

₁ Cultural evolution of football tactics: Strategic social
₂ learning in managers' choice of formation

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5 Abstract

6 In order to solve complex problems or make difficult decisions, people must strategically combine
7 personal information acquired directly from experience (individual learning) and social information
8 copied from others (social learning). The game of football (soccer) provides a wealth of real world
9 data with which to quantify managers' use of personal and social information in selecting team
10 formations. I analyse a 5-year dataset of all games ($n=9127$, 2012-2017) in the five top European
11 leagues (English Premier League, German Bundesliga, Spanish La Liga, French Ligue 1 and Italian
12 Serie A) to quantify the extent to which a manager's initial match formation is guided by their
13 personal past use or success with that formation, or other managers' use or success with that
14 formation. I focus in particular on the use of the 4231 formation, which was the dominant formation
15 at the start of this period but showed a gradual decline in use over time. I find that, as predicted,
16 a manager's choice of whether to use 4231 or not is influenced by both their recent use of 4231
17 (personal information) and the use of 4231 in the entire population of managers in that division
18 (social information). Contrary to expectations, managers appeared to rely more on personal than
19 social information, although this estimate was highly variable across managers and divisions. Serie
20 A managers, in particular, showed a much stronger use of personal information, likely due to the
21 rarity of 4231 in that division. Finally, there did not appear to be an adaptive tradeoff between
22 social and personal information use, with the relative reliance on each failing to predict managerial
23 success.

²⁴ Introduction

²⁵ When solving problems or making decisions, people use a combination of personal information
²⁶ acquired directly from the environment (individual learning), and social information acquired by
²⁷ copying others (social learning)^{1–7}. The strategic combination of individual and social learning is
²⁸ adaptive when decisions or problems are challenging, such as when environments change over time
²⁹ such that social information may become outdated^{2,3,7}, or when solutions are causally opaque or
³⁰ multidimensional, such that they cannot be acquired by individual learning alone and require the
³¹ social learning of accumulated past solutions^{1,2}. People show this strategic mix of individual and
³² social learning in the lab^{8–13} and the real world^{14,15} (although sometimes imperfectly¹⁶). When
³³ combined appropriately, individual and social learning can generate cumulative cultural evolution,
³⁴ where innovations generated via individual learning are preserved and accumulated over generations
³⁵ via social learning¹⁷.

³⁶ Beheim, Thigpen & McElreath¹⁴ provided an innovative demonstration of the strategic use of social
³⁷ and individual learning in the real world. They analysed decades of professional matches of the
³⁸ board game Go to understand the spread of an opening move, the “Fourfour”. This move appeared
³⁹ in 1968 and then increased rapidly in frequency. Beheim et al. showed that Go players’ use of
⁴⁰ Fourfour is predicted by both personal information - the past use and win rate of Fourfour by that
⁴¹ player - and social information - the past use and win rate of Fourfour in the entire population
⁴² of Go players. They also showed considerable between-player variation, with some players using
⁴³ predominantly social information (e.g. Lee Sedol), and others using mostly personal information
⁴⁴ (e.g. Takemiya Masaki, the originator of Fourfour).

⁴⁵ Here I apply the methods and approach of Beheim et al. to another competitive real world sport,
⁴⁶ football (soccer). Football is enjoyed by millions of people worldwide, and European leagues alone
⁴⁷ have a revenue of almost €30 billion¹⁸. Football has been subject to historical analyses of tactics¹⁹
⁴⁸ and increasingly, by providing a wealth of fine-grained quantitative data, statistical analyses²⁰.

⁴⁹ The equivalent in a football match to a Go player’s opening move is a manager’s starting formation.
⁵⁰ This describes how the ten outfield players are initially organised on the pitch. Formations are
⁵¹ typically defined by three or four numbers specifying the number of players in each segment of

52 the pitch. For example, 442 comprises four defenders, four midfielders and two attackers. While
53 formations may change during matches in response to player substitutions or other in-game events,
54 all managers select one of a finite and, in practice, relatively small set of starting formations.
55 Formations are a key component of overall tactics. For example, 541 is more defensive than 343.
56 Historically, formations and tactics have gradually evolved over time, with noticeable long-term
57 trends and short-term cycles¹⁹.

58 The key question addressed here is the extent to which managers use personal and social information
59 to decide on their starting formation. This is a challenging decision, as defined above. The success
60 of a formation depends partly on what formation the opposing manager plays, making payoffs of the
61 same formation temporally variable and frequency dependent. Various other factors, from squad
62 strength to luck, determine match outcomes in addition to formation, making the true contribution
63 of the latter difficult to determine. And in the high stakes of football management (the median
64 tenure of English Premier League managers as of August 2019 was 1 year, 158 days), there are
65 limited opportunities to directly trial formations, especially if those trials are unsuccessful.

66 To maintain tractability and comparability to Beheim et al., I examine a manager's choice of
67 whether to play the 4231 formation or not. 4231 was the dominant formation during the period
68 of study (Figure 1): in the top five European domestic leagues from 2012-2017, it was used 37%
69 of the time, more than double the next most common formations (18% for 433 and 14% for 442).
70 However, 4231 also showed a clear decline in frequency during this period, from 47% in the 2012/13
71 season to 28% in the 2016/17 season. This decline was more extreme in some leagues than others;
72 for example, the Spanish La Liga saw a decline in 4231 use from 78% to 37%.

73 Here I use a 5-year dataset of all games (n=9127, 2012-2017) in the five top European leagues
74 (English Premier League, German Bundesliga, Spanish La Liga, French Ligue 1 and Italian Serie
75 A) to test the following hypotheses, derived from the above theory and the results of Beheim et
76 al.¹⁴. All hypotheses and analyses were preregistered before running any analyses on the original
77 data (<https://osf.io/er4dx>).

- 78 • H1: A manager's choice of whether to play 4231 is determined by a combination of personal
79 and social information.

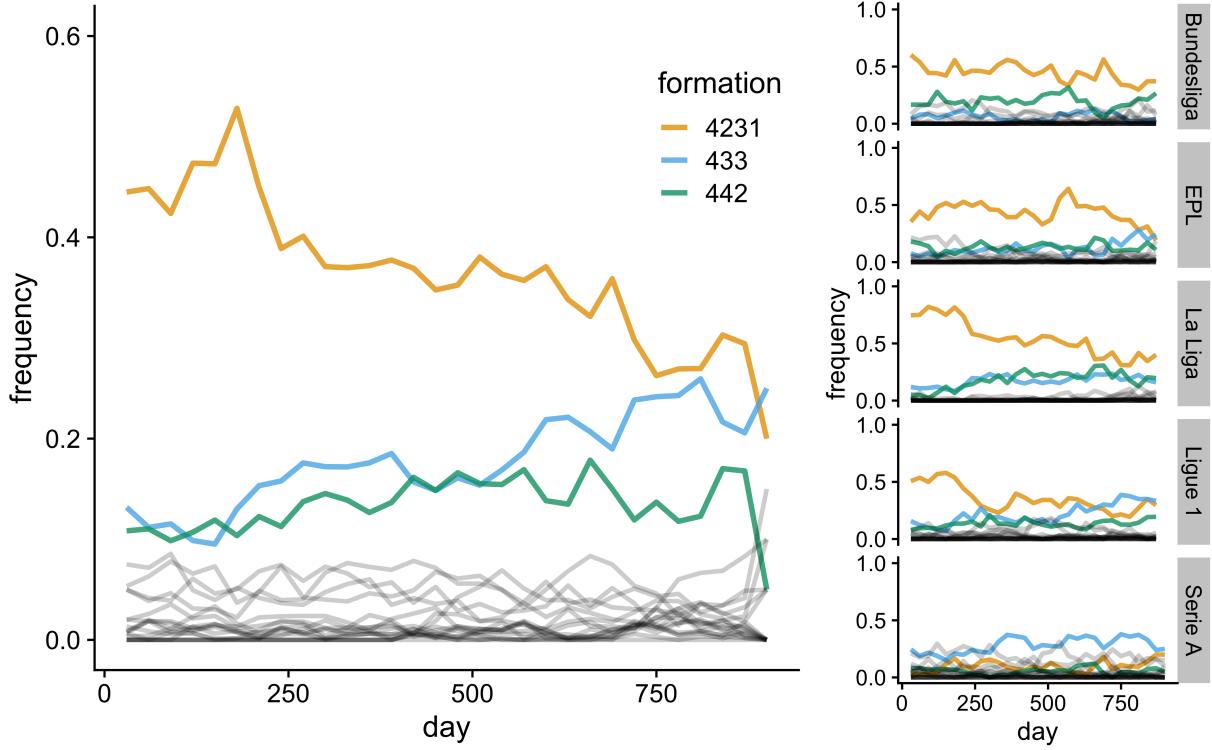


Figure 1: Frequencies of initial formations across all leagues (large image) and in the five separate leagues (right panels). The three most common formations are shown: 4231 (orange), 433 (blue) and 442 (green). Other less common formations are shown in grey. Frequencies are calculated as the proportion of all matches in consecutive 30-day bins that started with that formation. 'Days' are consecutive match days across five seasons from 2012-2017, omitting days on which no matches were played.

- 80 • H2: On average, there is greater reliance on social than personal information, as found by
81 Beheim et al. for Go players.
- 82 • H3: There is more variation between managers in both personal and social information use
83 compared to randomised data.
- 84 • H4: There is an n-shaped relationship between the ratio of population:personal information
85 use and a manager's success, indicating that an overreliance on either form of information is
86 less effective than strategically combining the two.

87 **Methods**

88 **Data**

89 The original dataset was downloaded from the website Kaggle, originally compiled by Jemilu Mo-
90 hammed from various online sources including whoscored.com, dated 6th July 2017 (version 3)
91 and with licence CC0: Public Domain. There are 9127 games in the dataset, which gives 18254
92 starting formations (two per game, one for each team). The downloaded dataset is available as
93 Supplementary Information.

94 Data was preprocessed to correct inconsistent spelling of manager names (e.g. Arsène Wenger and
95 Arsene Wenger were merged, as were Gus Poyet and Gustavo Poyet), add one missing formation
96 and one missing manager, add season indicators using official season start and end dates, and create
97 predictor variables.

98 **Predictors**

99 Following Beheim et al., predictors were created using a moving time window of X days previous
100 to the formation choice in question. That is, for each formation choice, predictors were calculated
101 from all games played in the previous X days, not including the day on which that formation was
102 played. In the analyses reported below $X = 30$, and analyses are repeated in the Supplementary
103 Information using $X = 20$, $X = 40$ and $X = 60$ (these choices were preregistered, and generated

104 qualitatively identical results to those presented below for $X = 30$). The X -day window was reset
105 at the start of each season, so games played in the first X days of each season were not included
106 in the analyses. The Bundesliga, unlike the other leagues, has a mid-season break of more than
107 30 days; this was reduced to 10 days in each season so that all X -day windows yielded prior game
108 data.

109 Personal predictors were (a) personal use of 4231: the proportion of games in the X -day window
110 played by that manager in that division and season in which 4231 was chosen, out of all games
111 played by that manager in that division and season in the X -day window, centred on 0.5; (b)
112 personal 4231 win rate: the proportion of games played with 4231 by that manager in that division
113 and season in the X -day window that were won, centred on the equivalent win rate for games
114 played with a non-4231 formation; (c) the interaction between personal 4231 use and personal 4231
115 win rate; and (d) the interaction between personal 4231 use and the managers' overall win rate
116 with any formation, with the latter centred on the overall win rate of all managers in that division
117 and season.

118 Population predictors were (e) population 4231 use: the proportion of games in the X -day window
119 played in that division and season in which 4231 was chosen, out of all games played in that division
120 and season in the X -day window, centred on 0.5; (f) population 4231 win rate: the proportion of
121 games played with 4231 in that division and season in the X -day window that were won, centred
122 on the equivalent win rate for games played with a non-4231 formation; (g) the interaction between
123 population 4231 use and population 4231 win rate; and (h) the interaction between population
124 4231 use and the managers' overall win rate with any formation, with the latter centred on the
125 overall win rate of all managers in that division and season.

126 Additional predictors were an indicator variable denoting whether the formation was used home
127 or away, and a measure of team strength which was the proportion of games won by that team in
128 that entire season, centred on the mean win rate of all teams in that division in that season.

¹²⁹ **Analyses**

¹³⁰ Bayesian multi-level regression models were run using the rethinking package and book^{21,22}. All
¹³¹ models contained varying effects for manager and division. The null model contained only the
¹³² home/away and team strength predictors. The personal model contained home/away, team strength
¹³³ and the four personal information predictors. The population model contained home/away, team
¹³⁴ strength and the four population information predictors. The full model contained home/away,
¹³⁵ team strength and all eight personal and population variables. In addition to varying intercepts
¹³⁶ for manager and division, the personal model contained varying slopes for personal information use
¹³⁷ and win rate, the population model contained varying slopes for population information use and
¹³⁸ win rate, and the full model had both sets of varying slopes. Full model specifications can be found
¹³⁹ in the Supplementary Information.

¹⁴⁰ **Predictions**

¹⁴¹ Hypotheses H1-H4 specified in the Introduction were tested statistically via the following predic-
¹⁴² tions:

¹⁴³ *H1 predictions:* The full regression model with personal (individual) and population (social) pre-
¹⁴⁴ dictors has better fit to the data than the personal-only model, the population-only model, and the
¹⁴⁵ null model with neither personal nor population predictors. Fit is indicated by model comparison
¹⁴⁶ using WAIC. Additionally, in the full model, there are effects of (a) personal 4231 use, (b) per-
¹⁴⁷ sonal 4231 win rate, (c) population 4231 use and (d) population 4231 win rate, and interactions
¹⁴⁸ between (e) personal 4231 use and win, and between (f) population 4231 use and win rates. Effects
¹⁴⁹ are indicated by the parameter estimates' 89% CI (specifically, 89% percentile interval, see²²) not
¹⁵⁰ including zero in the full model.

¹⁵¹ *H2 prediction:* The ratio of population:personal use, calculated by dividing the estimate for pop-
¹⁵² ulation use in the full model by the estimate for personal use in the full model, is reliably greater
¹⁵³ than one, as indicated by 89% CIs not overlapping one.

¹⁵⁴ *H3 predictions:* The standard deviation of the varying effects for managers' (a) personal 4231 use
¹⁵⁵ and (b) population 4231 use in the best-supported regression model will be larger than the equiv-

Table 1: Model comparison to test hypothesis H1.

	WAIC	pWAIC	dWAIC	weight	SE	dSE
Full model	12273.11	338.30	0.00	1	144.03	NA
Personal model	12346.35	298.20	73.24	0	144.19	15.16
Population model	13547.72	356.86	1274.61	0	137.23	88.05
Null model	14331.91	251.01	2058.79	0	135.11	101.69

156 latent standard deviations in a model generated with dummy data that has randomised formation
 157 and win rates across managers.

158 *H4 prediction:* In a regression model with manager as unit of analysis which contains the managers'
 159 population:personal information use ratio and their personal win rate relative to other managers in
 160 that division and season, the win rate is reliably predicted by the square of the population:personal
 161 use ratio (i.e. a negative coefficient in a quadratic polynomial).

162 Results

163 H1 predictions: combination of population and personal information use

164 As predicted, the full model containing both personal and population predictors was best supported,
 165 containing all of the model weight compared to the personal, population and null models (Table
 166 1). However, the WAIC of the personal model came much closer to the full model WAIC than the
 167 population or null models.

168 Table 2 shows the parameter estimates for the full model. As predicted, there are effects of personal
 169 4231 use, personal 4231 win rate and an interaction between these two predictors. There is also an
 170 effect of population 4231 use. However, there were no reliable effects of population 4231 win rate,
 171 nor interactions between personal 4231 use and personal overall win rate, nor interactions between
 172 population 4231 use and either population 4231 win rate or personal overall win rate.

173 Figure 2 shows how past personal 4231 use (Figure 2A) and population 4231 use (Figure 2B)
 174 increase the probability of 4231 being chosen. The interaction between personal 4231 use and
 175 personal 4231 win rate revealed in Table 2 can be seen in Figure 2A: for managers who have seldom
 176 used 4231 in recent games, a higher win rate with 4231 increases their likelihood of choosing 4231,

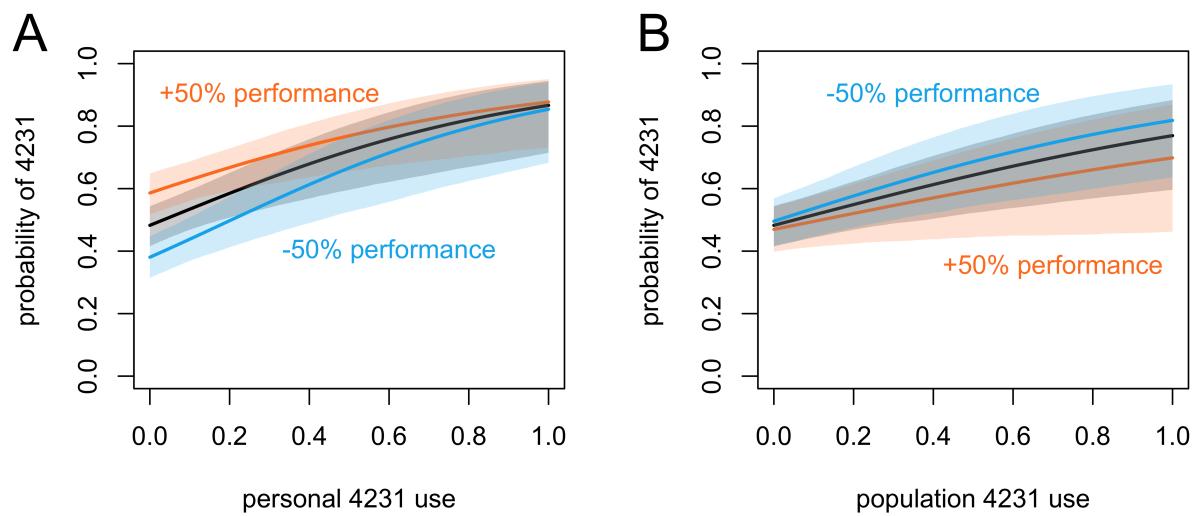


Figure 2: (A) The predicted probability of using 4231 as a function of personal 4231 use, assuming that the 4231 win rate is the same as the non-4231 rate (black line, grey shading showing 89% CI), assuming that the personal 4231 win rate is 50% higher than the non-4231 win rate (orange line and shading), and assuming that the personal 4231 win rate is 50% lower than the non-4231 win rate (blue line and shading). (B) The equivalent predictions for population 4231 use, and +50% or -50% population 4231 win rates relative to non-4231 population win rates.

Table 2: Parameter estimates for the full model. Home/away is an indicator trait with separate estimates for formations used home and away. Varying effects show the standard deviations of the varying intercepts and slopes. See SI for full model specification and priors.

	mean	sd	5.5%	94.5%
Fixed effects:				
Home/away: Home	-0.01	0.17	-0.27	0.24
Home/away: Away	-0.14	0.17	-0.41	0.11
Team strength	0.03	0.27	-0.39	0.46
Personal 4231 use	2.08	0.63	0.96	2.92
Personal 4231 win rate	0.84	0.13	0.63	1.06
Personal 4231 use * personal 4231 win rate	-0.64	0.21	-0.98	-0.30
Personal 4231 use * personal win rate	0.11	0.35	-0.46	0.66
Population 4231 use	1.34	0.48	0.55	2.03
Population 4231 win rate	-0.11	0.20	-0.43	0.22
Population 4231 use * population 4231 win rate	-0.62	0.67	-1.69	0.45
Population 4231 use * personal win rate	-1.07	0.51	-1.87	-0.24
Varying effects:				
Manager	0.71	0.07	0.60	0.83
Manager * personal 4231 use	1.26	0.14	1.04	1.50
Manager * population 4231 win rate	2.00	0.42	1.35	2.67
Division	0.27	0.19	0.05	0.62
Division * personal 4231 use	1.25	0.59	0.57	2.32
Division * population 4231 win rate	0.69	0.53	0.06	1.66

177 and a lower win rate decreases that likelihood. Also consistent with Table 2, Figure 2B reveals
 178 no reliable interaction between population 4231 use and population 4231 win rate, with the higher
 179 and lower performance lines falling within the average performance CI shading.

180 **H2 predictions: ratio of population to personal 4231 use**

181 The ratio of population:personal use, as calculated using the full model (see Table 2), had a mean
 182 of 0.68 (89% CI[0.24, 1.41]). Contrary to hypothesis H2, this suggests that personal information
 183 was more influential than population (i.e. social) information. As indicated by the wide confidence
 184 intervals, however, this estimate was highly uncertain, and there was a lot of variation in this ratio
 185 across managers and divisions.

Table 3: Tests of the differences between varying effects from the real data and varying effects from randomised data, to test hypothesis H3. Values shown are real minus randomised standard deviations.

	mean	sd	5.5%	94.5%
Manager * personal 4231 use	1.07	0.19	0.78	1.37
Manager * population 4231 use	1.78	0.46	1.04	2.48
Division * personal 4231 use	1.16	0.59	0.45	2.24
Division * population 4231 use	0.46	0.58	-0.27	1.47

Table 4: Model estimates for the quadratic regression model with manager as unit of analysis, to test hypothesis H4. Parameter a is the intercept, b1 is the linear coefficient and b2 the quadratic coefficient. Win rate is modelled as normally distributed with standard deviation sigma. See SI for priors.

	mean	sd	5.5%	94.5%
a	0.03	0.14	-0.19	0.26
b1	-0.16	0.18	-0.44	0.11
b2	0.10	0.07	-0.01	0.21
sigma	1.00	0.04	0.94	1.06

186 H3 predictions: variation across managers and divisions

187 Table 3 shows that, as predicted, there was more variation across managers in the effects of both
 188 personal 4231 use and population 4231 use compared to randomised data. Also as predicted, there
 189 was more variation across divisions in the effect of personal 4231 use compared to randomised data,
 190 but not in the effect of population 4231 use.

191 H4 predictions: population to personal use ratio and win rate

192 Contrary to hypothesis H4, there was no n-shaped quadratic relationship between manager win rate
 193 and population:personal information use ratio (Table 4 and Figure 3). There was also no reliable
 194 linear relationship: as shown in Figure 3, for most use ratios the relationship with win rate is flat.
 195 Managers with very high ratios, indicating more reliance on population 4231 use than personal
 196 4231 use, had higher win rates, but the shaded 89% CIs always included zero, and this increase is
 197 likely unduly influenced by the right-most outlier.

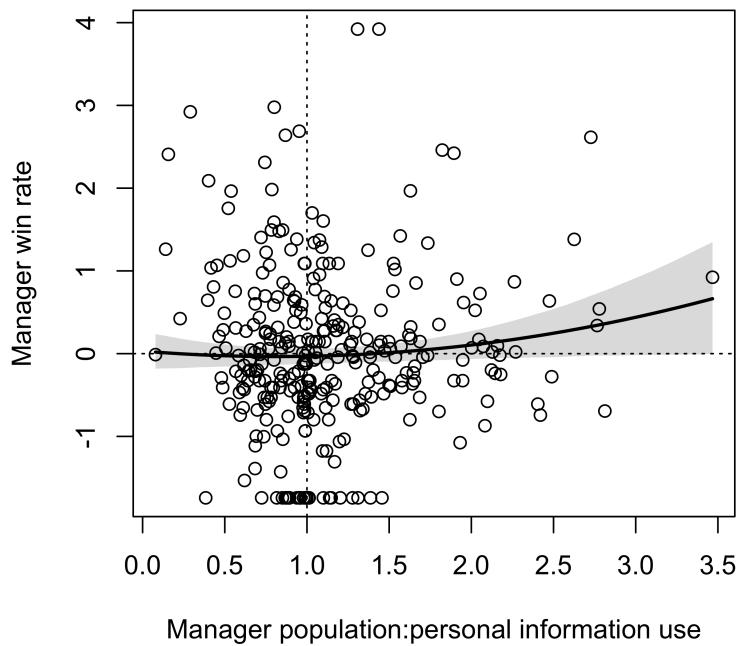


Figure 3: Relationship between each manager's win rate relative to the average manager's win rate and each manager's population:personal information use ratio as generated from the full model. Dotted lines indicated the average win rate and equal ratio. The thick line shows the predicted mean win rate at each value of the ratio, with shaded 89% CIs.

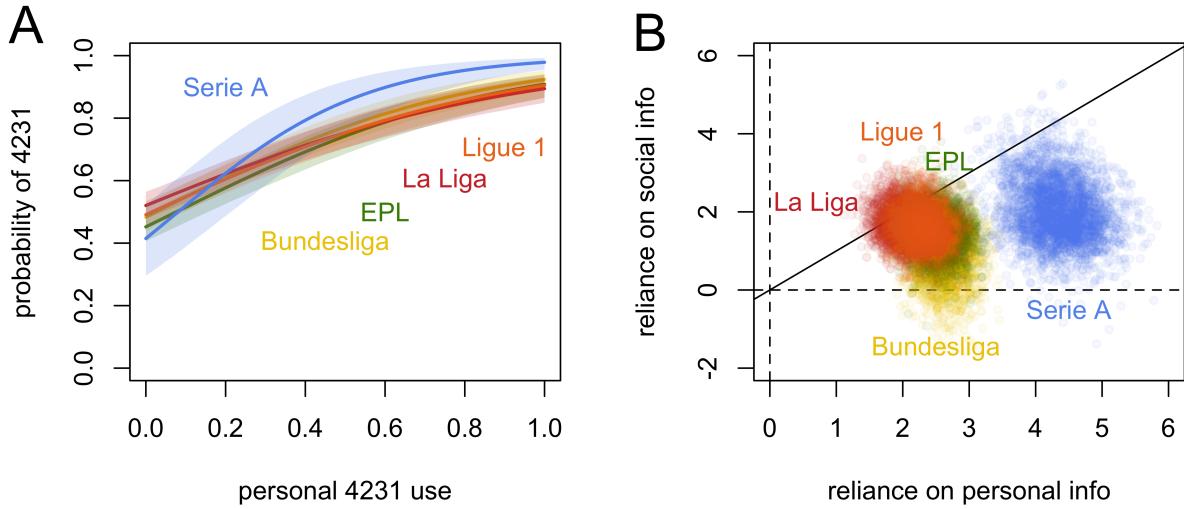


Figure 4: (A) Effect of personal 4231 use on probability of choosing 4231 broken down by division. (B) Joint posterior densities of the relative reliance on personal and social information, for the five divisions. The solid black diagonal indicates equal personal and population influence. EPL = English Premier League.

¹⁹⁸ Exploratory analysis: between division effects

¹⁹⁹ Figure 4 shows the variation across the five divisions in the effect of personal 4231 use. Four of
²⁰⁰ the divisions are almost identical. The Italian Serie A, however, shows a much stronger effect of
²⁰¹ personal information use. This is likely because of the low overall frequency of 4231 in this division,
²⁰² as shown in the Serie A inset in Figure 1. The majority of managers in Serie A never or seldom
²⁰³ used 4231 during this period; out of 67 managers who managed in Serie A, only three used 4231
²⁰⁴ in more than 50% of their games, only ten used it in more than 25% of their games, and 35 never
²⁰⁵ used it. The small number of managers who used 4231 in a majority of their games would have
²⁰⁶ disproportionately influenced the model's predicted probability of subsequently picking 4231 at
²⁰⁷ high values of personal 4231 use, as seen in Figure 4A.

²⁰⁸ Exploratory analysis: between manager effects

²⁰⁹ Figure 5A shows variation across five successful managers who played over 100 games in our study
²¹⁰ period: Antonio Conte (78% win rate, 101 games), Josep Guardiola (74% win rate, 124 games),

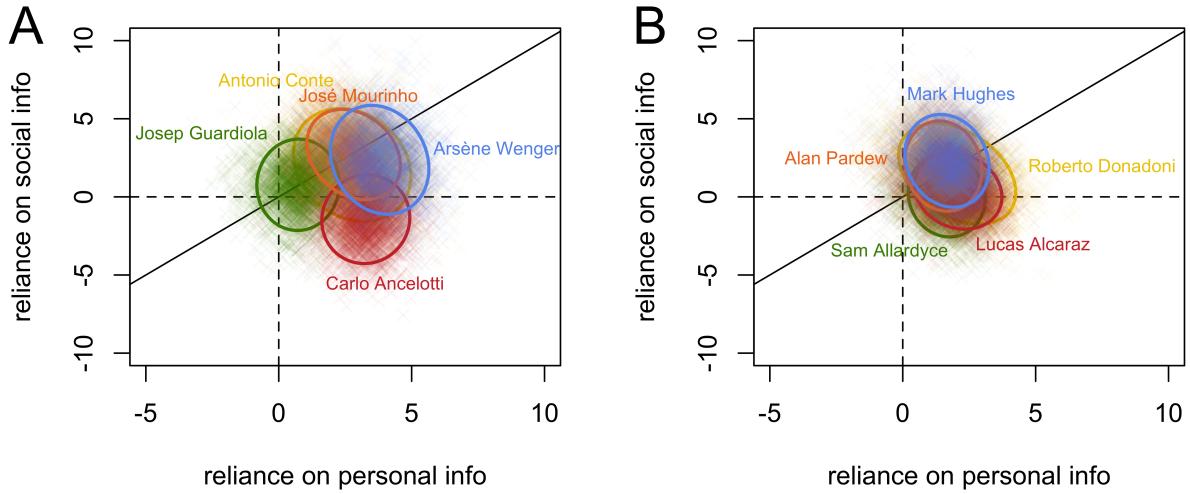


Figure 5: Joint posterior densities of the relative reliance on personal and social information, for (A) five managers with high win rates and (B) five managers with low win rates, all of whom have managed more than 100 games in the period of study. Ellipses indicate the 80% confidence region for each manager. The solid black diagonals indicate equal personal and population influence.

211 Carlo Ancelotti (73%, 131 games), José Mourinho (59% win rate, 149 games) and Arsene Wenger
 212 (59% win rate, 170 games).

213 Figure 5B shows variation across five relatively unsuccessful managers who played over 100 games
 214 in our study period: Roberto Donadoni (30% win rate, 161 games), Sam Allardyce (32% win rate,
 215 151 games), Alan Pardew (34%, 147 games), Lucas Alcaraz (27% win rate, 107 games) and Mark
 216 Hughes (35% win rate, 144 games).

217 While exploratory, we can see in these figures that successful managers seem to be more different
 218 to one another in information use strategies than unsuccessful managers. Carlo Ancelotti has
 219 less reliance on social information than the other successful managers, while Josep Guardiola has
 220 relatively less reliance on personal information. The unsuccessful managers show substantial overlap
 221 with one another over a smaller combined area than the successful managers. Whether this pattern
 222 is robust, and the reasons for it, are worthy of further study. Perhaps there are more ways to be
 223 successful than there are to be unsuccessful in football management.

²²⁴ **Discussion**

²²⁵ Complex decisions often require the strategic combination of personal information acquired via
²²⁶ individual learning and population-wide information acquired via social learning, each of which has
²²⁷ distinct advantages and disadvantages. Beheim et al.¹⁴ analysed decades of games of Go to show
²²⁸ that professional Go players combine personal and social information when deciding on opening
²²⁹ moves, and these individual-level strategic decisions generated long-term evolutionary dynamics.
²³⁰ Here, I applied the same methodological approach to the game of football, where the equivalent to
²³¹ an opening Go move is a manager's choice of starting formation. Consequently, I examined personal
²³² and social influences on a manager's choice of whether to use the most popular 4231 formation or
²³³ not.

²³⁴ Over five seasons from 2012-2017 across the five top European leagues, it is indeed the case (sup-
²³⁵ porting Hypothesis H1) that a manager's choice of whether to play 4231 is on average determined
²³⁶ by both their own recent use of 4231 (personal information) and the frequency within which 4231
²³⁷ is recently used in the entire population of managers from the same league (social information), as
²³⁸ well as the manager's personal win rate with 4231.

²³⁹ Contrary to the more specific prediction (Hypothesis H2) that managers should rely more on
²⁴⁰ social than personal information, given the difficulty of personally trialling different formations in
²⁴¹ the high stakes world of football management and previous findings to that effect by Beheim et
²⁴² al.¹⁴, there was if anything more reliance on personal information. This is puzzling not only for
²⁴³ the aforementioned reasons (the difficulty of individual learning should favour reliance on social
²⁴⁴ learning, plus the previous findings of Beheim et al.), but also the fact that the population provides
²⁴⁵ much more information overall in the same time period: for the 30-day time window used here,
²⁴⁶ a manager using population-wide information can draw on a mean of 76 games played across
²⁴⁷ the entire division, while personal information only provides data from a mean of 3.6 games. The
²⁴⁸ preference for personal information may be evidence for an egocentric bias, with managers weighting
²⁴⁹ their own experience higher than others' experience. Previous lab experiments have found similar
²⁵⁰ over-reliance on individual learning at the expense of social learning^{9,11,13,16,23,24}.

²⁵¹ On the other hand, such estimates of the relative reliance on personal and population information

252 were very uncertain, with confidence intervals so wide as to be consistent with a reliance on either
253 form. This is due to the extensive variation in information use strategy across both managers and
254 divisions, much more than would be expected if decisions were random (Hypothesis H3).

255 However, this variation does not seem to exhibit an adaptive tradeoff (Hypothesis H4): managers
256 with different ratios of population:personal information use did not vary in their success, contrary to
257 the expectation that an overreliance on either type of information should be detrimental. Perhaps
258 in team sports like football, starting formations do not reliably translate into success in the way that
259 opening moves in Go do, given the many other factors that determine success and the possibility
260 of changing formations during a game.

261 Exploratory analyses showed that one league, Serie A, showed a much stronger effect of personal
262 information than the other leagues. This is likely because of the low overall use of 4231 in this
263 league, with very few managers using this formation; this small number of managers drove the
264 effect, given that if a manager used 4231 previously, they were highly likely to be one of the few
265 managers to use it in the future. This illustrates two points: first, the importance of including
266 league (or any other grouping variable) as a varying effect in the analysis, to account for unusual
267 patterns such as this, and second, the influence of overall trait frequency on the learning strategies
268 that are employed. Rare traits may be driven more by personal experience, when a manager is
269 unable to draw on the experience of others.

270 Future analyses might apply more generative models to data such as this, for example reinforce-
271 ment, memory decay or Bayesian updating models to more directly model how managers might
272 be updating their beliefs in response to constantly changing personal and social information. This
273 may necessitate different implementations of the time window. Here this was a fixed X -day time
274 window preceding the formation choice. More advanced models might include all previous games
275 in a season/division, weighted by recency, or even social network ties amongst managers.

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