

Scotland's Rural College

Using a typology to understand farmers' intentions towards following a nutrient management plan

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38 1. Introduction

39 Farmers often receive mixed political messages concerning their use of resources. On the one
40 hand they are told to reduce their use of inputs whereas on the other they are encouraged to
41 intensify food production to meet growing demand (FAO, 2017; Yoshida *et al.*, 2018). To
42 address this conflicting demand, farmers are increasingly being encouraged to improve the
43 efficiency of agricultural input use (Buckley and Carney, 2013; McGlynn *et al.*, 2018). One
44 important area of attention is improving the efficiency of organic and chemical fertiliser use on
45 farms (Sutton *et al.*, 2011; Buckwell and Nadeu, 2016; McGlynn *et al.*, 2018). Such substances,
46 whilst vitally important to crop production, remain significant sources of diffuse pollution to
47 water and air (Montemurro and Diacono, 2016; Rohila *et al.*, 2017). In the European Union,
48 nutrient inputs are regulated under the Nitrates Directive (ND) (European Commission, 1991).
49 However, there is a growing interest in moving away from traditional command and control
50 methods towards encouraging voluntary adoption by stimulating individual responsibility for
51 the maintenance of normative standards (Barnes *et al.*, 2013a; Peth *et al.*, 2018). Moreover,
52 due to limited financial resources, policy makers are keen to understand how best to improve
53 their use of differential targeting of resources, in order to ensure maximum adoption of
54 recommended practices (Blackstock *et al.*, 2010; Walder and Kantelhardt, 2018).

55 Best practice in the area of nutrient management has received increasing interest from policy
56 makers due to the ability of associated practices to deliver both financial and environmental
57 benefits (Sutton *et al.*, 2013; McGlynn *et al.*, 2018). Nutrient management is a set of
58 “specialized activities dealing with all nutrient sources and transformations within a defined
59 system so as to achieve both economic and environmental targets” (Oenema and Pietrzak,
60 2002: 160). One important and widely recommended practice for achieving more efficient
61 management of nutrients is following a nutrient management plan (NMP) (Beegle *et al.*, 2000;
62 Easton *et al.*, 2017; Ulrich-Schad *et al.*, 2017). Research has suggested that following a NMP
63 is essential for ensuring that fertiliser (chemical and organic) is applied in line with crop
64 requirements (Roberts *et al.*, 2017). This results in better targeting of nutrient applications to
65 crops with a reduced risk of loss of excess nutrients to the environment (Thomas *et al.*, 2007;
66 Schulte *et al.*, 2009; Amon-Armah *et al.*, 2013). Despite proven universal benefits and
67 extensive promotion, the number of farmers that follow a NMP remains limited globally
68 (Buckley *et al.*, 2015; Osmond *et al.*, 2015; Ulrich-Schad *et al.*, 2017; Brown *et al.*, 2019).

69 A limited number of studies have sought to reveal variables which influence farmers to develop
70 a NMP. These variables often include farm and farmer characteristics and, to a lesser extent,
71 socio-psychological issues (e.g. attitudes and social pressure). Development of a NMP has been
72 found to be positively and significantly associated with farm size (Ribaudo and Johansson,
73 2007; Lawley *et al.*, 2009; Ulrich-Schad *et al.*, 2017), number of animals (Lawley *et al.*, 2009),
74 intensity of production (Savage and Ribaudo, 2013; Brown *et al.*, 2019), income (Ribaudo and
75 Johansson, 2007), education (Savage and Ribaudo, 2013) and contact with agricultural
76 extension (e.g. advisor, workshops and demonstration meetings) (Genskow, 2012; Ulrich-
77 Schad *et al.*, 2017). Whereas, age and off-farm employment have been found to reduce the
78 likelihood of a farmer developing an NMP (Buckley *et al.*, 2015). Farmers with more a positive
79 attitude towards the adoption of various nutrient management practices (e.g. soil testing and
80 conservation tillage) tend to have higher adoption rates (Flett *et al.*, 2004; Reimer *et al.*, 2012a).
81 Similarly, farmers with a positive attitude towards the environment, and or those with a greater
82 level of environmental awareness, have been found to have a greater likelihood of developing
83 an NMP (Reimer *et al.*, 2012b; Buckley *et al.*, 2015). A number of studies have also found that
84 farmers who perceive a higher level of social pressure from fellow farmers or other food chain

85 actors are more likely to develop a NMP (Welch and Marc-Aurele, 2001; Ribaud and
86 Johansson, 2007; Yoshida *et al.*, 2018). Finally, farmers' perceptions of their ability to adopt
87 several nutrient management practices, including fertiliser application timing and method, have
88 also been found to constrain adoption (Zhang *et al.*, 2016; Wilson *et al.*, 2018).

89 Despite providing important insights into farmer decision making, previous studies have three
90 primary limitations. Firstly, studies typically focus on the development of a NMP and therefore
91 typically fail to explicitly consider farmers' intentions towards following a NMP, which is
92 required if full benefits are to be achieved (Ulrich-Schad *et al.*, 2017). Secondly, although
93 common across the adoption literature more widely (Adnan *et al.*, 2017; Floress *et al.*, 2017),
94 previous studies in relation to the development of a NMP typically fail to consider socio-
95 psychological variables. Those that do, often apply qualitative methods (e.g. McGuire *et al.*,
96 2013; Yoshida *et al.*, 2018) and therefore results from such studies are difficult to generalise.
97 Finally, a number of previous studies which examine the development of NMPs have been
98 found to treat farmers as a homogenous group (e.g. shared motivations and constraints). This
99 is too strong an assumption if policy makers are to be provided with information that will help
100 them to understand how different segments of a farming population might respond to proposed
101 interventions (Hammond *et al.*, 2017).

102 We address the limitations of previous research in this paper in a number of ways. Firstly, we
103 examine farmers' intentions to follow a NMP rather than solely focusing on the development
104 of a NMP. Secondly, we incorporate socio-psychological variables into our analysis using the
105 Theory of Planned Behaviour (TPB) (Ajzen, 1991). Thirdly, a typology is generated in order
106 to account for heterogeneity among the sample of farmers. Such typologies have been useful
107 for increasing the relevance of recommendations for farm improvement and the provision of
108 extension services (Chikowo *et al.*, 2014; Kamau *et al.*, 2018), as well as better targeting of
109 policy initiatives (Emtage *et al.*, 2007; Walder and Kantelhardt, 2018).

110 In this article, we aim to explain farmers' intentions towards following a NMP using Irish farm
111 survey data. Specifically we address whether there are differences in the drivers of intentions
112 to follow a NMP between groups of farmers. Ultimately, we use this information to provide
113 policy makers with insights into farmer behaviour that can be used to better target initiatives
114 designed to further encourage farmers to follow a NMP.

115 The Republic of Ireland (henceforth, Ireland) provides a suitable context to study farmers'
116 intentions towards following a NMP for a number of reasons. First, agricultural area accounts
117 for around 70% of the total land area, thus covering a range of climatic conditions and soil
118 types (CSO, 2016). Second, the structure of Irish agriculture is diverse in terms of farm and
119 farmer characteristics, which provides an opportunity for classifying farmers (CSO, 2016).
120 Third, Irish food policy (DAFF, 2010; DAFM, 2015) reflects the global focus on increasing
121 food production whilst ensuring that such increases do not lead to a greater risk of nutrient
122 discharge from agricultural sources to water and to air (Buckwell and Nadeu, 2016; FAO,
123 2017). Finally, similar to elsewhere (Osmond *et al.*, 2015; Ulrich-Schad *et al.*, 2017; Brown *et al.*,
124 2019), the number of farmers who follow a NMP remain limited and it is unclear as to the
125 best method(s) for increasing the number of farmers who follow a NMP in the future (Buckley
126 *et al.*, 2015).

127 2. Nutrient management plans

128 NMPs are management tools that divide farms into management units (usually fields or sub-
129 field plots/paddocks). NMPs can be simple or complex; they can be written with a paper and

130 pencil or developed using a computer (Beegle *et al.*, 2000). The fundamental principle
131 underpinning NMPs is the allocation of nutrients in a way that maximises the economic benefit
132 of the nutrients, while minimising the risk of nutrient loss to water courses and the air
133 (Genskow, 2012). Agricultural advisors often play a key role in the development of NMP due
134 to the technical nature of the information required (Lawley *et al.*, 2009). Without developing a
135 NMP, the risk of over or under applying nutrients to fields can increase (Shepard, 2005; Roberts
136 *et al.*, 2017). Moreover, the benefits of following a NMP include increased yields and
137 efficiency of input use (Shepard, 2005; Thomas *et al.*, 2007; Schulte *et al.*, 2009).

138 Whilst farmers may choose to voluntarily develop a NMP, typically to aid production
139 decisions, others may be required to develop one on a mandatory basis due to policy
140 requirements (Beegle *et al.*, 2000; Ketterings *et al.*, 2017). As manifested in an Irish context,
141 the Nitrates Directive (ND) mandates farmers to develop a NMP as a condition of a permit
142 (derogation) to operate above and beyond the regulatory limits on livestock density (McDonald
143 *et al.*, 2019). Furthermore, farmers are also required to develop a NMP if they participate in
144 the main national agri-environment scheme (GLAS: Green Low Carbon Agri-environmental
145 Scheme) (Image, 2016). However, whilst policy makers can enforce farmers to develop a NMP
146 and penalise those farmers who have not developed a NMP, monitoring whether farmers
147 follow the NMP is difficult and hard to regulate (Perez, 2015). Therefore, policy makers are
148 keen to understand what motivates farmers not only to develop a NMP but also to follow it
149 (Tao *et al.*, 2016; Ulrich-Schad *et al.*, 2017).

150 3. Theoretical framework

151 Socio-psychological models of behaviour take into account the variety of beliefs that
152 individuals hold and how these beliefs and cognitive processes influence decision making
153 (Burton, 2004). One widely applied model to understand how salient beliefs may promote or
154 restrict adoption of certain practices within the agricultural domain is the Theory of Planned
155 Behaviour (TPB) (Ajzen, 1991). According to the TPB, human behaviour is driven by the
156 intention to accomplish the behaviour in question. For the purpose of this study we examine
157 the intention of farmers to follow a NMP in the near future.

158 Intention is in turn determined by an individual's attitude, subjective norm and perceived
159 behavioural control (Ajzen, 1991). In line with the TPB, attitude can be defined as an
160 individual's positive or negative evaluation of the outcomes of performing the behaviour.
161 Subjective norm is the level of social pressure or approval an individual perceives to be exerted
162 on them to engage in a particular behaviour. Finally, perceived behavioural control relates to
163 whether an individual feels that s/he is capable of carrying out the behaviour, which is also
164 connected to the presence of factors that may promote or hinder the performance of the
165 behaviour. In general, the more favourable the attitude, the higher the level of social pressure
166 and perception of control, the stronger the intention will be to perform the given behaviour
167 (Ajzen, 1991).

168 The TPB has been used to explain farmers' intentions towards agricultural practices in a variety
169 of contexts. Both Wauters *et al.* (2010) and Rezaei *et al.* (2018), found attitude towards the
170 practice to be the most important variable determining farmers' intentions towards the use of
171 soil conservation in Belgium and on-farm food safety practices in Iran. Whereas, Läßle and
172 Kelley (2013) and Borges and Oude Lansink (2016) found subjective norm to be the most
173 important variable to be positively associated with farmers' intentions to convert to organic
174 farming in Ireland and to adopt improved grassland management in Brazil. Elsewhere,
175 perceived behavioural control was found to be an important positive predictor of farmers'

176 intentions to reuse agricultural biomass in China (Jiang *et al.*, 2018) and to apply fertiliser on
177 the basis of soil test results in Ireland (Daxini *et al.*, 2018). The mixed results for TPB variables
178 are expected, as the relative importance of the influences typically vary across behaviours and
179 situations (Ajzen, 1991).

180 Despite these successful applications of the TPB, various researchers have argued for the
181 inclusion of other context specific variables (Yazdanpanah and Forouzani, 2015; Martinovska
182 Stojcheska *et al.*, 2016). Ajzen (1991) suggests that if additional predictors can help to increase
183 the predictive utility of the TPB then they can be included. We use a number of background
184 variables (e.g. farm size, system and education) to create our typology (see section 4); however,
185 we hypothesise that two context specific variables will directly influence farmers' intentions
186 to follow a NMP. This approach is similar to other TPB research within the agricultural domain,
187 which focus on examining the direct relationships (as opposed to indirect relationships)
188 between additional background variables and intentions (e.g. Areal *et al.*, 2012; Micha *et al.*,
189 2015; Daxini *et al.*, 2018; Wang *et al.*, 2018).

190 Figure 1 presents the final theoretical framework used for the purpose of this study. The first
191 addition to the model includes a variable which is designed to capture the effect of agricultural
192 extension on farmers' intentions. The role that extension services play in the promotion of
193 agricultural management practices is well established (Kania *et al.*, 2014). Both individual and
194 group based extension contact (also known as discussion groups - groups of farmers that meet
195 frequently to discuss technical issues, share information and solve problems, facilitated by
196 an agricultural advisor) have been shown to positively influence adoption of agricultural
197 management practices (Baumgart-Getz *et al.*, 2012; Prager and Creaney, 2017). However, the
198 differential impact of extension on farmer decision making between groups of farmers has not
199 been explored to as great an extent. Therefore, it is important to capture the influence of
200 extension services on farmers' intentions to follow a NMP.

201 The second addition to the model is a policy variable. Policy is an important driver of the
202 development of NMPs, both in an Irish context (Image, 2016; McDonald *et al.*, 2019) but also
203 more widely (Osmond *et al.*, 2015; Perez, 2015). Based on this, we also consider a variable
204 which is designed to examine whether farmers who have developed a NMP due to mandatory
205 policy requirements (see section 2) are more likely to follow the plan compared to those that
206 are not subject to such requirements. Whilst a positive relationship may be intuitive, research
207 has found that farmers who have developed a NMP do not always follow it (Buckley *et al.*,
208 2015; Osmond *et al.*, 2015), which has led some authors to conclude that adherence to plans is
209 largely voluntary (Perez, 2015).

210
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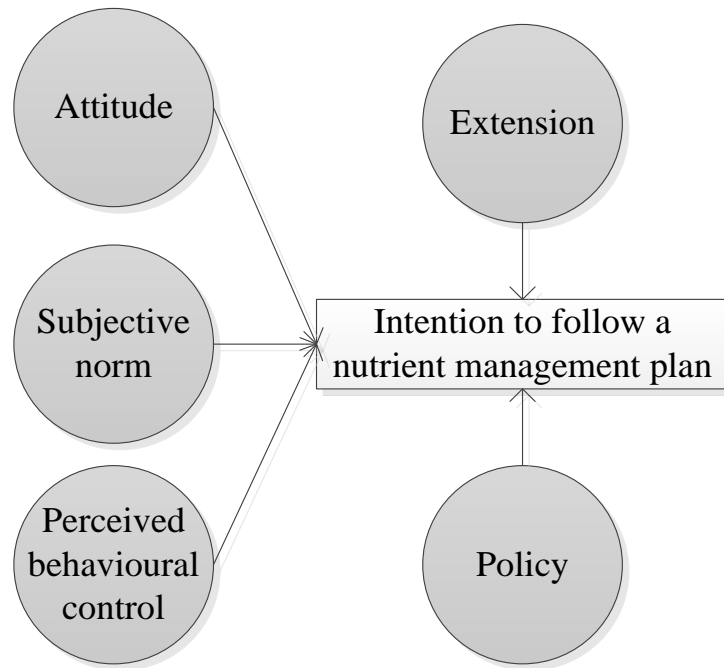
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216 **Figure 1: Theoretical framework based on the Theory of Planned Behaviour**



217

218 4. Methodology

219 *Survey design*

220 In order to explain farmers’ intentions towards following a NMP, data were collected using a
 221 cross-sectional survey. The survey comprised of three sections, with the first section containing
 222 questions on farm and farmer characteristics, which were used to generate a farmer typology.
 223 The second section collected information on farmer engagement with extension and policy, to
 224 be used as explanatory variables in the regression analysis. In the final section, participants
 225 were asked to evaluate a number of statements on a five-point Likert scale. These statements
 226 were designed to reveal their intentions, attitude, subjective norm and perceived behavioural
 227 control towards following a NMP.

228 In order to measure the TPB constructs, recommendations by Ajzen (1985) were followed and
 229 scales containing multiple statements were developed. Following suggestions from Ajzen
 230 (2002a) and Francis *et al.* (2004), the construction of these statements was based partly on
 231 information obtained from a series of interviews with farmers and agricultural advisors and
 232 partly on an in-depth literature review (e.g. Läpple and Kelley, 2013; Borges *et al.*, 2014;
 233 Yazdanpanah and Forouzani, 2015; Martinovska Stojcheska *et al.*, 2016). Survey respondents
 234 were asked to rank the statements on a five-point Likert scale from strongly disagree (1) to
 235 strongly agree (5). Five-point Likert scales have been used in previous TPB style agricultural
 236 research (e.g. Gorton *et al.*, 2008; Adnan *et al.*, 2017b; Morais *et al.*, 2018) and are deemed to
 237 be short enough to allow respondents to distinguish meaningfully between the response options
 238 (Hansson *et al.*, 2012). Examples of the statements used to measure attitude, subjective norm
 239 and perceived behavioural control are shown in Appendix 1.

240 Intention was measured using one statement on a five-point Likert scale. Respondents were
 241 asked to state their level of agreement with the statement “I intend to follow a NMP in the near
 242 future”. In order to ensure that respondents had a consistent understanding of what a NMP was,
 243 survey recorders read out a definition, prior to farmers answering questions pertaining to this
 244 measure. Furthermore, in order to eliminate any potential problems with the survey such as

245 timing, complexity and suitability, a pilot survey was conducted prior to administering the
246 survey to the full sample. Feedback from the pilot resulted in a number of minor changes to the
247 survey, which included a reduction in length, improvements in the wording of questions and a
248 restructuring of the order of some of the questions.

249 The survey data were then collected through face-to-face interviews with farmers. Data
250 collection began in December 2016 and was completed in April 2017. A survey company was
251 hired to conduct the interviews with farmers. In all cases, the main decision maker on the farm
252 participated in the interviews. A quota controlled sampling method was used to ensure that the
253 sample was representative of Irish farms by the dominant farm systems (cattle, dairy, sheep
254 and tillage) and sizes (hectares) (see Daxini *et al.*, 2018 for further detail). Here, tillage refers
255 to a system which focuses on crop production. The quotas used were based on known
256 population distribution figures in relation to specific farm types taken from the Irish Central
257 Statistics Office (Hennessy & Moran, 2016). In order to acquire a representative sample of
258 farmers, the survey company began by stratifying the sample by electoral divisions. At each
259 sampling point, the interviewer followed a quota control scheme, based on the known quantity
260 of farm types and population distribution statistics within each location (Howley *et al.*, 2015).
261 Interviewers then visited residences that appeared to be a farm household (observing the
262 surrounding landscape) and proceeded to interview farmers until they filled their quotas
263 (Howley, 2013). The final sample consisted of 1009 farmers.

264 *Principal Component Analysis (PCA)*

265 The statements describing the TPB variables (attitude, subjective norm and perceived
266 behavioural control) were condensed using principal component analysis (PCA) which was
267 rotated using the varimax method to form a reduced number of interpretable variables (Howley
268 *et al.*, 2015). PCA helps to determine the statements underlying the TPB variables with a
269 similar structure, reduce complexity and prevent any issues associated with multicollinearity
270 (Hair *et al.*, 2010; Chinedu *et al.*, 2018). The Kaiser-Meyer-Olkin (KMO) measure of sampling
271 adequacy was 0.94 which suggests suitability of the data for PCA (Kaiser, 1974). The Bartlett's
272 test of sphericity is significant at the $p = 0.0000$ level which leads us to accept the alternative
273 hypothesis that a significant relationship among the variables exists (Field, 2009). Predicated
274 on the eigen values, we keep three components where component loadings are above 0.30. The
275 choice about the quantity of relevant statements loaded on each component is led by theory and
276 interpretation of the components (Hair *et al.*, 2010). The final components are also assessed for
277 internal consistency and reliability using the Cronbach's Alpha (Nunnally, 1978). The results
278 of the Cronbach's Alpha are all above 0.88 where a value of 0.60 is considered as acceptable
279 (Jolliffe, 2002). The statements that successfully produced the TPB variables are shown in
280 Appendix 1. These derived variables can then be used as independent variables to explain
281 farmers' intentions to follow a NMP.

282 *Latent class analysis (LCA)*

283 A common approach used to quantify unobserved heterogeneity that exists among a population
284 is a latent class analysis (LCA) (Schreiber, 2017). LCA is a model-based approach to defining
285 the underlying structure of the data, in order to predict the probability that each observation
286 belongs to a particular class (Hair *et al.*, 2010). The central assumption of the latent class model
287 is that different and distinct classes of farmers exist and that respondents in each class share
288 homogenous characteristics, but characteristics of respondents differ between classes (Zhang
289 *et al.*, 2016). The optimal number of discrete classes and the class to which a farmer belongs
290 are determined by the data, such as the characteristics of the farm and farmer. LCA is based on

291 robust estimation algorithms for choosing the correct number of classes among a population
 292 for a given criteria of characteristics and therefore, unlike cluster analysis, the choice of cluster
 293 criteria are less arbitrary (Morey *et al.*, 2008; Rhead *et al.*, 2018).

294 For latent classes to be generated, a number of ‘classifying variables’ must be chosen on which
 295 to assess heterogeneity (Dean and Raftery, 2010). Variables that have been highlighted as
 296 important attributes of heterogeneity include the characteristics of the farm and the farm
 297 operator (Knowler and Bradshaw, 2007; Valbuena *et al.*, 2008; Daloğlu *et al.*, 2014).
 298 Therefore, the psychological decision making process may vary between groups of farmers
 299 based on such characteristics. Thus, based on the literature outlined above (see section 1), the
 300 final set of classifying variables used in the LCA is shown in Table 1. It is important to note
 301 that different farm systems typically generate varying levels of income per hectare. For
 302 example, dairy farms in Ireland on average generate a higher income rate per hectare due to
 303 higher returns from the market (Dillon *et al.*, 2018). The inclusion of the ‘total income’
 304 variable, used as part of the classification process in the LCA, is important in accounting for
 305 this issue in our model.

306 **Table 1: Description of variables used to classify farmers**

Variable	Description
Drainage	Perception of average land drainage on farm (1 = well drained, 0 = poorly drained)
Farm system	Main system of farming (1 = Cattle, 2 = Dairy, 3 = Sheep, 4 = Tillage)
Total income from farming per annum (€)	Farm income (1 = 4,000–9,999, 2 = 10,000–19,999, 3 = 20,000–29,999, 4 = 30,000–39,999, 5 = 40,000–49,999, 6 = 50,000–59,999, 7 = 60,000 and over, 7 = refused)
Farm size (ha)	Farm size (1 = < 20, 2 = 20–30, 3 = 31–50, 4 = 51–100, 5 = 101+)
Farmer age (years)	Age of farm operator (1 = under 35, 2 = 35–44, 3 = 45–50, 4 = 51–64, 5 = 65+)
Off-farm job	Farm operator has an off-farm job (1 = yes, 0 = no)
Education	Highest level of formal education received by farm operator (1 = some secondary and above, 0 = otherwise)

307 To test for potential multicollinearity between the chosen classifying variables, Variance of
 308 Inflation (VIF) values were computed. The maximum VIF was 1.2, suggesting that
 309 multicollinearity is not an issue between the classifying variables (Hair *et al.*, 2010). In fact,
 310 some correlation amongst the classifying variables should be expected as no correlation would
 311 suggest there is no latent structure within the data, on which to classify farmers (Higgins *et al.*,
 312 2016).

313 The final stage involved in the generation of latent classes is the identification of the optimal
 314 number of classes. An exploratory approach was used and a number of statistical information
 315 criteria were evaluated to judge the best model fit (Barnes *et al.*, 2013b). The number of classes
 316 retained is based on examining the log-likelihood (LL), Akaike Information Criteria (AIC) and
 317 Bayesian Information Criteria (BIC), with smaller values indicating better fit (Nylund *et al.*,
 318 2007). Entropy values (from 0 to 1 = perfect fit), which are a measure of correctly classifying
 319 individuals and goodness of class separation, are also examined (Ulbricht *et al.*, 2018). Table
 320 2 illustrates the results for the fit statistics of the latent classes, which are estimated from one
 321 to five classes. From a statistical point of view, the addition of the fourth and fifth classes
 322 results in only a marginal improvement of the LL. The AIC is minimised at a four class solution

323 whereas the BIC is minimised at a three class solution. The BIC is recommended over the AIC
 324 when larger sample sizes are under consideration (Forster, 2000; Nylund *et al.*, 2007). The AIC
 325 has also been reported to often overestimate the number of classes (Nylund *et al.*, 2007).
 326 Entropy is the highest for the three class model. Based on these criteria, we deem the three
 327 class solution to be the best model fit.

328 **Table 2: Fit statistics for the latent classes**

Number of classes extracted	LL	AIC	BIC	Entropy
1	-8403.37	16862.74	17000.41	NA
2	-8006.93	16127.86	16408.11	0.73
3	-7822.10	15816.20	16239.04	0.77
4	-7763.11	15756.23	16321.65	0.74
5	-7739.41	15756.82	16440.25	0.73

329 Notes: LL = Log-likelihood, AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria.

330 *Latent class binary logistic regression*

331 During the generation of latent classes we set farmers' intentions to follow a NMP as the
 332 dependent variable. This enables us to assess which of the hypothesised explanatory variables
 333 influence farmers' intentions to follow a NMP for each class (Figure 1). Table 3 provides a
 334 description of the variables used in the latent class binary logistic regression. The effects of the
 335 explanatory variables on intentions are estimated at the same time as the latent classes are
 336 generated, i.e., with the membership of class probabilities. This approach does not change class
 337 membership probabilities and therefore is deemed as more statistically advantageous, as it
 338 allows for the removal of estimation bias from the two-step approach (Vermunt, 2010).

339 **Table 3: Description of the variables used in the latent class regression**

Variable	Description
<u>Dependent variable</u>	
Intention	Intention to follow a NMP (1 = yes, 0 = no)
<u>Explanatory variables</u>	
<u>TPB</u>	
Attitude	PCA result
Subjective norm	PCA result
Perceived behavioural control	PCA result
<u>Additional variables</u>	
Extension contact	Level of extension contact by farm operator (0 = zero contact, 1 = contact with an agricultural advisor only, 2 = one-to-one contact with an agricultural advisor and contact with a discussion group)
Policy	Farm operator participates in the Irish GLAS agri-environmental scheme and/or receives a permit (derogation) to farm above the restrictions imposed by the ND (1 = yes, 0 = otherwise)

340 Ordered regression estimation methods are frequently applied to explain ordinal outcomes. As
 341 mentioned previously, intention is measured on a five-point Likert scale from strongly disagree
 342 to strongly agree. However, such models require the proportional odds assumption to be met
 343 (Hair *et al.*, 2010). If this assumption is violated, then the scale used to measure intention may
 344 be collapsed to form a binary outcome variable and a latent class binary logistic regression

345 employed. Due to the limited number of responses in the strongly disagree and disagree
346 categories, for the purpose of this study we group together the farmers who respond “strongly
347 disagree”, “disagree” and “unsure” and label this group as “no intention” (0) with the remaining
348 farmers being classified as “intenders” (1).

349 To test for potential multicollinearity between the independent variables, a separate binary
350 logistic regression model was run for the full sample (n=1009) with intention to follow a NMP
351 set as the dependent variable. Here, the TPB, extension contact and policy variables were
352 inserted as independent variables. VIF values were then assessed. The maximum VIF value
353 was 2.01, which is below the cut-off point of 10 (Hair *et al.*, 2010). This suggests that
354 multicollinearity was not an issue in our analysis.

355 The results of the regression analysis are also shown as marginal effects. A larger marginal
356 effect represents a greater influence of the independent variable on the dependent variable (Hair
357 *et al.*, 2010). In terms of calculation, the marginal effects for the binary variables are measured
358 as the discrete change from 0 to 1, holding all other variables constant. Whereas for continuous
359 variables, the marginal effects are interpreted as the instantaneous rate of change in the
360 probability of the outcome, caused by a one unit change in the independent variable (Hair *et*
361 *al.*, 2010).

362 5. Results

363 *Farm and farmer characteristics*

364 The ensuing descriptive statistics represent the entire sample of farmers surveyed (n=1009).
365 Based on the quotas, around 50% of the sample consists of cattle farms whereas dairy
366 comprises 26%, with sheep at 17% and tillage consisting of 6% of the total. In terms of farm
367 size, the median is 31-50ha whereas for farmer age, the grouping 51-64 is found to be the
368 median. These figures correspond with national averages (CSO, 2018). In terms of education,
369 just over half of the sample has an education above secondary level whereas 30% have an off-
370 farm job. In relation to extension contact, 39% of farmers are in contact with just an agricultural
371 advisor whereas only 29% are in one-to-one contact with an agricultural advisor and participate
372 in a discussion group. In total, 47% of farmers report that they have a NMP. In relation to
373 policy, 42% of farmers in our sample are either part of GLAS and/or have been granted a
374 derogation to farm above the limits imposed by the ND (see section 2). In Ireland,
375 approximately 40% of the farming population is required to develop a NMP on a mandatory
376 basis due to GLAS/derogation requirements (Image, 2016; DAFM, 2018) and therefore our
377 sample reflects the national situation.

378 *Description of latent classes*

379 The LCA produced three classes of farmers. The first latent class is estimated to have a class
380 membership probability of around 33%, this means that about 33% of the sample is estimated
381 to be in this class. The estimated class membership probability for Class 2 is approximately
382 38% and around 29% for Class 3. Table 4 provides descriptive statistics for the classes in terms
383 of the unobserved variables used to classify farmers. Chi-square statistics show that all
384 variables are statistically different across the three classes. Statistical differences are also
385 computed between classes in order to interpret classes based on what is typical for a particular
386 class compared to other classes. We draw on suggestions made by Daloğlu *et al.* (2014) to
387 further interpret and label our classes.

Table 4: Percentage response probabilities by class (rows, by variable, sum to 100%¹)

Classification variables		Full sample	Class 1	Class 2	Class 3	Chi-square
		%	%	%	%	P-value
Drainage	Well drained	75	68 ^a	69 ^a	86	***
	Poorly drained	25	32 ^a	31 ^a	14	-
Farm system	Cattle	51	70 ^a	68 ^a	22	***
	Dairy	26	5 ^a	5 ^a	60	***
	Sheep	17	22 ^a	24 ^a	6	***
Total income from farming per annum (€)	Tillage ³	6	3 ^a	3 ^a	12	***
	4,000–9,999	15	27 ^a	21 ^a	0	***
	10,000–19,999	16	26 ^a	21 ^a	3	***
	20,000–29,999	13	16 ^a	18 ^a	7	***
	30,000–39,999	10	6	11 ^a	12 ^a	**
	40,000–49,999	7	1	4	13	***
	50,000–59,999	4	0 ^a	1 ^a	10	***
	60,000 and over	7	0 ^a	0 ^a	17	***
	Refused	28	23 ^a	23 ^a	37	***
	Farm size (ha)	Under 20	19	35	26	0
20–30		22	29 ^a	33 ^a	8	***
31–50		29	28	32	27	***
51–100		22	7 ^a	8 ^a	45	***
101 and over		8	1 ^a	1 ^a	19	***
Farmer age (years)	Under 35	7	0	12 ^a	10 ^a	***
	35–44	13	1	23	15	***
	45–50	15	1	22 ^a	21 ^a	***
	51–64	38	32	43 ^a	39 ^a	*
	65 and over	27	66	0	14	***
Off-farm job	Yes	30	21	65	11	***
	No	70	79	25	89	-
Education	Above secondary level	54	7	88	70	***

	Secondary level or below	46	93	11	30	-
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389 Notes: ¹Due to rounding the probabilities do not always sum to 100. ²Calculated between Class 1, Class 2 and
390 Class 3. ³A system a system which focuses on crop production. Where two classes share a superscript this
391 means there is no significant difference (as per chi-square test) between the classes in terms of the particular
392 variable. *** p<0.01, ** p<0.05, * p<0.1.

393 *Class 1: Traditional farmers (33%)*

394 Farms and farmers in Class 1 have characteristics that are typically related to low likelihood of
395 following a NMP. This class is dominated by cattle (70%) and sheep (22%) farm systems,
396 which tend to be farmed less intensively in Ireland (Dillon *et al.*, 2017). Around 68% of farmers
397 in this class perceive their land to be well drained. A large proportion of farms (53%) earn
398 under €19,999 a year and a substantial number of farms (64%) are under 30 ha. A large
399 proportion of farmers in this class are over 65 years of age (66%). Education levels among this
400 class are low with only 7% having attained an education beyond secondary level. Finally, a
401 relatively small proportion (21%) of farmers in Class 1 has an off-farm job. In summary, Class
402 1 is defined by older, less educated farmers, managing small holdings consisting predominantly
403 of cattle and sheep systems on a full time basis, generating low incomes. Based on these
404 characteristics we call Class 1, ‘traditional farmers’.

405 *Class 2: Supplementary income farmers (29%)*

406 The characteristics of farms and farmers in Class 2 are related to a low to medium likelihood
407 of following a NMP. Similar to Class 1, Class 2 also contains a large proportion of cattle (68%)
408 and sheep farms (24%). In terms of perceptions of land drainage, 69% of farmers in this class
409 perceive their land to be well drained. A significant numbers of farms earn a low income with
410 42% earning under €19,999 a year. In terms of farm size, 59% of farms in this class are below
411 30 ha. In relation to farmer age, a significant proportion of farmers are under the age of 44
412 (35%) with significantly high levels of off-farm employment (65%) and formal education
413 above secondary level (88%). Overall, this class is defined by cattle and sheep farms with low
414 to middle level incomes and farm sizes. Such farms are operated on a part time basis, by
415 relatively younger farmers, who are highly educated. This leads us to define Class 2 as
416 ‘supplementary income farmers’.

417 *Class 3: Business-oriented farmers (38%)*

418 Class 3 presents a structure that is usually associated with a high probability of following a
419 NMP. A defining feature of Class 3 is its significantly higher proportion of dairy (60%) and
420 tillage (12%) farm systems, compared to the other classes. Such farm systems tend to operate
421 more intensively in Ireland compared to cattle and sheep enterprises (Dillon *et al.*, 2017). In
422 total, 86% of farmers perceive their land to be well drained. Only a small proportion (3%) of
423 farmers in this class earn an income of below €19,999 a year and only 8% of farms are below
424 30ha in size. In terms of farmer age, the majority (60%) are middle aged (45 to 64) and few
425 have an off farm job (11%). Education levels above secondary level are fairly high (70%). To
426 summarise the key features of Class 3, this class is dominated by full time farmers, earning
427 high incomes from operating dairy and tillage systems on relatively productive agricultural
428 land. Predicated on the dominant characteristics of Class 3, we term this class ‘business-
429 oriented farmers’.

430 *Intentions to follow a NMP*

431 In terms of the dependent variable, intentions to follow a NMP (Table 5), 61% of traditional
 432 farmers stated a positive intention whereas 66% of supplementary income farmers and 67% of
 433 business-oriented farmers indicated a positive intention. Business-oriented farmers have a
 434 significantly higher level of intention compared to traditional farmers ($x^2 = 4.63$, $p = 0.03$). No
 435 other significant differences are detected. Interestingly, it appears that regardless of class, the
 436 level of intention to follow a NMP is relatively similar. This result appears to contradict typical
 437 findings across the literature, which suggest that certain farm and farmer characteristics (as
 438 discussed in the introduction) should be associated with differential probabilities of following
 439 a NMP. However, as discussed in Section 6 in more detail below, this study focuses on
 440 intentions to follow a NMP rather than the development of a NMP and therefore this result is
 441 not counterintuitive.

442 **Table 5: Percentage response probabilities^a by class (rows, by variable, sum to 100%)**

		Full sample	Traditional farmers	Supplementary income farmers	Business-orientated farmers	Chi-square ¹
Dependent variable		%	%	%	%	
Intention	Yes	65	61 ^a	66 ^{ab}	67 ^b	*
	No	35	39	34	33	

443 Notes: Where two classes share a superscript this means there is no significant difference (as per chi-square test)
 444 between the classes in terms of the particular variable. ¹Calculated between traditional farmers, supplementary
 445 income farmers and business-orientated farmers.* $p < 0.1$.

446 *Latent class binary logistic regression analysis: Traditional farmers*

447 In relation to the variables which influence farmers' intentions, Table 6 shows that for
 448 traditional farmers', intentions are influenced significantly and in a positive direction by
 449 attitude (5% level), subjective norm (1% level), perceived behavioural control (1% level),
 450 extension contact 2 (5% level) and policy (5% level). All of the significant variables also have
 451 significant marginal effects (Table 7). As the level of the psychological variables (attitude,
 452 subjective norm and perceived behavioural control) increase by one unit, the probability of a
 453 farmer following a NMP increases by 3.0%, 7.6% and 4.6% respectively. In terms of the
 454 additional variables, farmers with high levels of extension contact (i.e. extension contact 2) and
 455 those who participate in policy are around 20% and 10% respectively, more likely to have a
 456 positive intention towards following a NMP.

457 *Latent class binary logistic regression analysis: Supplementary income farmers*

458 Table 6 also illustrates the results for supplementary income farmers. Intentions are influenced
 459 significantly and in a positive direction by the psychological variables subjective norm (1%
 460 level) and perceived behavioural control (1% level), however attitude fails to reach statistical
 461 significance. Extension contact 2 and the policy variable are also positively associated with
 462 intentions at the 5% and 1% levels respectively. In terms of marginal effects (Table 7), the
 463 variables subjective norm and perceived behavioural control increase the probability of a
 464 farmer following a NMP by 8.2% and 4.6% respectively. Extension contact 2 and policy both
 465 significantly increase the probability of having a positive intention by 19%.

466 *Latent class binary logistic regression analysis: Business-orientated farmers*

467 For business-orientated farmers, intentions are positively and significantly correlated with
 468 three variables (Table 6). These include subjective norm (1% level), perceived behavioural

control (1% level) and policy (1% level). All of the significant variables also have significant marginal effects (Table 7). However, in addition, attitude also becomes significant at the 10% level. The estimated marginal effects show that attitude, subjective norm and perceived behavioural control increase the likelihood of a farmer following a NMP by 2.4%, 7.3% and 9.5% respectively. Being subject to mandatory policy requirements increases the probability of a farmer displaying a positive intention to follow a NMP by 9.4%.

Table 6: Results of the latent class logistic regression (coefficients)

Explanatory variables	Traditional farmers		Supplementary income farmers		Business-orientated farmers	
	Coeff.	Std.err	Coeff.	Std.err	Coeff.	Std.err
<i>TPB</i>						
Attitude	0.23**	0.09	-0.02	0.11	0.27	0.19
Subjective norm	0.59***	0.12	0.66***	0.16	0.82***	0.18
Perceived behavioural control	0.36***	0.12	0.37***	0.14	1.06***	0.36
<i>Additional variables</i>						
Extension contact 1 ^a	0.16	0.35	0.54	0.47	-0.31	0.45
Extension contact 2 ^a	1.55**	0.62	1.46**	0.60	0.08	0.54
Policy	0.81**	0.37	1.54***	0.46	1.10***	0.40
Cons	-0.64	0.26	-0.77	0.34	1.16	0.45

Notes: *** p<0.01, ** p<0.05, * p<0.1. ^aReference category: no extension contact.

Table 7: Results of the latent class logistic regression (marginal effects)

Explanatory variables	Traditional farmers		Supplementary income farmers		Business-orientated farmers	
	Marginal effect	Std.err	Marginal effect	Std.err	Marginal effect	Std.err
<i>TPB</i>						
Attitude	0.0297***	0.0113	-0.0247	0.0137	0.024*	0.0141
Subjective norm	0.0762***	0.0144	0.0816***	0.0170	0.0730***	0.0125
Perceived behavioural control	0.0461***	0.0149	0.0458***	0.0157	0.0947***	0.0183
<i>Additional variables</i>						
Extension contact 1 ^a	0.0233	0.0531	0.0776	0.0672	-0.0276	0.0400
Extension contact 2 ^a	0.2042***	0.0760	0.1898**	0.0763	0.0068	0.0463
Policy	0.1043**	0.0452	0.1923**	0.0588	0.0939**	0.0383

Notes: *** p<0.01, ** p<0.05, * p<0.1. ^aReference category: no extension contact.

6. Discussion

Efforts to encourage farmers to follow a NMP have been less than successful globally (Osmond *et al.*, 2015; Brown *et al.*, 2019) and in Ireland (Buckley *et al.*, 2015). This study addresses the limitations of previous studies by utilising a unique approach based on combining the TPB with a LCA in order to explain farmers' intentions towards following a NMP. The typology reveals that there are three discrete classes of farms/farmers and thus confirms that farm and farmer characteristics are a useful way to categorise the farming population and account for heterogeneity (Emtage *et al.*, 2007; Daloğlu *et al.*, 2014). Whilst the results reveal that intentions are somewhat similar across classes of farmers, the reasons why farmers intend to follow a NMP vary by class. This suggests that dissimilar groups of farmers are likely to respond in different ways to the same intervention designed to further encourage them to follow a NMP. These diverse reactions must be taken into account when designing policy interventions aimed at further encouraging farmers to follow a NMP (Emtage *et al.*, 2007; Guillem *et al.*, 2012).

493 According to previous studies (Ribaudo and Johansson, 2007; Prokopy *et al.*, 2008; Ulrich-
494 Schad *et al.*, 2017), business-orientated farmers display characteristics that should be
495 associated with a higher propensity towards following a NMP than traditional and
496 supplementary income classes. One reason for the relatively similar level of intention across
497 the classes may pertain to the ‘optimism bias’, which suggests that people often overestimate
498 their goals (Weinstein, 1980; Sharot, 2011). Alternatively, the survey data collected were ‘self-
499 reported’ which often results in individuals responding to questions in a ‘socially desirable’
500 way that paints them in a positive light (Floress *et al.*, 2018). However, it is important to note
501 that behavioural intention is an antecedent of behaviour but not a flawless predictor of it
502 (Fishbein and Ajzen, 2010). Thus, farmers may indeed have a positive intention, but due to
503 barriers associated with, for instance, personal ability to follow a NMP, they are unable to act
504 on their positive intentions.

505 In line with previous studies (Reimer *et al.*, 2012a; Borges *et al.*, 2014; Adnan *et al.*, 2018),
506 traditional and business-orientated farmers who have a positive attitude towards following a
507 NMP are more likely to do so than their counterparts. For the majority of these classes of
508 farmers, farming is their main occupation and therefore they are highly reliant on income
509 generated from farm production. Thus, such farmers are generally attentive to financial
510 concerns, yield and profitability (Daloğlu *et al.*, 2014). Our measure of attitude focuses mainly
511 on the production benefits of following a NMP, which may explain why attitude is an important
512 determinant of the intentions of these classes of farmers. Pannell *et al.* (2006) put forward the
513 argument that farmers will adopt a management practice if s/he perceives that the innovation
514 in question will enable them to achieve their personal goals. In line with others, our result
515 implies that it is important to consider how the underlying motivation for farming varies
516 between groups and how this potentially influences intentions towards following a NMP
517 (Buckley *et al.*, 2015).

518 Interestingly, the influence of attitude towards following a NMP on intentions is relatively
519 weak compared to previous findings (Burton, 2004; Garforth *et al.*, 2006; Reimer *et al.*, 2012a;
520 Rezaei *et al.*, 2018). Wauters *et al.* (2010) found that attitude was the most important
521 determinant of farmers’ intentions in relation to soil conservation practices in Belgium.
522 However, they also concluded that farmers in their study perceived it to be easy to adopt the
523 practices in question. One possible reason for the relatively low influence of attitude, compared
524 to Wauters *et al.* (2010), may be due to the fact that following a NMP is relatively difficult
525 compared to other farm management practices (Walters and Shrubsole, 2014). Developing and
526 following a NMP requires the collection of site specific data (e.g. soil fertility levels and
527 stocking rate) to be translated into nutrient application rates and potential changes to
528 management routines (Beegle *et al.*, 2000; Walters and Shrubsole, 2014). This requires learnt
529 skills and knowledge which farmers may not possess (Osmond *et al.*, 2015). Without such
530 expertise or access to affordable advice, following a NMP becomes more difficult and thus the
531 role of perceived behavioural control becomes more important relative to other variables, such
532 as attitude towards following a NMP (Ajzen, 2002b).

533 Perceived behavioural control is an important predictor of farmers' intentions regardless of
534 class. This means that farmers who perceive that they are able to and have the necessary
535 knowledge to follow a NMP, are more likely to have an intention to do so (Ajzen, 2002b). This
536 finding supports the results of both Zhang *et al.* (2016) and Wilson *et al.* (2018) who found
537 perceptions of ability to be positively associated with farmers’ intentions to adopt various
538 nutrient management practices (e.g. fertiliser application timing and placement) in the US.
539 These practices, like following a NMP, also require technical expertise to conduct and therefore

540 issues of perceived behavioural control are important (Wilson *et al.* 2018). However, the
541 marginal effect for perceived behavioural control is the largest for business-orientated farmers.
542 This class is focused on high-value products (e.g. milk and arable crops), short-term returns
543 from production and are less constrained by financial resources (Daloğlu *et al.*, 2014).
544 Therefore, a lack of capability or confidence in following a NMP on their farm is likely to take
545 a more prominent role as farmers become more concerned with the ‘how’ instead of the ‘why’
546 (Prochaska and Velicer, 1997).

547 The significant influence of subjective norm on intentions across the classes concurs with the
548 studies of Läpple and Kelley (2013) and Borges and Oude Lansink (2016). Both studies found
549 subjective norm to be a highly important determinant of farmers’ intentions to adopt farm
550 management practices in Ireland and Brazil respectively. This result may be because farmers
551 are increasingly subject to external social pressures from food chain actors and policy makers
552 to adopt management practices that offer both environmental and financial benefits (Yoshida
553 *et al.*, 2018). Furthermore, farmers are typically reliant on external support from consultants
554 and agricultural advisors for making decisions associated with nutrient applications to
555 fields/crops (Lawley *et al.*, 2009; Stuart *et al.*, 2018). Such actors may increase social pressure
556 on farmers to follow a NMP and, due to this pressure, farmers may want to behave in a way
557 that would be approved of by important referents (Martínez-García *et al.*, 2013).

558 The characteristics of the traditional (e.g. low income, small farm sizes, low levels of formal
559 education) and supplementary income (e.g. low income, small farm sizes, high levels of off-
560 farm employment) classes are typically associated with a low level of likelihood of following
561 a NMP (Baumgart-Getz *et al.*, 2012; Savage and Ribaud, 2013; Läpple *et al.*, 2015). However,
562 the results indicate that traditional and supplementary income farmers who are in one-to-one
563 contact with an agricultural advisor and participate in a discussion group are more likely to
564 have an intention to follow a NMP than their counterparts. This may be because extension can
565 enable farmers to understand the applicability of following a NMP on their particular farm
566 system, dispel myths about the perceived costs of following a NMP and alleviate pressures
567 associated with time constraints by assisting in the development of a NMP (Burton, 2014;
568 Wilson *et al.*, 2018).

569 Policy is an important driver of intention to follow a NMP across all three classes. A number
570 of authors have suggested that nutrient management policy initiatives can have a positive
571 influence on the adoption of farm management practices because farmers will often undertake
572 voluntary action as a means of demonstrating stewardship and protecting themselves from
573 future policy (Savage and Ribaud, 2013; Reimer *et al.*, 2018). However, the results in Table
574 7 show that the magnitude of the effect is the greatest for supplementary income farmers. Policy
575 makers could capitalise on the fact that the majority of farmers in this class are highly educated
576 and relatively younger than farmers in the other classes and design appropriate measures to
577 improve the likelihood that farmers follow their NMP.

578 Overall, the mixed influence of policy on intentions confirms previous findings across the
579 literature which suggest that different groups of farmers often respond in different ways to the
580 same policy (Barnes *et al.* 2011; Buckley, 2012). Further research is required to explore
581 potential reasons for the mixed effects in the context of following a NMP.

582 Increasing social pressure on farmers to follow a NMP is likely to increase the likelihood that
583 they do so across the classes. Barnes *et al.* (2013) suggest increasing the use of catchment
584 management approaches which raise the visibility of individual farmer practices and encourage
585 group sharing of information. This can stimulate an increase in social pressure to adopt given

586 practices. However, whilst there has been a growing emphasis on farmer-to-farmer learning in
587 recent years (Prager and Creaney, 2017; Laforge and McLachlan, 2018), not all farmers will
588 know, trust or even talk with one another and therefore careful targeting of behavioural change
589 strategies is required (Blackstock *et al.*, 2010). Social pressure is often best leveraged by people
590 that farmers trust and these may not be the same for traditional, supplementary income and
591 business-orientated farmers (Blackstock *et al.*, 2010). Further research is required to establish
592 the most effective ways of leveraging social pressure among different groups of farmers in a
593 way that further encourages them to follow a NMP.

594 Ensuring that individuals understand the benefits of a given practice is an important aspect for
595 inducing positive behavioural change (Wilson *et al.*, 2014). Based on the results, convincing
596 farmers classified as traditional and business-orientated of the specific benefits of following a
597 NMP on their particular farm, is likely to increase their intentions towards following a NMP.
598 This effect is linked to an improvement in attitude towards this practice. Demonstration events
599 are a popular and effective method for illustrating the benefits of adopting farm management
600 practices (Prager and Creaney, 2017). However, in line with Wilson *et al.* (2018), we argue
601 that greater opportunities should be presented at such events for farmers to engage in discussion
602 about the costs and benefits of, in this case, following a NMP, and ways to better tailor NMPs
603 to particular farming situations.

604 Motivational theories suggest that an individual is likely to act to solve a problem when they
605 feel they have the ability to act on their values and motivations (Zhang *et al.*, 2016). The results
606 suggest that improving farmers' level of perceived behavioural control over following a NMP
607 is likely to have a positive influence on the likelihood of them following the plan in the future.
608 In line with McDonald *et al.* (2019), we argue that increasing the level of engagement between
609 agricultural advisors and farmers in terms of both developing and assisting farmers to follow a
610 NMP may help to increase perceived levels of control across each class of farmers. However,
611 targeting business-orientated farmers with an intervention to improve perceived behavioural
612 control is likely to have a greater influence on their intentions to follow a NMP. This provides
613 policy makers with a potentially cost-effective strategy for increasing the probability of farmers
614 following a NMP among these classes of farmers.

615 The results also imply that an increase in effort to engage traditional and supplementary income
616 classes of farmers with both one-to-one and group based agricultural extension should be made.
617 This is because increased levels of engagement is likely to have a large impact on the likelihood
618 of these classes of farmers following a NMP in the future (Micha *et al.*, 2018). Supplementary
619 income farmers are also found to be highly receptive to mandatory policy. Therefore, efforts
620 should be made to provide additional information alongside policy requirements to further
621 stimulate farmers to follow their NMP. This information should be tailored to the
622 characteristics of this group of farmers and explains, for instance, how to effectively follow a
623 NMP on their type of farm (Osmond *et al.*, 2015).

624 Finally, a limitation of this study lies in the fact it does not test indirect relationships. Variables
625 such as extension contact and policy, may have an indirect influence on intentions mediated
626 via attitude, subjective norm and perceived behavioural control. One reason why indirect
627 relationships are not considered is due to an issue with sample size once farmers are assigned
628 to distinct groups. Nevertheless, as mentioned previously, this study adopts a similar approach
629 to previous research which focuses on the direct relationships between additional variables and
630 intentions.

631 7. Conclusion

632 NMPs offer a pathway for addressing dual policy interests which aim to encourage farmers to
633 improve or increase production whilst also reducing the risk of nutrient loss to water and air.
634 This paper extends the literature on the development of NMPs by specifically examining
635 farmers' intentions towards following (rather than just developing) a NMP. Moreover, this
636 study also accounts for heterogeneity among farmers and incorporating socio-psychological
637 variables into the analysis. A key result emerging from this study relates to the diversity in the
638 variables which influence the intentions of farmers across the classes. This diversity is likely
639 to be due to the varying composition of the classes in terms of farm and farmer characteristics.
640 This result suggests that we cannot assume that farmers with different characteristics who
641 operate varying types of farms will always respond in the same way to initiatives designed to
642 stimulate them to follow a NMP. Therefore, for policies to effectively encourage farmers to
643 follow a NMP, it is important to target specific groups (Emtage *et al.*, 2007). Overall, the results
644 from this study confirm that farmer typologies are critical for representing diversity in the
645 variables which influence farmers' intentions to follow a NMP. Interventions that are carefully
646 planned and targeted at the different classes of farms/farmers are likely to further encourage
647 farmers to follow a NMP in the future.

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663 Appendix 1

664 **Principal components (PC) with loadings for farmers' intentions to follow a NMP (only**
665 **statements that produced PCs are displayed).**

	PC 1	PC 2	PC3
Survey question	Attitude	Perceived behavioural control	Subjective norm
Following a NMP increases production levels	0.36		
Following a NMP produces higher quality grass and/or crop	0.34		
Following a NMP improves profits	0.34		
Following a NMP decreases input costs	0.30		
Following a NMP saves time	0.31		
Following a NMP improves soil fertility levels	0.32		
Following a NMP improves knowledge about your fields	0.31		
Following a NMP makes fertiliser application decisions easier	0.31		
If I want to follow a NMP, I have a clear understanding of how to do so		0.35	
If I want to follow a NMP, I have access to sufficient information and/or sources to do so		0.33	
If I want to follow a NMP, I have confidence in my ability to do so		0.42	
If I want to follow a NMP, it is under my control to do so		0.48	
If I want to follow a NMP, it depends completely on me and not on the factors permitting or inhibiting me from doing so		0.45	
If I want to follow a NMP, it is easy to do so		0.36	
When it comes to following a NMP, most people whose opinion I value regarding farming think that I must do so			0.53
When it comes to following a NMP, most people whose opinion I value regarding farming encourage me to do so			0.53

When it comes to following a NMP, most people whose opinion I value regarding farming would agree with my decision to do so 0.49

Most farmers I am aware of follow a NMP 0.39

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