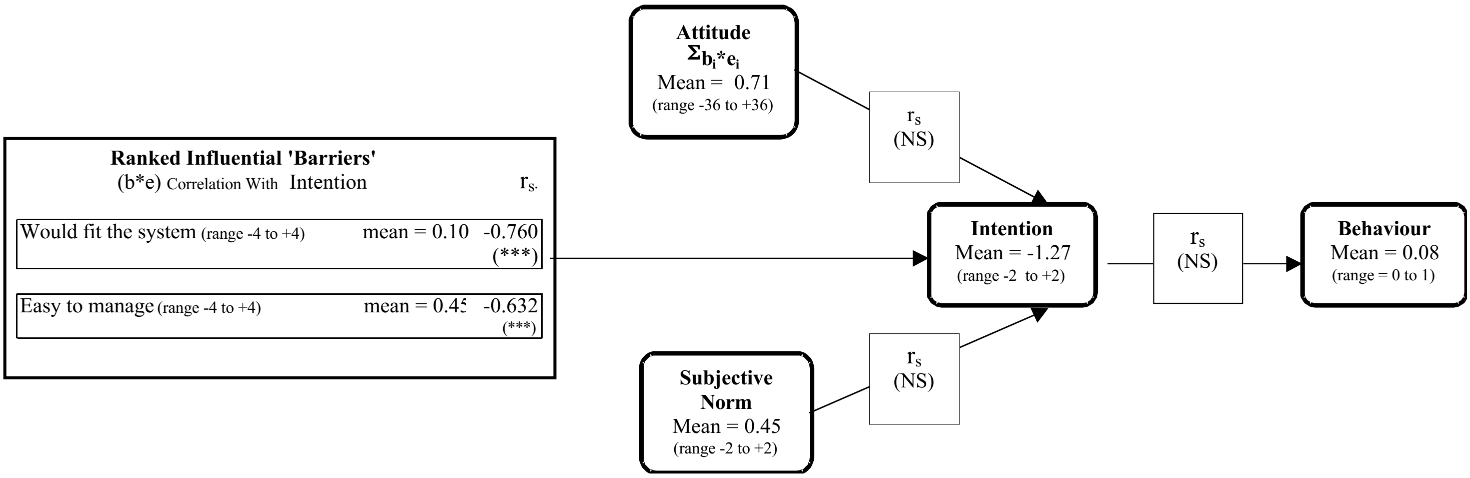

Notes:
1. Only the Spearman correlation coefficients (r_s) are shown that are significant at <0.050. (*, **, *** denote significance (p) at the 0.05, 0.01 and 0.001levels respectively).
2. In the case of MDC observation times only 2 cognitive 'barriers and no cognitive 'drivers' are observed when the sub sample of organic farmers is considered.
3. The possible range and the mean score registered regarding each of the variables considered are presented
4. The Subjective Norm presented is the stated rather than calculated measure

Figure 3: TORA analysis of the MDC observation time findings (Organic farmers)

Notes:
1. Only the Spearman correlation coefficients (r_s) are shown that are significant at <0.050. (*, **, *** denote significance (p) at the 0.05, 0.01 and 0.001levels respectively).
2. In the case of MDC observation times only 2 cognitive 'barriers and no cognitive 'drivers' are observed when the sub sample of organic farmers is considered.
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Figure 3: TORA analysis of the MDC observation time findings (Organic farmers)

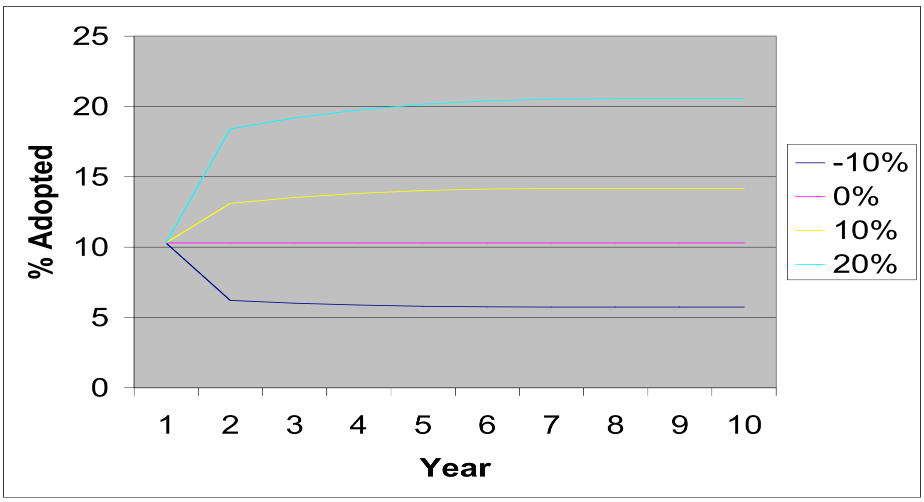

Figure 4: Predicted rate of adoption of MDC recommended observation times for specialist dairy farms assuming changes in attitude score

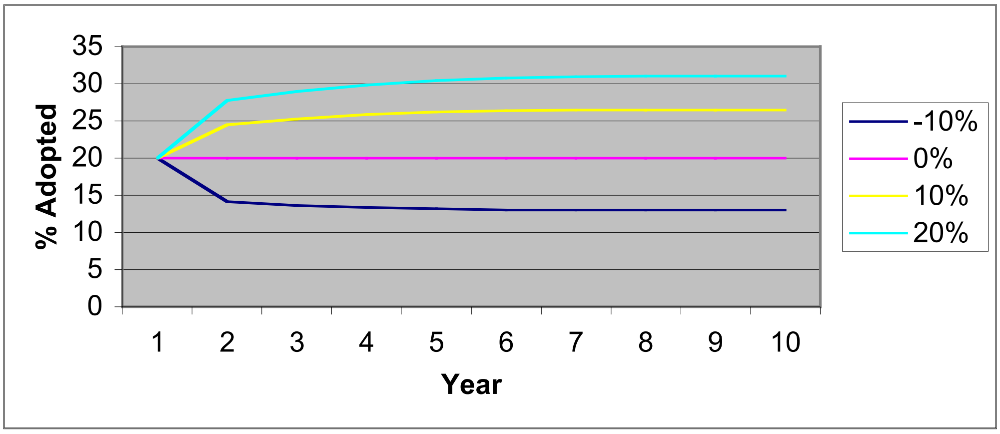

Figure 5: Predicted rate of adoption of MDC recommended observation times for mainly dairy farms assuming changes in attitude score

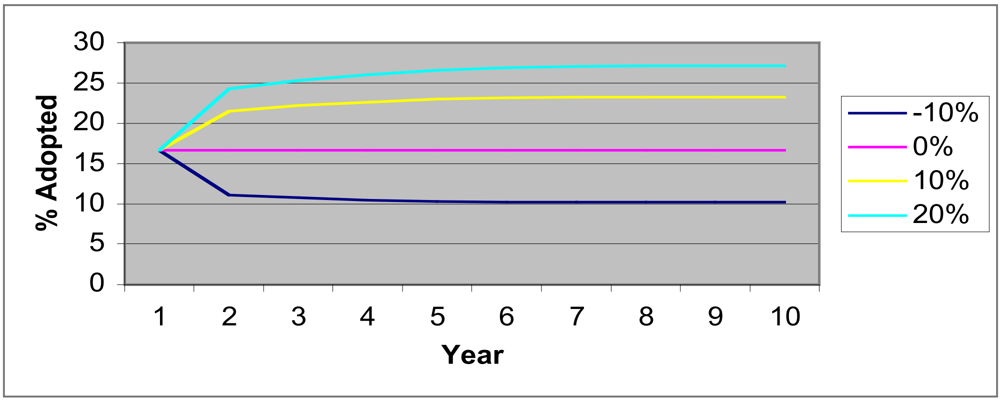

Figure 6: Predicted rate of adoption of MDC recommended observation times for mixed farms assuming changes in attitude score

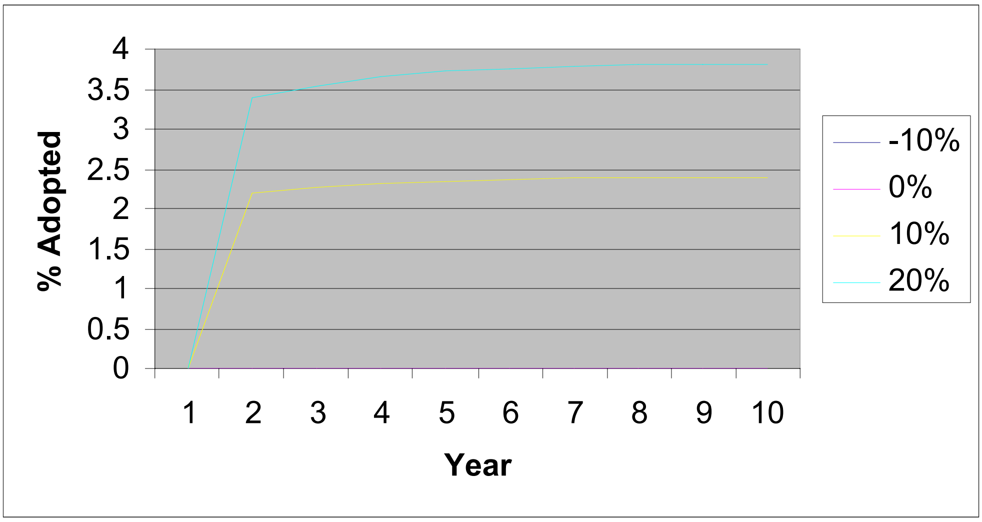

Figure 7: Predicted rate of adoption of MDC recommended observation times for hill and upland farms assuming changes in attitude score

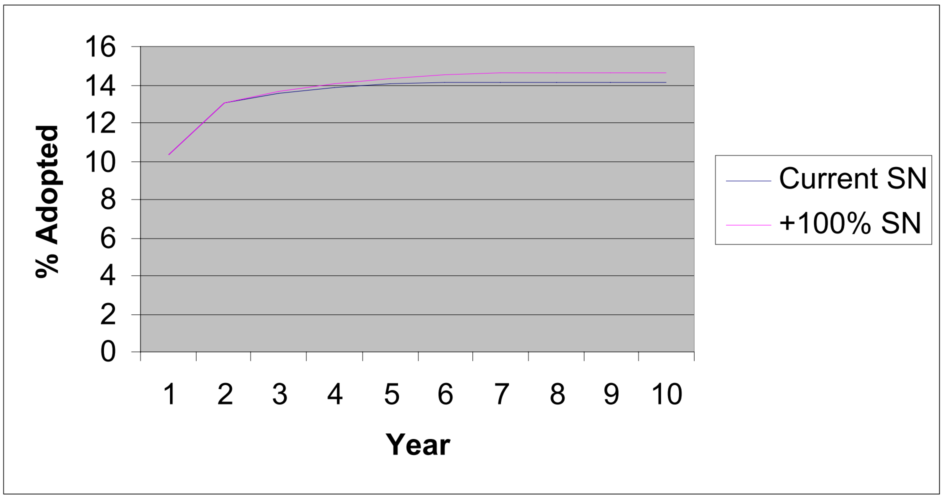

Figure 8: Predicted rate of adoption of MDC recommended observation times for specialist dairy farms under a 10% increase to attitude score and 100% increase in social norm