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Fires and fire risk perception predictors on Finnish farms

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ABSTRACT

The physical and operational farm environment has become more complex, challenging risk management. This study aimed to identify the number and typical features of farm fires and the factors connected to farmers' assessments of fire risk. The data comprised a subset extracted from the national accident database of the Finnish rescue services from 2000 to 2021 (3,989 farm fire alarm calls) and farm survey data collected in the spring of 2021 (506 valid responses). The descriptive analysis of the fire incident data showed that the most typical fire sites on farms were dairy cattle buildings, grain dryers, and heating plants. Most farmers (83.4%) assessed the probability of fire as intermediate or high. The Bayesian machine learning approach used to analyse the survey data suggested the control of malfunctions, failures of machinery and equipment, and educational efforts were key elements in fire risk management.

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Risk management; education; agriculture

Introduction

While the number of Finnish farms has dramatically decreased over the last two decades, the ratio of farm fires to the number of farms has not shown a similar reduction (Figure 1). The farm environment is characterized by many factors that predispose it to fires, such as heat sources, highly flammable and combustible materials, and conditions that embrittle and wear out equipment and installations. Farm fire risk studies have been rare in recent decades (Leppälä, 2016).

Recent studies concerning farm risk management highlight the increasing complexity and diversity of farm risks, emphasizing the need to investigate both multiple sources of risks and how these risks are connected (Leppälä, 2016; Duong et al., 2019; Kaustell, 2020; Komarek et al., 2020). Moreover, the factors that affect farmers' perception of risks should be better understood (Leppälä, 2016; Duong et al., 2019). Risk is usually defined as a product of hazardous event consequences and their probability of occurrence (ISO 31000, 2018). Risk perceptions in various study fields like medical, work accident, psychology or economic risk research are analysing the connection between the degree of risk and people behaviour (Wildavsky and Dake 1990; Wauters et al. 2014). For example, risk preferences measure people's willingness to take a risk based on certain expected utility outcome. However, farmers' risk-taking behaviour differs significantly, if they are risk takers or risk preventers (Hardaker et al. 2004; Myyrä and Liesivaara 2015). In Finland, farm fires are defined as major damages when the damage cost exceeds 200,000 euros (Leppälä et al. 2008; Mero 2011). In this study, we clarify the fire risk perception on Finnish farms.

It is obvious that in complex systems, each phase, from the identification of risks to assessing and managing risks, is becoming more difficult. At the same time, the average profitability of farms has remained low (Luke EconomyDoctor, 2022), and farmers are having difficulties with workload, increased activities and demands (Mattila et al., 2020; Mattila et al., 2022), which may weaken their opportunities to cope with the multiple risks they face.

This study aimed to identify (1) the number and typical features of farm fires and (2) factors connected to the farmers' assessments of fire risk. The results amend current knowledge of farm fires and risk perception, supporting targeted actions to promote fire risk management on farms.

Materials and methods

The analyses in this study used two datasets: (a) Fire incident data to identify the number and typical features of farm fires, and (b) Survey data to assess the factors connected to farmers' assessments of fire risk.

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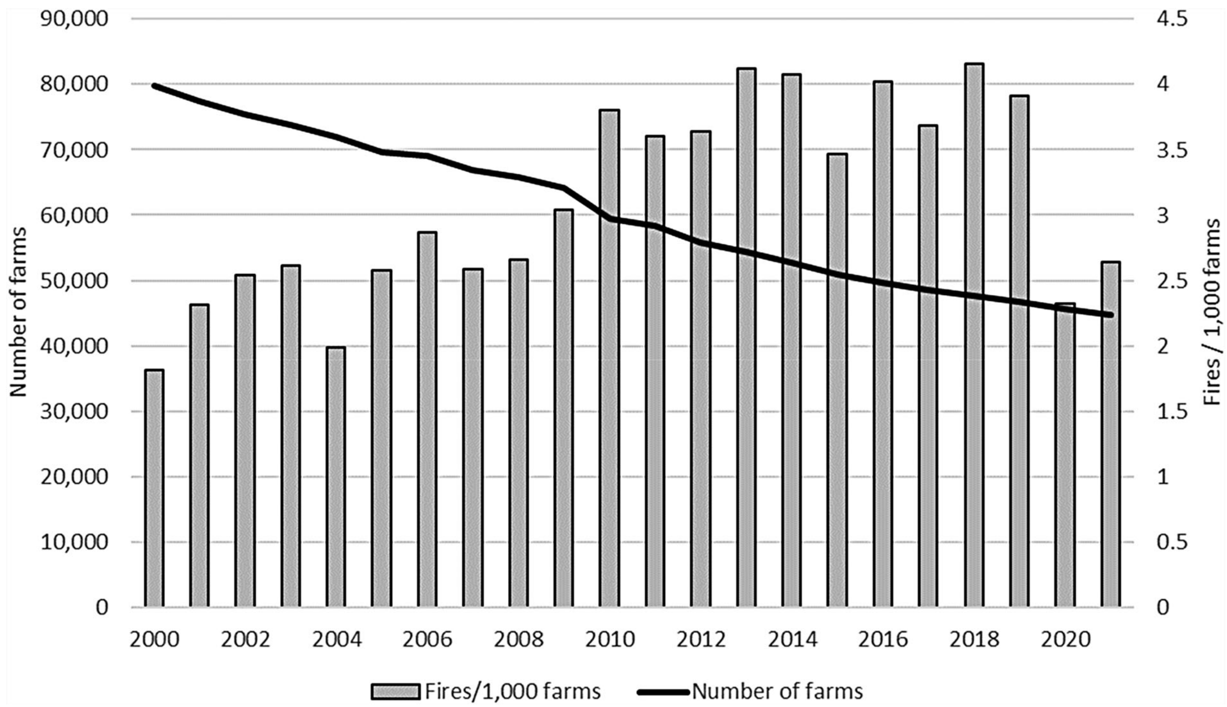

Figure 1. The number of farms and rate of fires per 1,000 farms in Finland 2000–2021. Sources: Luke statistics database, 2022; www.prontonet.fi.

Fire incident data

The fire incident data used in this study is a subset of the national accident database of Finnish rescue services (PRONTO, www.prontonet.fi) from 2000 to 2021 (3,989 farm fire alarm calls). The fire incident data was used to assess the number and characteristics of farm fires. These data comprise all rescue service missions involving a farm production building and a fire on the farm. As the national accident database lacks a separate category for fire missions to farms, the database search was done using building types associated with agricultural production. The involved building types are listed in Table 1. The extracted data may contain cases where the actual fire ignition source was unrelated to the building, e.g. nearby slash burning, but in all cases, the production building had been affected by the fire.

Table 1. Fire sites on farms during 2000–2021 ($N = 3{,}989$).

Building type	*n*	%
Dairy cattle buildings	1,467	37
Other buildings for agri-/horticulture, or fisheries	1,379	35
Heating centrals 9%		
Barns and storage buildings 6%		
Machine sheds and shops 4%		
Other/unidentified 16%		
Grain dryers and storages	757	19
Other buildings for animals	222	6
Greenhouses	99	2
Horse stables	19	0
Buildings for fur animals	17	0
Piggeries	12	0
Buildings for beef	9	0
Buildings for poultry	3	0
Buildings for sheep and goats	2	0
Manure storages	1	0

Frequency analyses and crosstabulations were applied to variables describing the temporal occurrence (year, month, weekday, and hour of detection) of the fire, building type, source of ignition, and causation factors. To further refine the building type category 'Other buildings in agriculture, forestry, and fishery' ($n = 1{,}379$, or 35% of the observations), a phrase search was performed for three variables containing textual information about a 'more explicit description of the ignition location', a 'more explicit description of ignition cause', and a 'description of the development of the accident'. The search phrases comprised wording describing agricultural building types that were not listed in the building classification in the database, such as heating plants, various barns and storage buildings, and machine sheds and shops. The phrase search reduced the building type residual 'Other or unknown' category to 16% of all observed cases (Table 1).

Survey data

The survey data that we used in this study were a subset of a farm survey data ($N = 739$) collected by Natural Resources Institute Finland during the period from April to July 2021. The survey focused on risk assessment and risk management means and practices on farms. The randomized study participant sample acquired from the

Table 2. Descriptions of predictors used in the study.

		Description
Background factors	Farm field area	Total arable land of the farm (own and rented)
	Main production sector	Most significant production line of an agricultural enterprise
	Age of respondent	Age of the farmer at time of response
	Education	Level and farming relatedness of respondent's education
	Full-time farmer	Level of engagement in farming
	Single worker	Besides the respondent, no family members or hired workers are working on the farm
	Farm turnover	Farm turnover in 2020; a measure of economic activity
Composite risk factors	Malfunction of machinery or equipment	Occurrence of failures in the electrical system, in the ventilation system, in the automation systems, or a remarkable farm machinery failure during the last year
	Financial challenges	Occurrence of compromised liquidity or economic risk-taking capacity during the last year
	Work management challenges	Occurrence of work management challenges like lack of labour or problems in the farm relief worker system, in contracting work, in work time planning, or in organizing work and cooperation during the last year
	Challenges to well-being at work	Occurrence of a work injury, occupational disease, excessive physical workload or excessive mental workload during the last year
	Contingency planning	Existence of a written rescue plan and/or risk management plan

register of the Finnish Food Authority consisted of 6,100 farmers with an arable land area of a minimum of 20 ha. The survey was carried out using an online questionnaire, and email reminders were sent out twice. The response rate was 12%.

Among the respondents, grain farms, dairy farms, and farms with other bovine production were overrepresented, compared to their share of all agricultural production sectors in the official statistics (Luke statistics database, 2021). Correspondingly, farms with other than grain production were underrepresented. The mean turnover as well as mean age of the respondents, compared to official statistics (Luke EconomyDoctor, 2021, and Luke statistics database, 2021), was representative.

After excluding incomplete answers and farms whose main production sector was not dairy, other animal production, or plant production, our survey data set consisted of 506 valid observations.

Survey data set variables

In the survey, farmers were asked to assess the probability of a fire on their farm on the scale low–intermediate–high. In the analysis, the variable was dichotomized into two outcome classes for further analysis: low estimated probability ($n = 84$; 16.7%); and intermediate/high probability ($n = 422$; 83.4%). The original 'high' probability class had a frequency of 52 and a share of 8% of all responses. To handle class imbalance, we combined classes 'intermediate probability' and 'high probability'. Furthermore, we wanted to have as interpretable model as possible. In our opinion, a logistic regression model with a binary outcome is much more interpretable than an ordered logit with three outcome classes. This outcome variable is called the 'fire hazard probability' in the text.

Table 3. Potential quantitative predictors.

	Min	Median	Mean	Max
Farm field area, ha	20.1	53.3	70.1	590.9
Age, years	22.0	52.0	49.6	73.0

The potential predictors (Table 2, Table 3, Table 4) originate from either the respondents' background/demographic information or the actual fire hazard survey questions. In addition, five summary predictors were formulated based on responses concerning the probability of other risk types like malfunctioning machinery/equipment, financial difficulties, work management, well-being at work, and contingency planning. The idea behind formulating these summary predictors was to assess whether indicated other risk factors or risk management actions were associated with indications of fire risks. The statistics and frequencies of all potential predictor classes are presented in Table 3 and Table 4.

Table 4. Class frequencies of the potential qualitative predictors. Baseline classes for categorical predictors are in bold.

	Classes	*n*
Main production sector	**Dairy production**	122
	Other animal production	131
	Plant production	253
Education	**Degree in agriculture**	336
	Other degree	137
	No education/only courses	33
Full-time farmer	No	116
	Yes	390
Lone working	No	359
	Yes	147
Farm turnover	**< €100,000**	258
	€100 000–200 000	121
	> €200 000	127
Malfunction of machinery and equipment	**No**	438
	Yes	68
Financial difficulties	**No**	480
	Yes	26
Work management challenges	**No**	475
	Yes	31
Challenges to well-being at work	No	444
	Yes	62
Contingency planning	**0**	255
	1	174
	2	77

Statistical analyses of the survey data

We assumed to have a representative sample of the general population of interest, with the recognized over- and underrepresentation mentioned above. Furthermore, since we aren't aware of any inherent biases caused by self-selection, we didn't make any corrections to the model estimates.

The farmers' assessments of the fire hazard probability were modelled using a machine learning approach with the logistic regression model. A grid search was applied considering each predictor combination, along with age and turnover interaction. For each combination, the data were split into training and validation sets with proportions 0.75 and 0.25 respectively, and the validation accuracy was calculated. The predictor set that maximized the validation accuracy was considered the best predictor set. For the best predictor set, the validation accuracy with error bounds was estimated using out-of-bag bootstrapping with 5,000 iterations. Finally, the assessed probability of a fire on a farm was modelled using a Bayesian logistic regression model with the best predictors.

Results

Fire incident data

The number of farm fires in Finland showed a slightly decreasing trend during 2000–2021, with the two most recent years under this trend. However, the decrease in the number of farms has shown a steeper decline, and the fires per farm ratio has instead increased (Figure 1). The most typical fire sites on farms were dairy cattle buildings, grain dryers and storages, and heating plants (Table 1). By absolute number of fires per year, the number of fires in dairy cattle buildings showed the steepest decrease, whereas the corresponding figure for grain dryers and grain storages roughly doubled. For the rest of the building types, the numbers remained at the same level throughout 2000–2021. The median size of the buildings that caught fire was 231.5 m^2, and 95% of the buildings were smaller than 1,400 m^2.

Most fires happened in August and September ($n =$ 1,019, or 25.5% of all fires). Another concentration of fires occurred in May ($n = 417$ or 10.5% of all fires) (Figure 2). The number of elevated incident fires in August–September was due to the large number of fires associated with grain dryers and storages. The smaller peak of fires in May was associated with both dairy cattle buildings and the combined category of 'other buildings for agri-/horticulture or fisheries.

There was no significant difference in the number of fires between weekdays ($\bar{x} = 570$, SD = 12.9). The times of the fire alarms are shown in Figure 3. Fire alarm times represent an approximation of when the fires started, with an unknown time having passed between the ignition of the fire and when the rescue services were alerted.

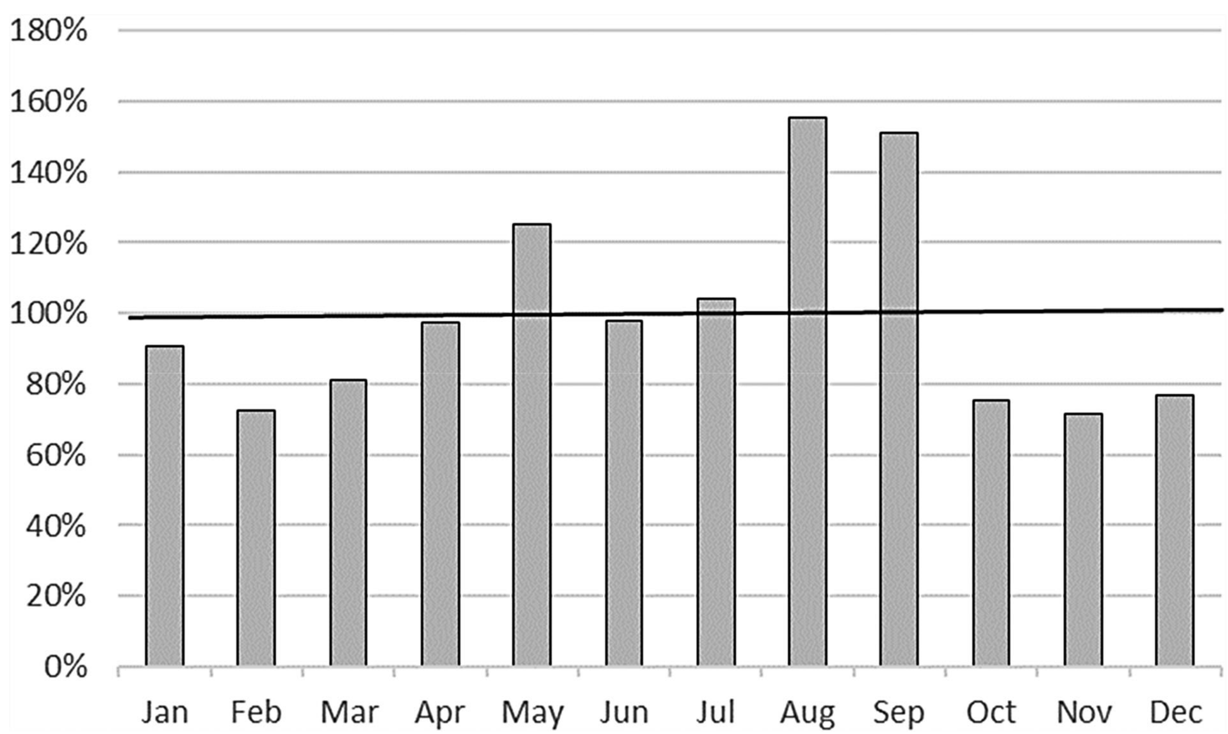

Figure 2. Monthly distribution of number of fires. The 100% line represents the overall mean frequency of alarms per month.

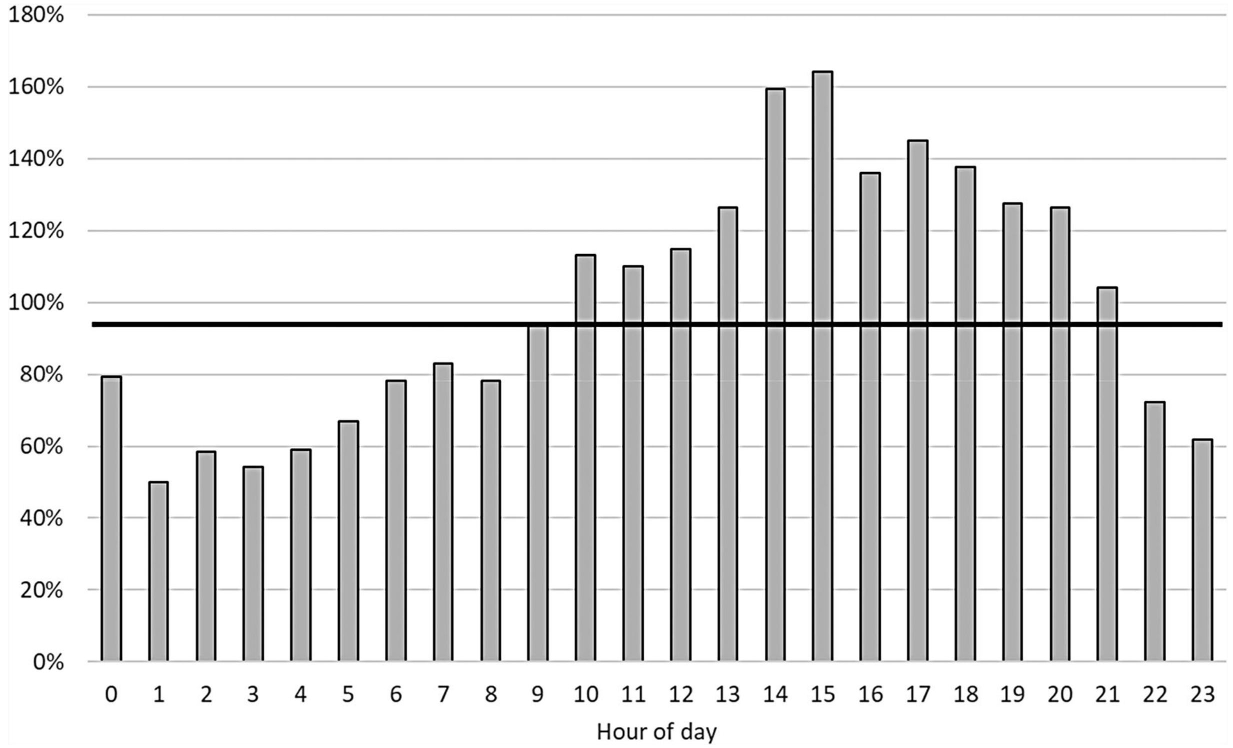

Figure 3. Hourly distribution of fire alarm times. The 100% line represents the overall mean frequency of alarms per hour.

Failures of machinery or equipment (40%) or human activity (21%) were the most typical estimated sources of ignition (Table 5). Of the individual causation factors, the number of cracks in, or escaped hot particles from, chimneys and furnaces increased in absolute numbers during 2000–2021. The number of short-circuits or ground faults in electrical appliances decreased significantly, from an annual 15 cases to less than 5 cases per year. The numbers of other causation factors follow the slightly decreasing trend of all farm fires.

In 1,660, or 41.6% of the cases, it was impossible to assess the cause of ignition. A list of causation factors as assessed by the rescue personnel is presented in Table 6.

A short case description example, extracted from a case in the national accident database, describes a chain of events in a piggery fire caused by an electrical installation:

> A fluorescent lamp attached to the ceiling of the piggery caught fire from a choke coil inside the lamp armature: it heated the lamp so much that dust caught fire on top of the lamp. The lamp was attached to the aluminium cladding, which was melted by the heat, causing the fire to spread to the attic.

This incident was classified under 'Fault in machine or equipment' as the source of ignition and under the 'Other electrical cause' causation factor.

Survey data

Out of 506 valid responses to the survey, 16.7% (84 farmers) assessed the probability of a fire as low, and 83.4% (422 farmers) as intermediate or high. The best predictor set for the fire hazard probability consisted of age, education, full-time, farm turnover, malfunction of machinery or equipment, work

Table 5. Sources of ignition and typical causation.

Source of ignition	*n*	%	Typical (indicated) causation factors
Fault in machine or equipment	1,591	40	Cracks or escaped hot particle from chimney; electrical faults: short-circuits; ground contact etc.; overheating
Human activity	823	21	Matches or other ignition equipment; rubbish burning; smoking; welding, metal grinding or other heat work; fireworks; controlled burning; open fire
Other sources of ignition	559	14	Hot or glowing object; sparks; ash from stoves; chimney fire
Natural phenomena	260	6	Lightning; mechanical spark
Combustible material	66	2	Self-igniting material (e.g. moist peat)
Animal	16	0	Short-circuits caused by damages created by animals (mostly rodents) to electrical insulations
Missing	6	0	
Unknown	668	17	

Table 6. Fire causation factors on farms during 2000–2021 (n = 2,329).

Assessed cause of ignition	n	% of assessed
Sparks from a chimney or furnace	360	15.5
A crack in the chimney or furnace	293	12.6
Short circuit or earth fault in an electrical appliance	184	7.9
Lightning	175	7.5
Hot or glowing object or ash	126	5.4
Overheated process	119	5.1
Other known cause	111	4.8
Match or similar fire-starting device	102	4.4
Welding or flame cutting	90	3.9
Burning of debris	85	3.6
Overheated equipment	80	3.4
Soot fire	71	3.0
Other electrical cause	63	2.7
Insufficient distance from a combustible structure	62	2.7
Cigarette or other tobacco product	62	2.7
Fireworks	49	2.1
Campfire or other open flame	46	2.0
Mechanical spark, shock spark	45	1.9
Loose connection of an electrical appliance	45	1.9
Spark from exhaust pipe or appliance	33	1.4
Other slash and burn	27	1.2
Reignition	25	1.1
Overloading of electrical equipment	20	0.9
Reaction heat / chemical cause (self-ignition)	17	0.7
Heat of abrasion	14	0.6
Candle or similar	11	0.5
Other natural cause	4	0.2
Installation fault in the electrical equipment	3	0.1
Sun	2	0.1
Silvicultural slash and burn	2	0.1
Explosive energy	2	0.1
Spread from another building	1	0.0
Not assessed	1,660	

management challenges, challenges to well-being at work, and contingency planning, without interactions.

The bootstrap accuracy for the final model was 83.1%, with 95% error bounds of 78.6% and 87.2% (lower bound and upper bound respectively) (Table 7). No information rate (the proportion of intermediate/high probability fire hazard farms) was 83.4%. Our model's predictive ability is therefore modest. However, the upper error bound goes well above the no information rate. It is thus possible that the model needed more data to give better results. It is also possible that the model is poor, or that the phenomenon is otherwise difficult to capture in a functional form.

Markov Chain Monte Carlo (MCMC) sampling was applied using a logistic regression model. The logistic regression model can be written as

$$\Lambda^{-1}(\pi) = log_e \frac{\pi}{1-\pi} = logit(\pi) = \beta^T x$$

where $E(y|x) = \pi$ and $\Lambda(z) = 1/(1+e^{-z})$ denotes the cumulative density function of the logistic distribution. Furthermore, y, x, and β denote fire hazard probability, predictors, and the corresponding model parameters respectively. The model has 12 parameters, including the intercept (see Table 8). Each predictor is categorical, except for age.

Table 7. Prediction (bootstrap) accuracy for the final model.

Accuracy (95% confidence interval)	No information rate
83.1% (78.6%; 87.2%)	83.4%

Table 8. Bayesian results.

	Median	2.5% Quant.	97.5% Quant.
(Intercept)	1.49891	0.16775	2.89788
Age	0.00514	−0.01891	0.02877
Education: Other degree	−0.37479	−0.92542	0.193
Education: No education/only courses	−0.77194	−1.59724	0.12686
Full-time farmer: No	0.262296	−0.39524	0.95819
Farm turnover: €100,000–200,000	0.10902	−0.54036	0.78396
Farm turnover: over €200,000	−0.01968	−0.74152	0.71223
Malfunction: Yes	0.803666	−0.0481	1.80222
Work management challenges: yes	−0.0544	−1.10384	1.16783
Challenges to well-being at work: yes	−0.27237	−0.97842	0.49729
Contingency planning: '1'	0.004104	−0.57785	0.60525
Contingency planning '2'	−0.34916	−1.07208	0.40762

The response y follows a Bernoulli distribution with mean π. Uninformative priors were applied for the model parameters: $\beta_i \sim N(0,\ 10^5)$, where β_i denotes the i^{th} parameter ($i = 0, \ldots, 11$). Three separate chains were sampled, and their convergence, autocorrelation, and Raftery-Lewis's diagnostics studied. Based on these diagnostics, 300,000 iterations were drawn. Finally, convergence was achieved, and a sufficiently large effective sample size was used to achieve credible inference regarding the 95% highest density interval (HDI) for each model parameter.

Figure 4 shows the posterior distribution with respect to the malfunction parameter (β_7). The peak of the distribution (mode) is clearly positive, with a value of 0.79.

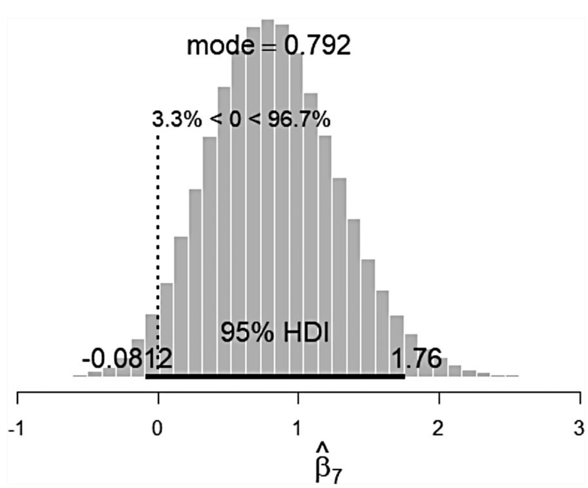

Figure 4. Posterior distribution for malfunction 'Yes' parameter (baseline class: 'No').

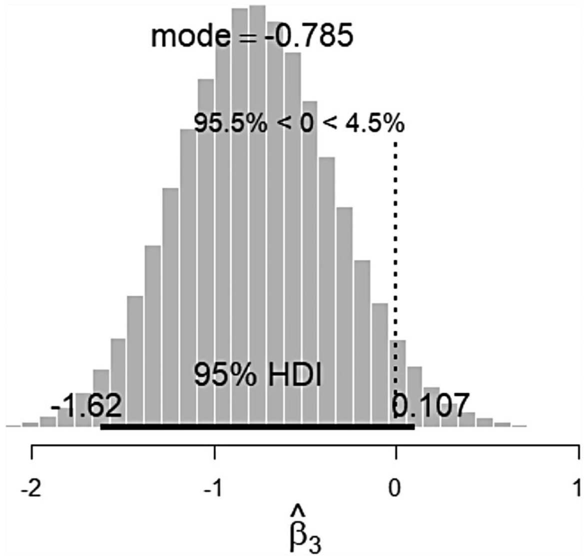

Figure 5. Posterior distribution for education 'no education/only courses' parameter (baseline class: 'degree in agriculture').

There is also a 96.7% probability that the underlying parameter value is above zero. Figure 5 shows the posterior distribution with respect to the education 'no education/only courses' parameter (β_3). The peak of the distribution (mode) is clearly negative, with a value of −0.79. There is also a 95.5% probability that the underlying parameter value is below zero. However, we also note that the 95% HDI includes zero. Thus, based on the posterior distributions, the parameters malfunction of machinery or equipment (class 'yes') and education class 'no education/only courses' are likely to differ significantly from the baselines (see Figure 4 and Figure 5).

The parameters for the malfunction 'yes' and education 'no education' differed from zero with more than a 95% probability. However, no threshold exists above which inferences are certain, and under which inferences are non-existent. The probability has a continuous scale, and it should be treated as such. In this regard, there were also interesting results regarding the other parameters in the model. With respect to the education parameter 'other degree', the mode of the posterior distribution is −0.38, and there is a 90.4% probability that the parameter is under zero (Figure A2 in the appendices). The posterior distribution for the challenges to well-being at work parameter 'no' has a mode value of −0.30, and there is a 76.3% probability that the parameter is below zero (see Figure A7 in the appendices). For contingency planning parameter '2' (i.e. having both a written rescue plan and a risk management plan), the mode of the posterior distribution is −0.37, and there is a 82.1% probability that the parameter is below zero (see Figure A9 in the appendices). For education parameter 'other degree' there is therefore quite high evidence that it differs significantly from its baseline. For contingency planning parameter '2' and challenges to well-being at work parameter 'no', there is some evidence of a difference from their corresponding baselines. However, for the other parameters, there is little evidence of any significant differences from baselines (see Figures A1–A9 in the appendices for the posterior distribution of all the parameters except for malfunction 'yes' and education 'no education').

Figure 6 shows the distribution of fire hazard probabilities for farms with a malfunction of machinery or equipment and no malfunction. The figures were achieved by generating 300,000 samples from the posterior distributions with respect to the model formulations for malfunction and non-malfunction respectively. This was done to obtain a more realistic view of the fire hazard probability instead of using only point estimates. Figure 6 shows that the average fire hazard probability is larger for farms with a malfunction (dark grey bars). However, there is some overlap between the distributions for farms with and without malfunction. This reflects the uncertainty with which we must assess the fire hazard probability for farms with or without a malfunction – the inference related to fire hazard probability is affected not only by the uncertainty of the malfunction parameter but other model parameters. Figure 7 shows correspondingly that the fire hazard probability is larger on average for farms with a degree in agriculture (dark grey bars) than for farms with no education/only courses. However, there is some overlap between the distributions.

The analyses were performed using R software (R Core Team, 2021) and the packages dplyr (Wickham et al., 2021), openxlsx (Schauberger and Walker, 2021), rjags (Plummer, 2021), and tidyverse (Wickham et al., 2019).

Discussion

The ratio of fires in production buildings per 1,000 farms increased between 2000 and 2019, and the absolute number of fires on farms per year also showed a slightly upward trend. In contrast, the number of all building fires in Finland showed a declining trend during 2010–2020 (Nordic fire statistics, 2023).

For the last two years of the observed period (2020 and 2021), the number of annual farm building fires decreased by about 40% compared to the mean of the previous 19 years. The main reason for this sudden decline was based on the fall in the number of grain dryer and storage building fires. Again, these were related to the reduced yield and weather conditions dependent need for drying of the crop.

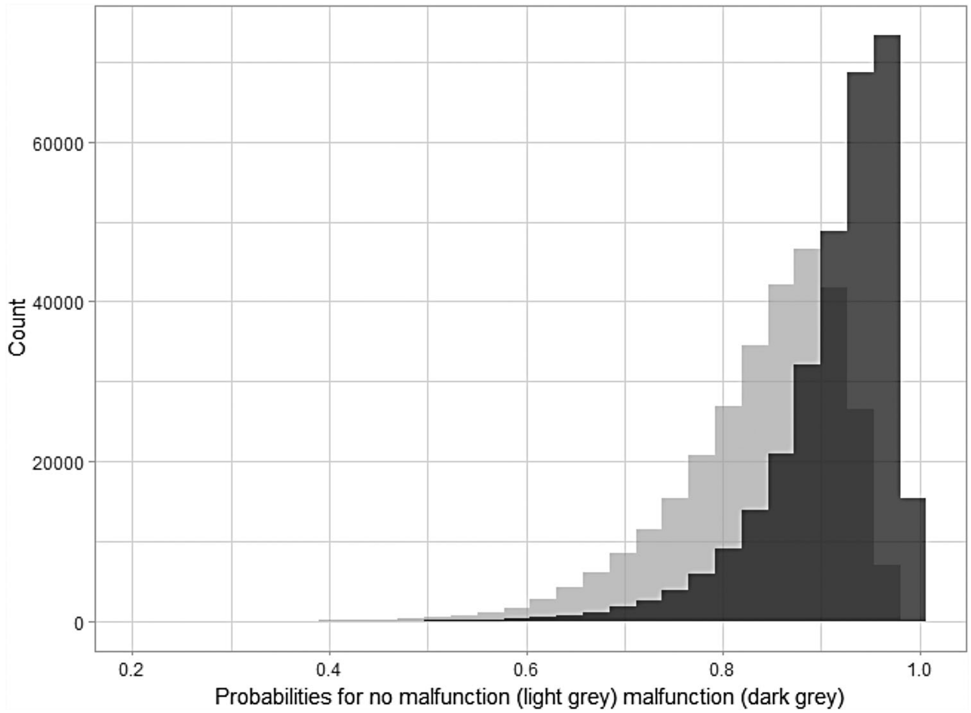

Figure 6. Fire hazard probability based on 300,000 samples from the posterior distribution examined for 'malfunction' (dark grey) and 'no malfunction' (light grey) farms. Other predictor values are set to their mode and median values (age = 52, education = degree in agriculture, turnover = less than EUR 100,000, full-time = yes, work management challenges = no, challenges to well-being at work = no, contingency planning = 0).

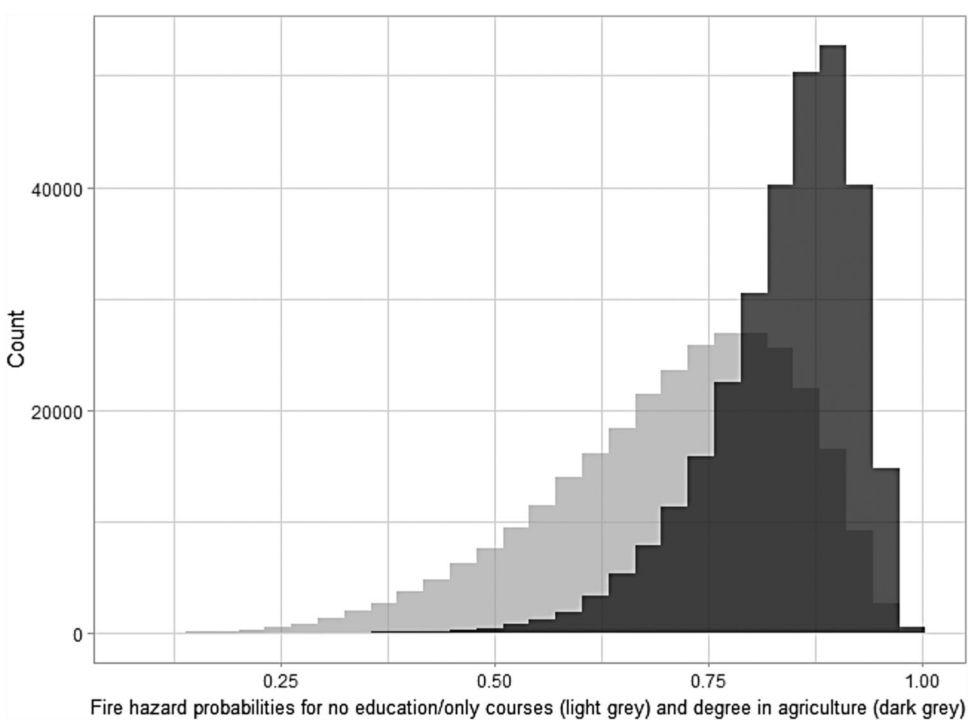

Figure 7. Fire hazard probability based on 300,000 samples from the posterior distribution, examined for 'no education/only courses' and 'degree in agriculture' farms. Other predictor values are set to their mode and median values (age = 52, malfunction = no, farm turnover = less than €100,000, full-time = yes, work management challenges = no, challenges to well-being at work = no, contingency planning = '0').

It is noteworthy that the number of fires used in this study are based on the reporting of actual alarm calls that activated the rescue services. Based on unpublished information by Finance Finland (https://www.finanssiala.fi/en/), Finnish insurance companies compensated on average 3.8 times more fire damage claims on farms during 2010–2020. These claims include all fire damage, including to dwellings and fires that were extinguished without the assistance of the rescue services. This fire burden renders the total fire ignition risk on farms. According to Fasold (2022), the ratio of the number of fire compensation claims by farms to fires requiring the rescue services' intervention is in the same order in Sweden.

Most farm fires are associated with dairy cattle buildings, as well as grain dryers and storages. Grain dryers and storages, generally located under the same roof, mostly catch fire during the drying season in August–September due to faults in their heating systems, overheated processes, or electrical causes. Most other fires are more evenly split between the months throughout the year. A small bump in the fire frequency in May is probably caused by increased activity during the start of the growing season. It is characterized by causation factors such as matches or other ignition equipment, cracks in the chimney or furnace, hot or glowing objects or ash, burning of debris, and campfires or other open flames. Of these causation factors, matches, burning of debris, and campfire may hypothetically be associated with the tradition of burning debris after the long winter. Hot or glowing objects may be associated with welding and other repair and field machinery maintenance work.

Farm production building fires are evenly distributed between weekdays, which is expected due to the nature of their use: e.g. dairy cattle buildings are in use 24/7/365. To some extent, fire detection times, assessed by using rescue services alarm times, reflect general human (an observer or persons working in or around the building) activity. These observations are in line with the observations of Tillander (2004) concerning fires in both residential and industrial buildings and warehouses.

The assessment of the causation and contributory factors of farm fires can be difficult. In the fire incident data used, the assessed cause of ignition was missing in 1,660, or 41.6%, of fires during 2000–2021. This assessment is made in conjunction with the firefighting mission. At a later stage, the authorities and experts working for insurance companies conduct additional investigations. The results of these investigations are not publicly available, but it has been estimated that in about one third of cases, the actual cause of the fire remains undetected.

From a fire prevention perspective, it is also important to assess the fire's contributory factors and to address them in fire safety communication and interventions. Among other factors, they can be found in the short case descriptions included in the national accident database of the Finnish rescue services (PRONTO), using a topical phrase search. This method has been used by Kaustell (2020) to identify contributory factors of occupational injuries. Case studies that include in-depth interviews on farms that have recently experienced fires could further deepen understanding of the human, management, and operational factors that contribute to fires (Kaustell et al., 2011).

According to the survey results, most of the farmers considered a fire to be possible or likely; only 16.7% considered the risk to be low. An increase in average farm size has probably led to the increased number of different facilities per farm, i.e. there are more buildings, machinery, and fuels on larger farms, which may partly explain the number of fires and probabilities remaining high. The results highlight the role of malfunctions and failures of machinery and electrical equipment. According to the rescue services' alarm statistics, these are the largest identified causes of fire. In farmers' risk assessments, the likelihood of fire also appears to be related to the occurrence of the malfunction of machinery or electrical equipment on the farm. This still leaves open the root causes of these failures and malfunctions – whether they are due to the wrong equipment for the farm conditions, do-it-yourself installations, or a lack of maintenance and inspection. Based on the study by Granqvist et al. (2007), these are the main fire accident causes on Finnish farms. Overall, the complexity to be managed and the level of technical expertise required is increasing all the time. New technologies such as robotics, rechargeable tools and equipment, and new energy solutions are becoming more common on farms.

The results also highlighted the importance of agricultural education in identifying and assessing risks. Farmers with no education/only courses assessed the probability of fire as lower than farmers with a degree in agriculture. In other words, trained people are better at identifying risks because of the skills they have acquired through education. This interpretation leaves room for a debate about whether education level and farm type, size, or e.g. mechanization level, are associated.

Previous studies indicate that educational level is related to the risk perception (Duong et al., 2019). For example, Ndamani and Watanabe (2017) reported that educated farmers were more likely to be concerned about the risk of climate change. Deeper fire safety culture expertise was found to be essential for improving fire safety on Finnish farms by Granqvist et al. (2007).

Added to this, improving health and safety literacy, along with farmers ability to obtain and process information, has reduced risks factors and had better results in safety behaviour changes (Mancini et al., 2009; Coman et al., 2020). Interestingly, concerning occupational injuries, a higher educational level seems to be a risk factor (Jadhav et al., 2016). Jadhav et al. (2016) explain that this may be partly because 'farmers with higher education may be able to recall injuries better than those with less education'. However, farmers with higher education may have bigger farms and use more time for agricultural activities, which may lead to more accidents (Leppälä et al., 2013).

The farm survey data were analysed using a Bayesian machine learning approach. A potential model and several risk factors of subjective evaluation of farm fire hazard probability were found. The modelling did not result in a strong view of which factors explained farmers' assessments of the likelihood of a fire, but it suggested interesting associations that could be used both in further studies and when designing preventive actions. In addition to the above discussed malfunctions of machinery and vocational education, contingency planning and well-being at work arose. If a farm had both a written emergency plan and a risk management plan, the estimated likelihood of a fire tended to be lower. If only one (or neither) was in place, no link with the fire risk assessment was found. No convincing statistical significance was found, but this still raises the question of the role of repeated interventions: how often and what kind of interventions should be made to reduce fire risks. Challenges related to well-being at work seem to increase the subjectively assessed fire risk. This is not statistically significant, but the direction is quite clear, and the observation raises the question of whether the role of human resources in risk management has been fully understood and considered in preventive measures. More sensitive measurement and a larger data set could give a better insight into the phenomenon.

Conclusions

The technical causes of fires on farms are quite well investigated and documented by various authorities. Risk management on farms, and specifically fire risk prevention, would benefit from a more in-depth investigation of the contributory (contextual) factors of fires, such as human, organizational, and operational factors. Risk management education for farmers should be promoted. It should focus on treating risks that build up due to insufficient maintenance and on more careful handling of fire and hot work.

Study limitations

The risk concept has traditionally been assessed using two dimensions, probability and the severity of a risk realizing. Many of the respondents to the risk survey only assessed risk probabilities and left the severity assessment unanswered. We therefore opted to use only risk probability as an estimate of the assessed risk.

It can be argued that the survey data is biased due to the respondents being more inclined to contemplate and assess risks – and evaluate risks to be higher – on their farms than the average farmer population. This may have resulted in a narrower sample of the experienced risk spectrum in the farmer population, thus restricting the possibility to reach statistically significant predictors for fire risk probability assessment.

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Appendix

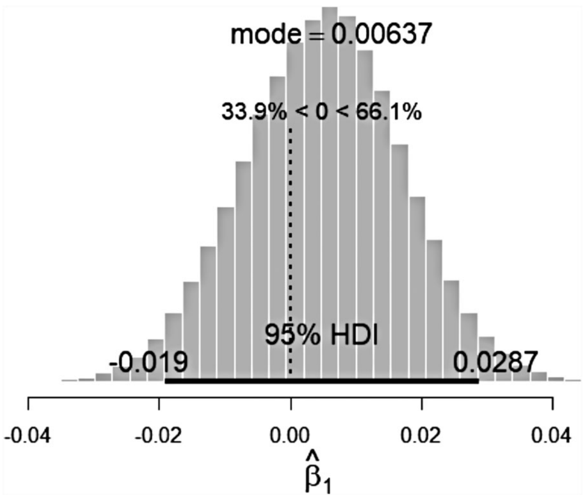

Figure A1. Posterior distribution for *age for respondent* parameter.

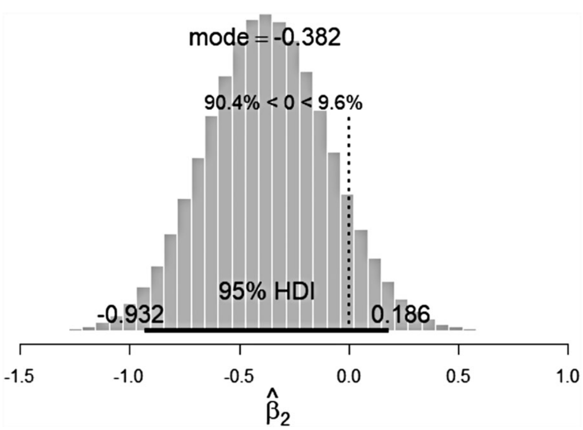

Figure A2. Posterior distribution for education ‘other degree’ parameter (baseline class: ‘degree in agriculture’).

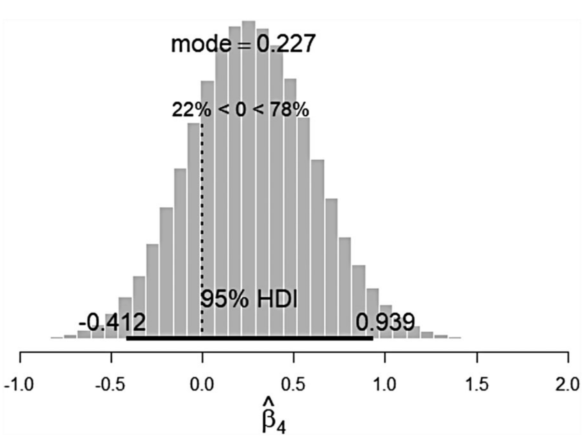

Figure A3. Posterior distribution for *full-time farmer* ‘No’ parameter (baseline class: ‘Yes’).

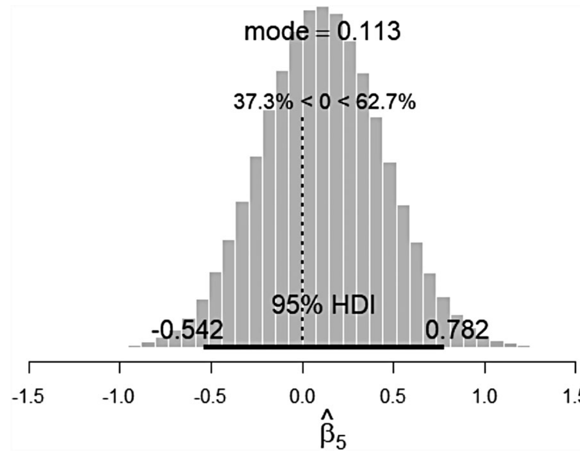

Figure A4. Posterior distribution for *farm turnover* ‘€100 000–200 000’ parameter (baseline class: ‘< €100 000’).

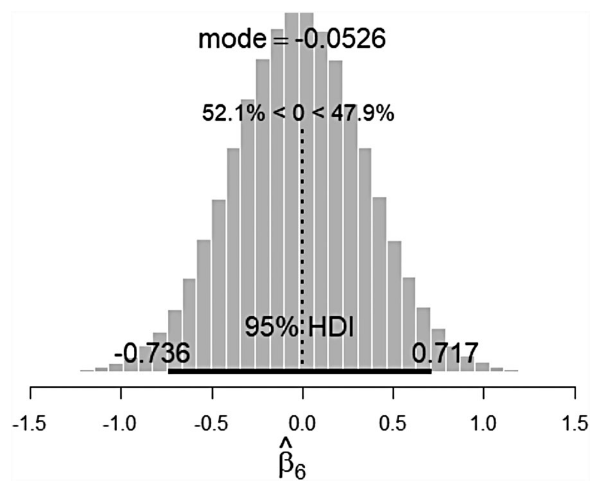

Figure A5. Posterior distribution for *farm turnover* ‘> €200 000’ parameter (baseline class: ‘< €100 000 e’).

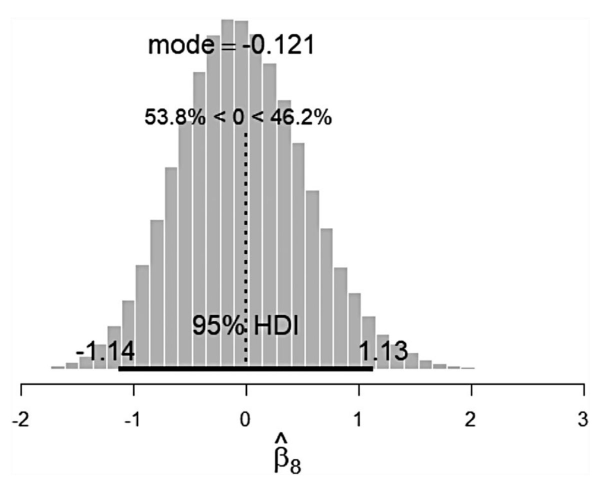

Figure A6. Posterior distribution for *work management challenges* ‘Yes’ parameter (baseline class: ‘No’).

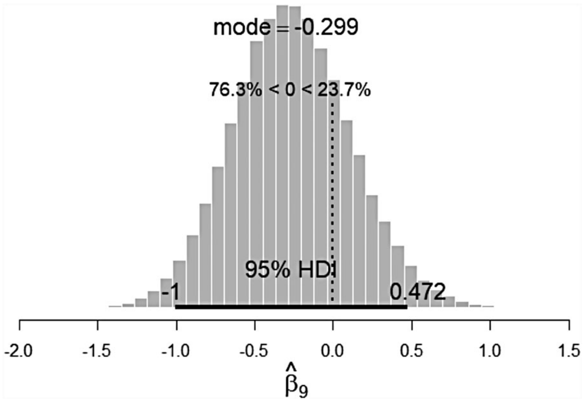

Figure A7. Posterior distribution for *challenges in well-being at work* 'No' parameter (baseline class: 'Yes').

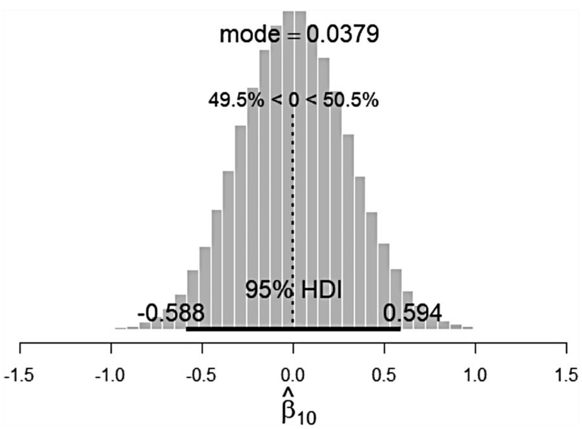

Figure A8. Posterior distribution for *contingency planning* '1' parameter (baseline class: '0').

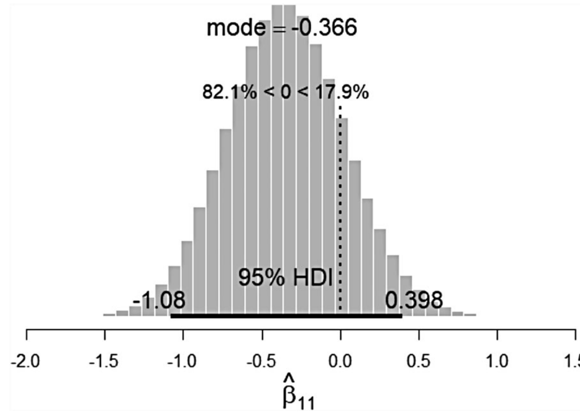

Figure A9. Posterior distribution for *contingency planning* '2' parameter (baseline class: '0').