Food Control 136 (2022) 108872

Contents lists available at ScienceDirect

Food Control

journal homepage: www.elsevier.com/locate/foodcont

Automated food safety early warning system in the dairy supply chain using machine learning

Ningjing Liu, Yamine Bouzembrak, Leonieke M. van den Bulk, Anand Gavai, Lukas J. van den Heuvel, Hans J.P. Marvin *

Wageningen Food Safety Research (WFSR), Akkermaalsbos 2, 67008WB, Wageningen, the Netherlands

ARTICLE INFO

Keywords:
Anomaly detection
Emerging risk
Bayesian network
Dynamic unsupervised anomaly detection
Detrended cross-correlation analysis
Milk safety

ABSTRACT

Traditionally, early warning systems for food safety are based on monitoring targeted food safety hazards. Optimal early warning systems, however, should identify signals that precede the development of a food safety risk. Moreover, such signals could be identified in factors from domains adjacent to the food supply chain, so-called drivers of change and other indicators. In this study, we show for the first time that such drivers and indicators may indeed represent signals that precede the detection of a food safety risk. The dairy supply chain in Europe was used as an application case. Using dynamic unsupervised anomaly detection models, anomalies were detected in indicator data expected by domain experts to impact the development of food safety risks in milk.

Additionally, a Bayesian network was used to identify the chemical food safety hazards in milk associated with an anomaly for the Netherlands.

The results showed that the frequency of anomalies varied per country and indicator. However, all countries showed in the period investigated (2008–2019), anomalies in the indicators "raw milk price" and "barely milk price" and no anomalies in the indicator" income of dairy farms". A cross-correlation analysis of the number of Rapid Alert for Food and Feed (RASFF) notifications and anomalies in indicators revealed significant correlations of many indicators but difference between countries was observed. Interesting, for all countries the cross correlation with indicator "milk price" was significant, albeit the lag time varied from 5 months (United Kingdom) to 22 months (Italy).

This finding suggests that severe changes in domains adjacent to the food supply chain may trigger the development of food safety problems that become visible many months later. Awareness of such relationships will provide the opportunity for food producers or inspectors to take timely measures to prevent food safety problems.

1. Introduction

Food safety, which is enforced by national and international legal requirements, is an important element to consider ensuring a safe and sufficient supply of food. Control and prevention measures are implemented to detect potential food safety risks, including chemical, biological and physical risks. Most of the implemented systems are symptom based (i.e., they check for the presence of a hazard or disease) and should therefore be considered reactive systems (Marvin & Kleter, 2014; Marvin et al., 2009). Such systems consequently detect food safety issues only when these issues have already developed and may pose a risk to human and/or animal health. An analysis of food safety incidents concluded that a wider recognition of the environment in which food is being produced is needed to ensure that a similar incident will not occur in the future (Costa et al., 2017; Kleter & Marvin, 2009; Maeda et al., 2005; Marvin & Kleter, 2014; Marvin et al., 2009). Approaches and procedures towards such proactive systems have been developed, including systems for the early detection of food safety issues or food fraud in (social) media using text mining (Kate et al., 2014) and ontologies (Luijckx et al., 2016; Van de Brug et al., 2014), system approaches to integrate data of impacting drivers of change and food safety monitoring data using Bayesian networks (BNs) (H.J. Marvin & Bouzembrak, 2020a; H.J.P. Marvin & Bouzembrak, 2020b; Marvin et al., 2016, 2020; Bouzembrak & Marvin, 2019), artificial neural networks (ANNs) (Lin et al., 2019), anticipation systems for food safety issues using autoregression-based screening tools (Verhaelen et al., 2018), support

* Corresponding author.
E-mail address: hans.marvin@wur.nl (H.J.P. Marvin).

https://doi.org/10.1016/j.foodcont.2022.108872
Received 17 August 2021; Received in revised form 5 January 2022; Accepted 31 January 2022
Available online 5 February 2022

vector machines (SVMs) (Zhang, 2020), and unsupervised machine learning applied on a media corpus (i.e., the Europe Media Monitor Medical Information System) to rapidly detect specific food fraud incidents in the media (Rortais, Barrucci, Ercolano, Linge, Anna, et al., 2021a, 2021b). Although these systems have shown great potential, successful future warning of food safety risk has been difficult to demonstrate. Recently, the usefulness of anomaly detection to identify risks was demonstrated in various studies (Li et al., 2016; Ryan et al., 2019; Salehi & Rashidi, 2018). Anomaly detection can not only detect the outliers of sample sets but also recognize rare events in nature as preliminary signals of risks (Rembold et al., 2019).

Within a system approach, the food supply chain is considered in its whole environment in which drivers of change and associated indicators, from within and outside the food supply chains, are evaluated for their potential to impact directly or indirectly the development of a food safety risk. Such impacts are very complex since each driver or indicator may act in various places in the supply chain at the same time, interact with each other and may induce multiple types of hazards (microbial, chemical or physical). Drivers of change and indicators are identified by means of expert consultations (Marvin et al., 2020; Marvin and Bouzembrak, 2020a, 2020b), although, generally, the experts have high uncertainty regarding the mode of action or the actual effect (Kendall et al., 2018).

In this study, we aimed to investigate whether anomalies in drivers of change & indicators, which have been selected by domain experts, can be used as an early warning for a future food safety risk. To test this hypothesis, the milk supply chain was selected as an application case because of its economic relevance for the EU, its complexity and the regular finding of food safety hazards in milk as judged by the reporting's in the European Rapid Alert for Food and Feed system (RASFF)[1] (Van Asselt et al., 2017).

As an application case, the milk supply chains of the six largest milk-producing countries in Europe (i.e., Germany, France, the UK, the Netherlands, Italy and Poland) were considered. Milk, as an outstanding nutrient source for various population groups (from infants to the elderly), is one of the most important foods worldwide (Papademas & Bintsis, 2010). In 2018, 683 million tons of milk was produced, 32% of which came from Europe (FAOSTAT, 2020). The dairy supply chain is complex: it involves feed production, raw milk production, processing by dairy companies, etc. (Van Asselt et al., 2017). Food safety hazards can enter various stages and cause food safety issues. For example, during the period of 2010–2019, 627 notifications related to milk and milk products were reported in RASFF. Therefore, it is essential to obtain advance alert signals and take appropriate measures to prevent a crisis.

In this work, we test the above-mentioned hypothesis and demonstrate that anomalies in several drivers of change & indicators identified and selected by domain experts show significant correlations with the number of food safety notifications in RASFF. By means of a dynamic unsupervised anomaly detection (DUAD), anomalies were detected in the data of each indicator, and detrended cross-correlation analysis (DCCA) was used to detect possible time lags between the anomalies in the indicators and the number of liquid milk reports in RASFF. To determine whether hazards can be associated to these anomalies, a Bayesian Network model was developed combining all data of the indicators and food safety reports in liquid milk. Unfortunately, due to data availability only chemical hazards and the Netherlands could be considered in this part of the study. To obtain an early warning system for food safety risks, we integrated the whole working process (i.e., data collection from indicators, data processing, anomaly detection, BN modelling) in a KNIME workflow to allow automatic real-time processing and analysis. The workflow also generates automatic warnings when anomalies are detected including associated food safety hazards.

Because of the observed lag times between this anomaly signal and observed food safety contaminations, risk managers have time to implement preventive actions.

In this study, we show for the first time that an anomaly in specific indicators of the drivers of change, such as milk price, feed price, and average monthly precipitation, can be statistically linked to a food safety hazard reported by monitoring programmes many months later. Furthermore, we predicted the specific type of hazards associated with such anomalies, thereby enabling stakeholders to take preventive actions.

2. Materials and methods

The applied approach consists of five distinct steps, as shown in Fig. 1: (1) identification of the main drivers and indicators of emerging and existing food safety risks in the dairy supply chain for the six largest milk-producing countries in Europe, including the Netherlands, Italy, Germany, France, United Kingdom, and Poland, (2) identification of data sources of the selected indicators, including a quality assessment, (3) creation of KNIME workflows to automatically retrieve, process and integrate the data of the indicators from the data sources, (4) development of an anomaly detection model for each indicator and (5) development of an automated BN model to predict the probability of contamination (on hazard type level) in liquid milk when an anomaly was observed in any of the indicators using the latest data.

2.1. Identification of drivers and indicators of emerging and existing food safety risks

In our research, four drivers of change and associated indicators (39 in total) that have a direct and/or indirect impact on the development of a food safety hazard in the diary supply chain were obtained from two early studies (SANC, 2013; van der Spiegel et al., 2012) and are provided in Supplement 1. An online questionnaire was designed to determine the three most important indicators for each driver. The draft questionnaire was tested for clarity, completeness and completion time by three dairy experts who were not members of the research team. Based on the feedback received, the questionnaire was modified and sent by email to 73 European dairy experts. These experts were senior having broad experience in the dairy supply chain and were identified based on a literature study, web search and consultation with various food safety authorities in Europe. Note that the objective of this step was to obtain the main indicators from the overall list, which then can be used for the further analysis and method development. Hence, the outcome will not represent the complete view of the stakeholders in the milk supply chain in Europe. The final questionnaire is attached in Supplement 1.

2.2. Identification and quality assessment of data sources

The data sources, which represented the selected indicators in step 1, were either provided by experts or found by the authors. All the selected data sources were open source. If multiple data sources represented the same indicator, a quality assessment was performed according to the method described by Rodgers and colleagues (Rodgers et al., 2011). This quality assessment consisted of eight criteria: relevance, accuracy, edition of the data source, timeliness, accessibility, clarity, comparability.

An overall summary of the quality criteria and the related weights and scores can be found in a table in Supplementary 2.

2.3. Data collection and integration in workflows

KNIME workflows were built for each indicator and associated data source to automate the data collection, processing, integration, analysis

[1] https://webgate.ec.europa.eu/rasff-window/portal/?event=SearchForm&cleanSearch=1.

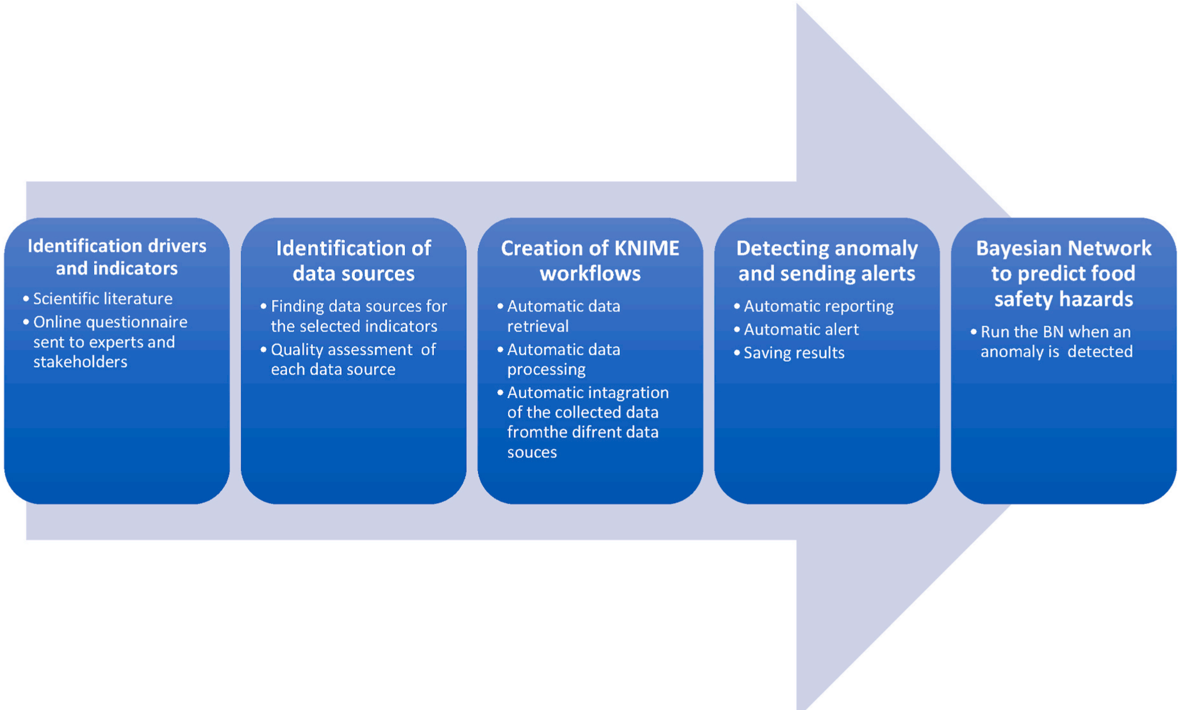


Fig. 1. Discrete steps in the automated food safety early warning system.

and visualization. KNIME[2] is an open-source software for creating data science workflows. It makes data analysis and data workflows reusable and accessible. It enables to model each step of the data analysis, control the flow of data, and ensure the automatic update of the parameters and the models.

Different data retrieving KNIME nodes (e.g., file reader, csv reader, and get request) were used depending on the type of data source (Warr, 2012). For each of the six countries, raw data from different sources were formatted into an integrated dataset X by means of a series of file handling and manipulation nodes to remove irrelevant columns and rows and structure the data indexed by time. Therefore, the series data (X_i^k) of indicator i in country k can be represented by the following formula:

$$X_i^k = \begin{pmatrix} x_{i,1}^k \\ x_{i,2}^k \\ \vdots \\ x_{i,t}^k \end{pmatrix} \tag{1}$$

where $x_{i,t}^k$ is the datum of indicator *i* in country *k* at time point *t*.

In this way, both historical and new data, once available in the data sources, were collected and processed automatically and made available for further analysis in the KNIME workflows. All workflows are available in a GitHub[3] repository.

2.4. Detecting anomalies

2.4.1. Dynamic unsupervised anomaly detection

DUAD models were developed for each indicator to detect anomalies in the collected data (Winters et al., 2014). The DUAD model of indicator *i* was developed as follows:

- A training set Y with the customized time window width (n) and lag interval (l) was constructed.
- An autoregressive model M_i was trained on the training set.
- The standard deviation (σ) of the absolute values of ε ($|\varepsilon|$) was calculated, where the letter E is interpreted to mean the expected value and $|\varepsilon|$ is absolute differences between the values observed and the values predicted by the regression model:

$$\sigma = \sqrt{\frac{1}{m}\sum_{k=1}^{m}(|\varepsilon_k| - E)^2} \tag{2}$$

- The confidential interval (CI) of ‘normality’ was defined with a one-tailed p value ($p = 0.05$):

$$\text{CI} = [0,\ 1.64 * \sigma) \tag{3}$$

- $x_{i,\,t}$ was predicted and the absolute value of the prediction error ($|\varepsilon_t|$) was calculated, where c is a real variable:

$$|\varepsilon_t| = x_{i,\,t} - \left(c + \sum_{k=1}^{n}\varphi_{n-k+1}x_{i,\,t+(k-n-1)*l}\right) \tag{4}$$

- was compared with CI: if $|\varepsilon_t| \notin CI$, an anomaly of indicator *i* at time point *t* was detected.
- $p_{i,t}$ was calculated as the probability of $|\varepsilon_t| \in |\varepsilon|$, which represents the probability of record t of indicator i being normal:

$$p_{i,t} = \frac{1}{\sqrt{2\pi}\sigma}exp\left(-\frac{(x_{i,\,t}-\mu)^2}{2\sigma^2}\right) \tag{5}$$

$$\mu = \frac{1}{t}\sum x_{i,\,t} \tag{6}$$

Seasonal trends should be considered before detecting anomalies; therefore, a seasonality test was conducted on the datasets of monthly or quarterly updated indicators. For the indicators with significant

[2] https://www.knime.com/.
[3] https://github.com/WFSRBigData/Demeter (access can be requested).

seasonality, the DUAD models were trained with the data of the same month for the past ten years, while the models of the indicators without significant seasonality impact were built using data from the past ten months. The DUAD models of all the yearly and quarterly updated indicators were trained with the data from the past three years or quarters.

2.5. Bayesian network model to predict food safety hazards

A BN is a graphical model that presents probabilistic relationships among a set of factors to represent a knowledge under uncertainty, and drawing conclusions based on available information (Cheng et al., 2002).

BNs are suitable for integrating data from several indicators, and such models often have high prediction accuracy for the factor for which they have been optimized (Bouzembrak & Marvin, 2019; Marvin & Bouzembrak, 2020a,b; Marvin et al., 2016). A similar approach was followed in this study using a naïve BN module available in KNIME. The objective was to trigger a BN analysis when an anomaly was observed in any of the indicators using the latest data. In this way, the probability of having contamination in liquid milk above a certain threshold (i.e., LOD) that is associated with this anomaly was obtained.

A BN model was developed using the monitoring data on liquid milk that was available only for the Netherlands. The records related to 'raw milk' performed in the time period of 2005–2018 were extracted from the Quality Program for Agricultural Products database (KAP) (Marvin & Bouzembrak, 2020a, 2020b). KAP database contains the results of the national monitoring program for chemical contaminants in agricultural products in the Netherlands. Hence, microbial contamination in milk is not reported in KAP. It is hosted by the National Institute for Public Health and the Environment (RIVM) in Bilthoven in the Netherlands. Each record contained the following information: reference number, date, product category, product name, hazard, hazard category, concentration, country of origin, country of notification, control point, the corresponding limit of detection (LOD), legislation level, and compliance to legislation.

This data set contains all results of the analytic analysis of liquid milk samples (i.e., positives and negatives) therefore provides an accurate representation of the safety level of liquid milk in the Netherlands. Based on the concentrations of the hazard reported and the LOD, all records were labelled with the corresponding 'risk class': (1) '<LOD' (i.e., hazard concentration was below the LOD); (2) '>LOD' (i.e., hazard concentration was above the LOD). To prepare the input dataset for the BN model, each record of the monitoring dataset was linked with the indicators dataset. Each row in this dataset is considered as a separate case (observation of a liquid milk contamination at a given time). The factors used in the BN model developments are agriculture R&D investment, antibiotic usage, average age of dairy farmers, farm income, feed barley price, feed maize price, feed wheat price, grassland share, machinery installations in dairy farms, milk price, monthly average precipitation, monthly average temperature, the number of patents, total population, urban population and the types of hazard. In the period of 2005–2018, 122299 records were extracted from KAP, of which 5096 records were positive (i.e., LOD >0) and 117203 were negative (i.e., LOD <0). The BN prediction model was trained with 80% of the collected records, which were randomly extracted from the total dataset. The remaining 20% were used to validate the model. In the BN model, the input parameters, including all the identified indicators, were used to predict the levels ('<LOD' or '>LOD') of the related records. The BN model was developed with 'Numeric Binner', 'Naïve Bayes Learner', and 'Naïve Bayes Predictor' from KNIME. Three performance metrics were used to evaluate the BN model performance: accuracy (percentage of records labelled correctly), sensitivity (percentage of '>LOD' records classified correctly) and specificity (percentage of '<LOD' records classified correctly).

2.6. Detrended cross-correlation analysis

The output of the DUAD models were compared with notifications of hazards in milk reported in the European Rapid Alert for Food and Feed (RASFF)[4] database to test whether an anomaly in an indicator can be used as an early warning for a potential food safety risk.

The RASFF online database has been established to support the control and safety of food and animal feed on the European market. It provides food and feed control authorities with an effective tool to exchange information about measures taken responding to serious risks detected in relation to food or feed. The database offers public access to summary information about the notifications most recently transmitted by RASFF Member States (EU-28 national food safety authorities, European Commission, EFSA, ESA, Norway, Liechtenstein, Iceland and Switzerland) as well as the ability to search for information on any notification issued in the past (Bouzembrak & Marvin, 2019).

Notifications in RASFF with the product category of 'milk and milk products and notification country of Germany, France, Italy, the Netherlands, Poland or the United Kingdom from 2005 to 2019 were extracted. Only liquid milk notifications were used, notifications related to different dairy products such as cheese, ice cream and yoghurt were removed from the dataset. The counts of the notifications in each country were summed by month and year. Consequently, for each country, two time series (counts of the notifications per month and per year) were constructed.

A DCCA was conducted to investigate whether there were significant correlations and time lags between the time series of level of anomaly (LA) and the time series of the number of RASFF records per month. Based on the normal probability ($p_{i,t}$) of indicator i at time t from the DUAD model, the level of the anomaly ($LA_{i,t}$) of indicator i (monthly updated) at time t was calculated as:

$$LA_{i,t} = \ln(1 - p_{i,t}) \tag{7}$$

DCCA defines correlation coefficients based on different time lags and time windows. In our case, the time lags refer to the number of months offset between the anomaly level and RASFF notifications, while time windows refer to the number of data points used in each pairwise analysis. For instance, $R_{(lag\ =\ 5,\ window\ =\ 10)} = 0.4$ means that the correlation coefficient between the anomaly levels in months 1–10 and the number of RASFF notifications in months 6–15 is 0.4. To determine when the coefficients are significant, a threshold $R_{0\ (lag,\ window)}$ was calculated using random data by repeating the calculations 500 times and taking the value at the 0.975 quantile. If the correlation $R_{(lag\ =\ I,\ window\ =\ j)}$ is larger than R_0, then the cross-correlation is significant at the specific lag and window. The detailed steps of DCCA can be found in Zebende (2011).

A similar DCCA analysis was performed between the time series of LA and the time series of the number of KAP records above LOD to explore whether there were correlations and time lags between these values. According to on the power test (Cohen, 1977), the data sizes of yearly updated indicators were not adequate; hence, DCCA was applied on monthly updated indicators only.

3. Results and discussion

3.1. Indicator selection and data collection

The questionnaire was sent by email to 73 European dairy experts, 16 completed questionnaires were received (i.e., response rate of 21.9%), of which seven (43.8%) came from experts working in the dairy industry, four (25%) came from public research institutes and three (18.8%) came from academia. The countries of residence of the respondents were the

[4] https://ec.europa.eu/food/safety/rasff_en.

Table 1
Indicators selected by experts and descriptions of related data sources.

Drive	Indicator	Rank	Votes	Data sources	Available countries	Update frequency	Time range	Data format
Economic	Raw milk price	1st	10	EU commodity price dashboard	FR, DE, IT, NL, PL, UK	Monthly	2005–2019	CSV file
	Feed price[a]	2nd	6	EU commodity price dashboard	FR, DE, IT, NL, PL, UK	Monthly	1991–2019	CSV file
	Income of dairy farms	3rd	6	European Statistical Office	FR, DE, IT, NL, PL, UK	Every two years	2005–2016	JSON file
Environmental	Usage of antibiotics	1st	8	Kerkgenootschap der Zevende-dags Adventisten Rapport, UK Veterinary Antibiotic Resistance and Sales Surveillance Report	NL, UK	Yearly	2009–2017	PDF file
	Share of land area used for pasture	2nd	5	Food and Agriculture Organization	FR, DE, IT, NL, PL, UK	Yearly	1992–2015	ZIP file
	Average temperature	3rd	4	Koninklijk Nederlands Meteorologisch Instituut	NL	Monthly	1906–2019	Generic data file
	Average precipitation	3rd	4	Koninklijk Nederlands Meteorologisch Instituut	NL	Monthly	1951–2019	Generic data file
Social	Total population	1st	9	European Statistical Office	FR, DE, IT, NL, PL, UK	Yearly	2000–2018	JSON file
	Average age of dairy farmers	2nd	5	European Statistical Office	FR, DE, IT, NL, PL, UK	Every four years	2005–2013	JSON file
	Urban population	3rd	3	Food and Agriculture Organization	FR, DE, IT, NL, PL, UK	Yearly		ZIP file
Technological	Investment in R&D related to dairy sector	1st	10	European Statistical Office	NL, PL, UK	Quarterly	2015–2019	JSON file
	Level of adoption of technology	2nd	7	European Statistical Office	FR, DE, IT, NL, PL, UK	Yearly	2005–2017	JSON file
	Number of patents related to dairy sector	3rd	4	European Patent Office	FR, DE, IT, NL, PL, UK	Yearly	1980–2019	Linked open data

[a] The 'Feed price' including the feed barley price, feed maize price and feed wheat price.

Netherlands (six respondents, 37.5%), Italy (three respondents, 18.8%), the United Kingdom (three respondents, 18.8%), Germany (two respondents, 12.5%), France (one respondent, 6.3%), and Ireland (one respondent, 6.3%). In literature, response rates between 20 and 25% have been indicated as reasonable scores (Frewer et al., 2011), which may be improved by personalized emails and repeated contacts with the target population (Muñoz-Leiva et al., 2010). Hence, improvement of the response rate may be reached by several actions such as using personal email addresses, involving only experts interested on emerging risks topic.

Feedback was received of respondents from all six main milk producing countries in EU, except Poland. The answers of the respondents will be influenced by their working environment and experience. However, the objective of this step was to obtain the main indicators from the overall list, which then can be used for the further analysis and method development. Hence, the outcome will not represent the complete view of the stakeholders in the milk supply chain in Europe. The impact of drivers and indicators on the dairy supply chain will differ among countries due to differences in economic size, organisation and technology level in the supply chain but it also will vary between the different actors within a country. Hence, the impact is complex but may be addressed adequately using a system approach and artificial intelligence (Marvin & Bouzembrak, 2020a, 2020b).

The three indicators with the highest votes per driver were considered the most important indicators and were included in this study (Table 1). All the results of the completed on-line questionnaires are available in Supplement 1.

As shown in Table 1, for each driver/indicator, the differences between the votes of the first and second indicators were larger than those between the second and third indicators per driver (except for the differences in technological indicators, which were the same). The results suggest that the respondents tended to reach agreement on the most important indicator while remaining divided over the second and third most important indicators.

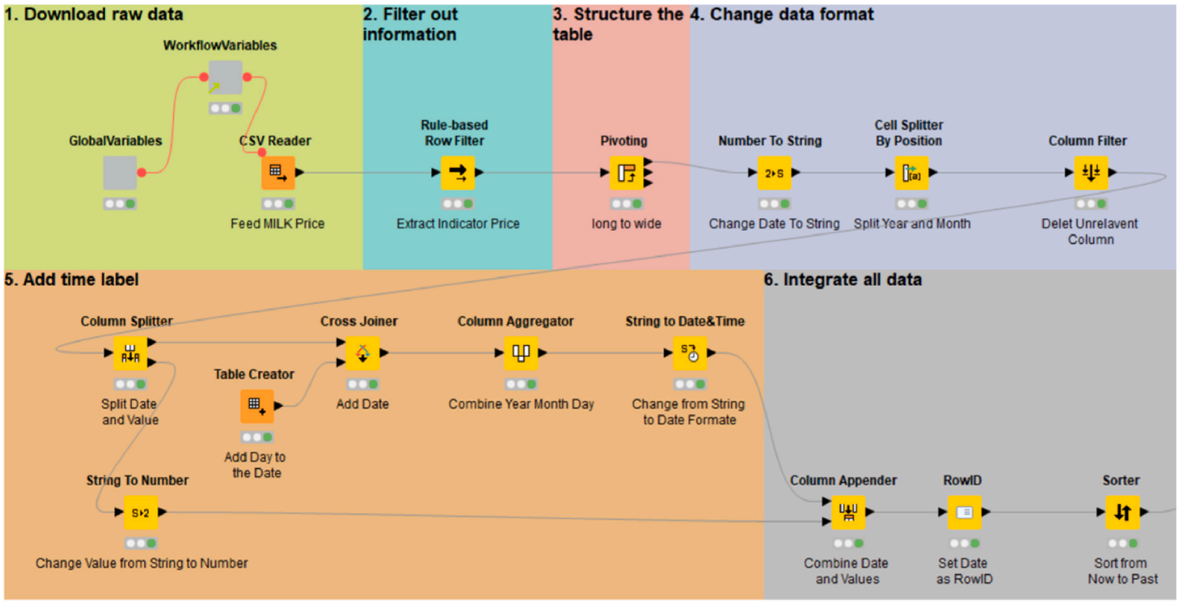
For the driver "economy", the indicator 'raw milk price' ranked highest. Clearly, milk price is related to many aspects such as policy, market demand but also relationships to quality parameters, such as the levels of fat and protein percentages (Dommerholt & Wilmink, 1986), and food safety hazards such as total bacteria counts and aflatoxin M1 have been reported (Hoffmann & Moser, 2017; Lindahl et al., 2018; Popescu & Angel, 2019). Regarding the environmental indicators, 'usage of antibiotics' was the most important indicator. Antibiotics, especially those with a broad antibacterial spectrum, can be applied to treat acute diseases in cows. However, these drugs can be deposited in cows' mammary glands and milk and eventually ingested by humans (Sachi et al., 2019). Most respondents selected 'population' as the most important social indicator of existing and emerging risks in the dairy supply chain. A growing population would result in a higher demand for milk and consequently a demand for more farmland. Competition with other land uses may pose constraints on the dairy supply chain and eventually lead to new or known food safety risks (Huws et al., 2018).

3.2. Identification and quality assessment of data sources

In total, 60 related data sources were identified by the authors and interviewed experts. Among them, 20 were classified as relevant by an expert panel. The total quality of these 20 data sources was scored, and all the relevant data sources received full scores on accuracy, accessibility and clarity but varied in timeliness. The Koninklijk Nederlands Meteorologisch Instituut (KNMI)[5] and European Patent Office (EPO)[6] data sources had the highest timeliness scores, followed by the EU commodity price dashboard. The data sources with the highest total quality scores per indicator are listed in Table 1. Four of the selected data sources were updated monthly, and one was updated quarterly. The update frequencies of the other data sources were equal to or longer than one year. The values of all the indicators except 'usage of antibiotic' could be extracted directly using modules available in KNIME. The data source of 'usage of antibiotic' was a PDF file; therefore, value extraction required additional text mining techniques. Thus, a script was written in R and inserted into the KNIME workflow.

[5] https://www.knmi.nl/over-het-knmi/about.
[6] https://www.epo.org/.

a.



b.

Row ID	S Date	D DE	D FR	D IT	D NL	D PL	D UK
2018-12-01	2018-12-01	36.47	36	37.2	37.25	33.2	32.9
2018-11-01	2018-11-01	37.16	36.73	37.08	37.25	32.85	34.8
2018-10-01	2018-10-01	36.63	36.71	36.81	38	32.57	34.6
2018-09-01	2018-09-01	35.43	35.98	35.44	37	31.6	34.3
2018-08-01	2018-08-01	33.83	34.63	35.26	35.75	30.72	33.09
2018-07-01	2018-07-01	33.19	33.7	35.25	35.75	30.38	31.26
2018-06-01	2018-06-01	32.56	32.63	34.86	34.25	30.4	30.06
2018-05-01	2018-05-01	32.38	32.43	34.89	34	30.69	29.63
2018-04-01	2018-04-01	32.99	32.9	35.24	34.5	31.96	30.51
2018-03-01	2018-03-01	34.21	33.85	35.81	35.5	32.41	31.32
2018-02-01	2018-02-01	34.88	35.04	35.98	35.75	32.95	32.31
2018-01-01	2018-01-01	36.76	35.27	36.57	37.5	34.02	33.35
2017-12-01	2017-12-01	39.96	36.01	38.08	41.5	36.07	34.79
2017-11-01	2017-11-01	40.52	36.4	38.02	41.75	35.8	34.92
2017-10-01	2017-10-01	40.34	36.17	37.68	41.75	34.46	34.52
2017-09-01	2017-09-01	39.39	36.6	37.7	40.5	33.71	32.82
2017-08-01	2017-08-01	37.44	35.11	37.15	38.5	32.57	30.97
2017-07-01	2017-07-01	35.89	34.04	36.78	37.25	31.61	30.53
2017-06-01	2017-06-01	34.38	32.32	36.62	36.75	31.25	29.64
2017-05-01	2017-05-01	33.83	32.43	36.62	36	30.95	30.41
2017-04-01	2017-04-01	33.49	33.61	36.32	36	30.66	30.81
2017-03-01	2017-03-01	33.56	32.61	36.64	36	30.52	30.81
2017-02-01	2017-02-01	33.97	33.26	36.43	35	30.57	31.25
2017-01-01	2017-01-01	34.13	34.23	36.25	34.5	30.21	30.39

Fig. 2. An example workflow of data extraction and processing from the EU commodity price dashboard (a) and the dataset obtained after the integration (b).

Table 2
Anomalies detected per indicator per country for the period of 2008-01-01 to 2019-01-01.

Indicators	Ratio of anomaly records per country					
	DE	FR	IT	NL	PL	UK
Raw milk price	6%	6%	5%	3%	4%	4%
Feed barley price	6%	4%	7%	7%	7%	6%
Feed maize price	7%	4%	4%	15%	9%	–
Feed wheat price	7%	6%		8%	6%	5%
Income of dairy farms	0%	0%	0%	0%	0%	0%
Usage of antibiotics	–	–	–	0%	–	67%
Share of land area used for pasture	0%	0%	0%	0%	13%	0%
Average precipitation	–	–	–	10%	–	–
Average temperature	–	–	–	9%	–	–
Total population	0%	0%	0%	0%	10%	0%
Urban population	0%	0%	0%	0%	0%	0%
Investment in R&D related to dairy sector	0%	20%	29%	0%	25%	0%
Level of adoption of technology	–	–	–	17%	17%	11%
Number of patents related to dairy sector	23%	23%	15%	15%	–	0%

3.3. *Collecting and integrating data automatically via workflows in KNIME*

A KNIME workflow was built for each indicator and data source; in total, 15 KNIME workflows were developed and integrated in one overall KNIME workflow. Fig. 2 presents an example of a workflow of extraction and processing of the milk price and integration of the dataset. As shown in Fig. 2(a), the extraction of the milk price from the EU commodity price dashboard consists of six steps: (1) download raw data; (2) filter out relevant information; (3) structure the data in a table; (4) change the data format; (5) add a time label; and (6) integrate all the data. These six steps were realized by means of a series of KNIME nodes. These steps were repeated for each country, and the results were combined in a single table. The result of this workflow (i.e., a table with milk prices per country per month) is presented in Fig. 2(b).

3.4. *Anomaly detection*

A KNIME workflow for anomaly detection was built for each indicator, which yielded in 15 workflows integrated to the data collection and processing workflows. The DUAD models developed to detect anomalies were integrated in KNIME. A significant seasonal impact was observed only for the indicators 'average temperature' and 'average precipitation' ($P < 0.05$). Therefore, the DUAD models of these two indicators were trained with the data of the same month from the past ten years, while the models of the other monthly updated indicators were trained with the data from the past ten months.

Table 2 shows the detected significant anomalies ($P < 0.05$) for each indicator and country together with their frequency (the ratio of anomalous records to all records). In Table 2, the ratios of anomalous records per indicator show different patterns among different countries. For instance, the ratios of anomalous records of milk price were similar among countries, while the ratios of anomalous records of feed maize price and number of patents differed. Extremely high or low anomaly ratios among some indicators, such as the anomaly ratios of 'average age of farmers' and 'farm income', were due to the limited number of available records. Elsayed (2012) suggested that a small data size would lead to inaccurate reliability prediction when applying multiple regression models. Since the DUAD models built in this study were based on linear regression, the limited observations of some indicators could be the reason for the extreme anomaly ratios.

Anomalies and trends may differ among countries, and to illustrate this possibility, the milk price is shown in Fig. 3. The milk prices in most countries showed a similar trend over the analysis period (2008–2020), showing upward trends from 2009 to 2014 and 2016 to 2020 and downward trends from 2008 to 2009 and 2015 to 2016. Several factors, including general demand, the energy market and various policies, could be responsible for the milk price trends. The considerable decline from 2015 to 2016 was mainly due to the lifting of the milk quota system in Europe, which had been effective since 1984 but was removed in 2015 (Kersting et al., 2016).

3.5. *Bayesian network KNIME workflow*

A BN model was constructed and integrated as a workflow in KNIME to assess the potential risk of finding food safety hazards (contaminations above LOD) in liquid milk in circumstances of anomalies. This workflow was constructed in such a way that when an anomaly is observed in any of the indicators, data are collected from all indicators.

Data of all the indicators were integrated in one table and used by the BN model to predict the levels (above or below LOD) of different hazard groups. Since RASFF database only contains reports on food safety incidents exceeding the legal limit, this database could not be used in this part of the study. However, such data was available from the reference data (KAP) for the Netherlands. Unfortunately, KAP database only contains monitoring data on chemical contamination in milk, which is only a small portion on the food safety issues observed (<5%). To

Table 3
Results of Naïve Bayes prediction model.

	Training set	Validating set
Sensitivity	74%	54%
Specificity	88%	92%
Accuracy	87%	90%

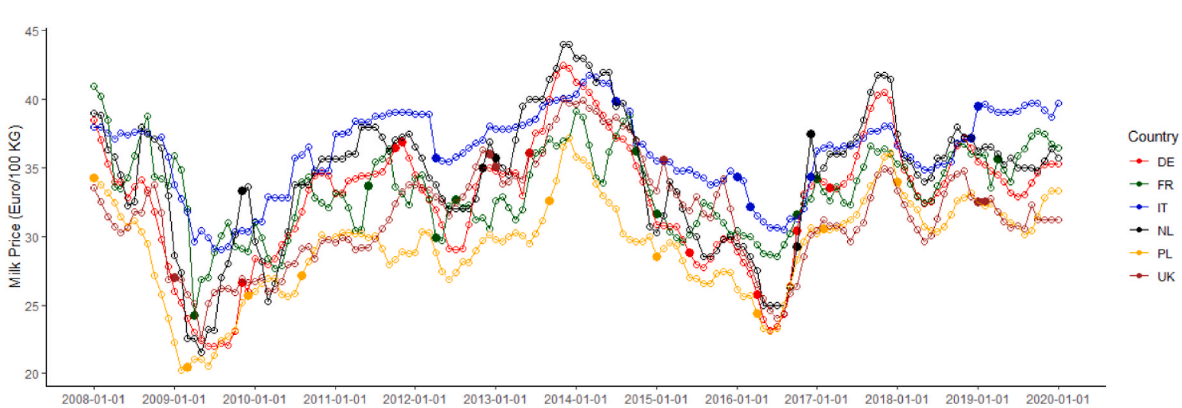


Fig. 3. Milk price and detected anomalies in DE, FR, IT, NL, PL, UK from 2008 to 2019. The month when an anomaly is observed is indicated as a filled circle.

Table 4
Months, in the period 2015–2019, having 1 or more RASFF notifications related to liquid milk for DE, FR, IT, NL, PL and UK.

Year	Month	FR	UK	IT	NL	DE	PL
2015	5	1	0	0	0	0	0
2015	8	1	0	0	0	0	0
2015	10	1	0	0	0	0	0
2016	3	0	0	1	1	0	0
2016	4	0	0	1	1	0	0
2016	5	0	0	1	0	0	0
2017	2	0	0	0	0	1	0
2017	3	1	0	0	1	0	0
2017	8	2	0	0	0	0	0
2017	10	0	0	0	0	1	0
2018	5	2	0	0	0	0	0
2018	8	1	1	0	0	0	0
2018	10	1	0	0	0	0	0
2018	11	0	0	0	1	0	0
2019	2	1	0	0	0	0	0
2019	3	0	0	1	0	0	1

demonstrate the principle of the approach proposed, KAP data was used despite its limitations.

The BN variables, description and a data overview used is presented in Supplement 3. The BN prediction results for the training set and validation set are presented in Table 3. The total accuracy and specificity of the training set and validation set were good (>85%), while the sensitivity of both sets was lower (74% and 54%). The lower sensitivity could be due to the limited number of positive records in the training set (Lee et al., 2015). An insufficient number of positive records ('>LOD') causes the model to place excess emphasis on negative records ('<LOD'), resulting in lower sensitivity. The sensitivity can be improved by using a more balanced dataset. The ROC curves of the training dataset (i.e., AUC is 0.92) and the validation dataset (i.e., AUC is 0.92) (data not shown).

In addition to providing probabilities of finding contaminations, the BN is used to indicate the corresponding hazard category. This information is sent by email to the registered user together with information about the observed anomaly; thus, the user knows what to check for.

3.6. Correlation between anomalous signals and food safety notification

To determine whether anomalies in any of the indicators can be used as an early warning signal for the presence of a food safety risk, a cross-correlation analysis was conducted. To this end, for each month, the number of notifications reported in RASFF (all hazard types including microbial) for liquid milk per country in the period 2015 to 2018 was counted. The months having counts >0 in any of the months investigated are presented in Table 4. Note that for the cross-correlation with anomalies in the indicators also the months with no notification reports are used. Furthermore, only indicators that are update monthly could be included in this analysis due to the limited number of data points in the yearly updated indicators.

A cross-correlation was conducted for all monthly updated indicators and the results are shown in Table 5. Significant correlations were observed for the indicators: milk price, feed maize price, feed wheat price, feed barley price, monthly average temperature, monthly average precipitation, but with varying lag times. Differences are observed between countries but the indicator "milk price" was for all countries significant, albeit the lag time varied from 5 months (United Kingdom) to 22 months (Italy). To illustrate this better, the correlation coefficients (R) between the anomaly level of milk price and the number of reported RASFF notifications related to liquid milk in the related countries are presented in Fig. 4.

A threshold $R_{0\ (lag,\ window)}$ was calculated and presented in Fig. 4 to indicate when the coefficients were significant. The figure shows that significant correlations between milk price anomaly levels and RASFF notification numbers occur in all six countries, with very weak correlations in Poland. Significant cross-correlation occurred under different time lags among the six countries. In the Netherlands and Germany, the highest peak appeared when the time lags were between 10 and 15 months, while in France and Italy, the corresponding time lags were between 20 and 23 months. The time lag with the most significant correlation in the United Kingdoms was five months, the shortest among the six countries.

These results suggest that, especially anomalies in the "milk price", can be used as an early warning for the potential contamination (chemical, microbial) of liquid milk many months later. Especially, time lags of >12 months are useful because then this signal can be considered when governmental organisations are planning the risk-based monitoring programme for the forthcoming year. Due to the low, but significant correlations, such signals should be taken as a (weak) warnings that a food safety risk has a higher chance to occur and may be a trigger for further investigations. Besides, a food safety risk is driven by many factors that are impacting directly and indirectly the food supply chain. Such complexity is not considered in this correlation analysis.

Besides, by linking the anomalies of indicators to hazard categories, as done in the BN model for the Netherlands for chemical contaminations, also the probability of the having a contamination of these hazards above LOD can be predicted at the time of observing an anomality, hence, giving a warning many months before the contamination occurs.

The whole process of data collection, processing, anomaly calculations for all indicators, and BN prediction has been automated in KNIME. In addition to warning about anomalies, the system also informs the user which associated hazard categories are most likely to be the cause of contamination; hence, the system indicates when to look for what factors. The system is fully automated and reflects the situation as it currently is in the market. Making the whole process automatic by implementing it KNIME has many advantages. It saves much time because i) for each data source multiple steps are needed to find, retrieve and process the needed data, and ii) the data then should be structured in a way that the models can consumes, which is a time-consuming activity. It also provides a quality assurance, since it is programmed to collect the newest data of each data source each week and will warn the operators when issues have occurred in this process. The data sources are updated at different frequency (monthly, yearly) at an unknown period of the year, and by programming a frequent data collection it is ensured that the newest data is used to update the anomaly detection models and the BN model continuously and can warn timely. The KNIME

Table 5
Significant correlations between the number of reported milk safety notifications in RASFF and the level of anomaly per indicator per country.

Indicator	RASFF											
	DE		FR		IT		NL		PL		UK	
	Lag	R	Lag	R	Lag	R	Lag	R	Lag	R	Lag	R
Raw milk price	10	0.38	21	0.37	22	0.35	10	0.41	11	0.27	5	0.38
Feed maize price	7	0.48	20	0.42	–	–	4	0.32	7	0.35	–	–
Feed wheat price	19	0.39	10	0.26	–	–	–	–	–	–	13	0.31
Feed barley price	19	0.33	–	–	3	0.36	24	0.34	5	0.46	–	–
Average temperature	13	0.44	–	–	–	–	–	–	–	–	–	–
Average precipitation	9	0.40	–	–	–	–	24	0.28	–	–	–	–

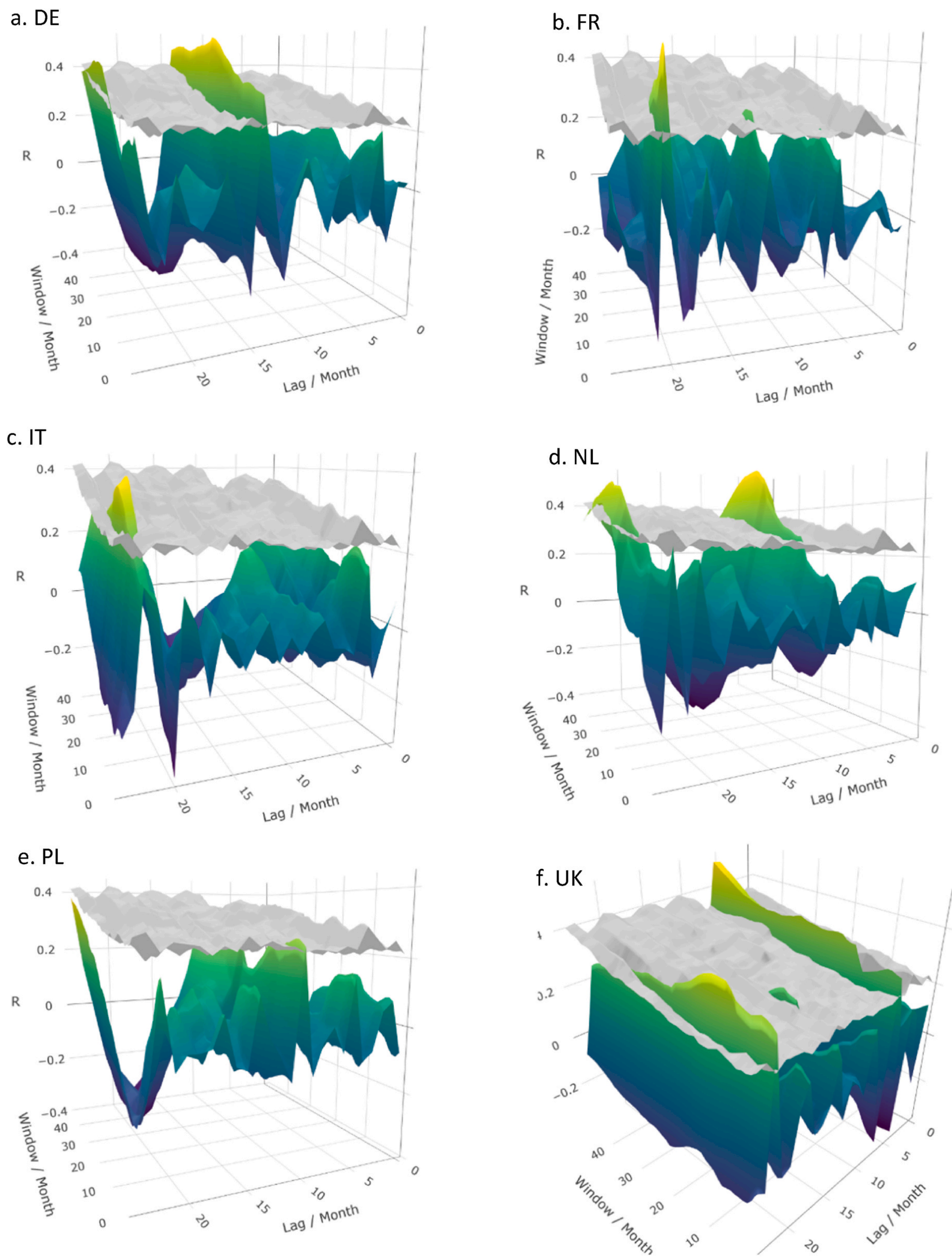


Fig. 4. Cross correlation coefficient with different time lags and windows between RASFF notifications and anomaly levels of milk price in (a) Germany; (b) France; (c) Italy; (d) Netherlands; (e) Poland and (f) United Kingdom. The threshold surfaces are coloured in grey.

workflows will reduce the costs of implementation by stakeholders, since the manual extraction, structuring and integration of these data is time-consuming, and it required expert knowledge to find the related information from the data source.

3.7. The early warning system limitations

The automated early warning system, as developed in this study, shows promising results but has various limitations that may hamper its direct use by authorities.

The complexity of the food supply chain implies an important degree of uncertainty in the food supply chain and sources of these uncertainties may be the environment or originate from the system itself such as the lack of information (Marvin et al., 2019). The indicators selected and data used in this study was derived from expert elicitations (questionnaire) and based on the available publicly available data. The indicators which were selected by experts are uncertain in nature because some information is unobtainable in a long-time horizon (3–5 years). Therefore, it is useful to consider the knowledge of experts about the indicators as a source of uncertainty (Marvin et al., 2019).

The response rates between 20 and 25% have been indicated as reasonable scores in literature which may be improved by personalized emails, repeated contacts with the target population and involving only experts interested on emerging risks topic. In addition, including more experts of different backgrounds may lead to other prioritised indicators. This may be especially valid for the 2nd indicator of each driver, since large agreement was observed for the most import one (Faber & Fonseca, 2014).

In the current research, more significant correlations were observed between the reference data RASFF and economic indicators. One of the main reasons leading to it can be that economic indicators have impact on the import/export volume of the countries, which would further influent the total number of reported notifications. Furthermore, in the current dataset, the availability (i.e., number of data points and time granularity) of more economic might make the correlations more significant. Currently, only publicly available data could be retrieved from the different data sources. It is apparent that the value of the model will increase when more data points of all indicators is available and can be included.

The BN model was trained on records reported in the KAP database, and therefore the model is only applicable for the Netherlands and is limited to chemical hazards. More data sources incorporating global monitoring data such as WHO Global Environmental Monitoring System (GEMS)/Food contaminants database and the European Food Safety Authority (EFSA) data warehouse could improve the system. In addition, several data sources used in the system were only updated annually or having a limited number of data points making their contribution to the system limited. For instance, for the indicators the 'average age of farmers' and 'farm income' only a limited number of records were available. This means there is a need for more frequently (e.g., daily, weekly) updated data sources to see the add value of the automatic system.

Although the automated system would require maintenance in case the structure of any data source will change over time and might even scrape the wrong data without warnings as websites update, requiring an expert intervention to update the system.

4. Conclusion

In this study, we developed an early warning system for a future food safety risk to detect anomalies in drivers of change & indicators, which have been selected by domain experts. The current research developed a KNIME workflow system for six EU countries to monitor data sources of indicators expected to impact food safety in liquid milk. In the period 2008–2019, anomalies were observed in all indicators except in indicator "income of dairy farms". Country variation is apparent, but all countries showed anomalies in the indicators "raw milk price" and "feed barley price". For the Netherlands, the developed system could warn for the present of a chemical hazard in milk above LOD at the time of the occurrence of an anomaly in any of the indicators. It was shown that anomalies may precede the finding/reporting of a food safety hazard, hence allowing timely mitigating measures. The system was built on an open-source workflow platform, which will reduce the costs of implementation by stakeholders (authorities, industries, etc.). The automated early warning system as developed in this study showed promising results but was built on publicly available data. It is expected that performance improvement will be realized when more detailed data (monitoring and indicators) can be used. Therefore, the presented system should be considered as a proof of principle.

We demonstrated that anomalies can be used as an early warning for contamination in liquid milk, and further research is needed to determine to what extent this methodology may be applicable for other food supply chain in other part of the world.

CRediT authorship contribution statement

Ningjing Liu: Conceptualization, Methodology, Writing – review & editing, Writing – original draft. **Yamine Bouzembrak:** Conceptualization, Methodology, Writing – review & editing, Writing – original draft. **Leonieke M. van den Bulk:** Methodology, Writing – review & editing, Visualizsation, Validation, Writing – original draft. **Anand Gavai:** Conceptualization, Methodology, Writing – review & editing, Writing – original draft. **Lukas J. van den Heuvel:** Writing – review & editing. **Hans J.P. Marvin:** Conceptualization, Methodology, Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The research leading to this publication received funding from the Dutch Ministry of Agriculture, Nature and Food Quality (LNV), contract number (WOT-02-002-004-RIKILT-4), and from the European Food Safety Authority (EFSA), contract number GA/EFSA/AFSCO/2016/01-01.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodcont.2022.108872.

References

Bouzembrak, Y., & Marvin, H. J. P. (2019). Impact of drivers of change, including climatic factors, on the occurrence of chemical food safety hazards in fruits and vegetables: A Bayesian network approach. *Food Control, 97*, 67–76.

Cheng, J., Greiner, R., Kelly, J., Bell, D., & Liu, W. (2002). Learning Bayesian networks from data: An information-theory based approach. *Artificial Intelligence, 137*(1), 43–90.

Cohen, J. (1977). CHAPTER 9 - F tests of variance proportions in multiple regression/correlation analysis. In J. Cohen (Ed.), *Statistical power analysis for the behavioral sciences* (pp. 407–453). Academic Press.

Costa, M. C., Goumperis, T., Andersson, W., Badiola, J., Ooms, W., Pongolini, S., Saegerman, C., Jurkovic, M., Tuominen, P., Tsigarida, E., Steinwider, J., Hölzl, C., Mikushinska, N., Gross-Bošković, A., Kanari, P., Christodoulidou, M., Babička, L., Korsgaard, H., Pesonen, S., … Robinson, T. (2017). Risk identification in food safety: Strategy and outcomes of the EFSA emerging risks exchange network (EREN), 2010–2014. *Food Control, 73*, 255–264.

Dommerholt, J., & Wilmink, J. (1986). Optimal selection responses under varying milk prices and margins for milk production. *Livestock Production Science, 14*(2), 109–121.

Elsayed, E. A. (2012). Overview of reliability testing. *IEEE Transactions on Reliability, 61*(2), 282–291.

Faber, J., & Fonseca, L. M. (2014). How sample size influences research outcomes. *Dental press journal of orthodontics, 19*(4), 27–29.

FAOSTAT. (2020). *Livestock Primary*.

Frewer, L. J., Bergmann, K., Brennan, M., Lion, R., Meertens, R., Rowe, G., Siegrist, M., & Vereijken, C. (2011). Consumer response to novel agri-food technologies: Implications for predicting consumer acceptance of emerging food technologies. *Trends in Food Science & Technology, 22*(8), 442–456.

Hoffmann, V., & Moser, C. (2017). You get what you pay for: The link between price and food safety in Kenya. *Agricultural Economics, 48*(4), 449–458.

Huws, S. A., Creevey, C. J., Oyama, L. B., Mizrahi, I., Denman, S. E., Popova, M., Munoz-Tamayo, R., Forano, E., Waters, S. M., Hess, M., Tapio, I., Smidt, H., Krizsan, S. J., Yanez-Ruiz, D. R., Belanche, A., Guan, L., Gruninger, R. J., McAllister, T. A., Newbold, C. J., … Morgavi, D. P. (2018). Addressing global ruminant agricultural challenges through understanding the Rumen microbiome: Past, present, and future. *Frontiers in Microbiology, 9*, 33.

Kate, K., Chaudhari, S., Prapanca, A., & Kalagnanam, J. (2014). FoodSIS: A text mining system to improve the state of food safety in Singapore. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 1709–1718).

Kendall, H., Kaptan, G., Stewart, G., Grainger, M., Kuznesof, S., Naughton, P., Clark, B., Hubbard, C., Raley, M., Marvin, H. J. P., & Frewer, L. J. (2018). Drivers of existing and emerging food safety risks: Expert opinion regarding multiple impacts. *Food Control, 90*, 440–458.

Kersting, S., Hüttel, S., & Odening, M. (2016). Industry dynamics under production constraints — the case of the EU dairy sector. *Economic Modelling, 55*, 135–151.

Kleter, G. A., & Marvin, H. J. (2009). Indicators of emerging hazards and risks to food safety. *Food and Chemical Toxicology, 47*(5), 1022–1039.

Lee, J., Wu, Y., & Kim, H. (2015). Unbalanced data classification using support vector machines with active learning on scleroderma lung disease patterns. *Journal of Applied Statistics, 42*(3), 676–689.

Li, L., Hansman, R. J., Palacios, R., & Welsch, R. (2016). Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring. *Transportation Research Part C: Emerging Technologies, 64*, 45–57.

Lin, X., Cui, S., Han, Y., Geng, Z., & Zhong, Y. (2019). An improved ISM method based on GRA for hierarchical analyzing the influencing factors of food safety. *Food Control, 99*, 48–56.

Lindahl, J. F., Kagera, I. N., & Grace, D. (2018). Aflatoxin M-1 levels in different marketed milk products in Nairobi, Kenya. *Mycotoxin Research, 34*(4), 289–295.

Luijckx, N. B. L., van de Brug, F. J., Leeman, W. R., van der Vossen, J. M., & Cnossen, H. J. (2016). Testing a text mining tool for emerging risk identification. *EFSA Supporting Publications, 13*(12), 1154E.

Maeda, Y., Kurita, N., & Ikeda, S. (2005). An early warning support system for food safety risks. In *Annual conference of the Japanese society for artificial intelligence* (pp. 446–457). Springer.

Marvin, H. J., & Bouzembrak, Y. (2020a). A system approach towards prediction of food safety hazards: Impact of climate and agrichemical use on the occurrence of food safety hazards. *Agricultural Systems, 178*, 102760.

Marvin, H. J. P., & Bouzembrak, Y. (2020b). A system approach towards prediction of food safety hazards: Impact of climate and agrichemical use on the occurrence of food safety hazards. *Agricultural Systems, 178*, 102760.

Marvin, H. J., Bouzembrak, Y., Janssen, E. M., van der Fels-Klerx, H.v., van Asselt, E. D., & Kleter, G. A. (2016). A holistic approach to food safety risks: Food fraud as an example. *Food Research International, 89*, 463–470.

Marvin, H., Bouzembrak, Y., van Asselt, E., Meijer, N., Kleter, G., Lorentzen, G., & Johansen, L.-H. (2019). Applicability of a food chain analysis on aquaculture of Atlantic salmon to identify and monitor vulnerabilities and drivers of change for the identification of emerging risks. *EFSA Supporting Publications, 16*(7), 1619E.

Marvin, H., & Kleter, G. (2014). Public Health measures: Alerts and early warning systems. In *Encyclopedia of food safety* (pp. 50–54). Academic Press.

Marvin, H., Kleter, G., Frewer, L., Cope, S., Wentholt, M., & Rowe, G. (2009). A working procedure for identifying emerging food safety issues at an early stage: Implications for European and international risk management practices. *Food Control, 20*(4), 345–356.

Marvin, H., van Asselt, E., Kleter, G., Meijer, N., Lorentzen, G., Johansen, L.-H., Hannisdal, R., Sele, V., & Bouzembrak, Y. (2020). Expert-driven methodology to assess and predict the effects of drivers of change on vulnerabilities in a food supply chain: Aquaculture of Atlantic salmon in Norway as a showcase. *Trends in Food Science & Technology, 103*, 49–56.

Muñoz-Leiva, F., Sánchez-Fernández, J., Montoro-Ríos, F., & Ibáñez-Zapata, J.Á. (2010). Improving the response rate and quality in Web-based surveys through the personalization and frequency of reminder mailings. *Quality and Quantity, 44*(5), 1037–1052.

Papademas, P., & Bintsis, T. (2010). Food safety management systems (FSMS) in the dairy industry: A review. *International journal of dairy technology, 63*(4), 489–503.

Popescu, A., & Angel, E. (2019). COW raw milk quality and its factors OF influence IN relationship with milk price. *Scientific Papers-Series Management Economic Engineering in Agriculture and Rural Development, 19*(1), 421–440.

Rembold, F., Meroni, M., Urbano, F., Csak, G., Kerdiles, H., Perez-Hoyos, A., Lemoine, G., Leo, O., & Negre, T. (2019). Asap: A new global early warning system to detect anomaly hot spots of agricultural production for food security analysis. *Agricultural Systems, 168*, 247–257.

Rodgers, C. J., Roque, A., & López, M. M. (2011). Dataquest: Inventory of data sources relevant for the identification of emerging diseases in the European aquaculture population. *EFSA Supporting Publications, 8*(1), 90E–n/a.

Rortais, A., Barrucci, F., Ercolano, V., Linge, J., Anna, C., Cravedi, J.-P., Garcia-Matas, R., Claude, S., & Svečnjak, L. (2021a). A topic model approach to identify and track emerging risks from beeswax adulteration in the media. *Food Control, 119*, 107435, 2021.

Rortais, A., Barrucci, F., Ercolano, V., Linge, J., Christodoulidou, A., Cravedi, J.-P., Garcia-Matas, R., Saegerman, C., & Svečnjak, L. (2021b). A topic model approach to identify and track emerging risks from beeswax adulteration in the media. *Food Control, 119*, 107435.

Ryan, C., Murphy, F., & Mullins, M. (2019). Semiautonomous vehicle risk analysis: A telematics-based anomaly detection approach. *Risk Analysis, 39*(5), 1125–1140.

Sachi, S., Ferdous, J., Sikder, M. H., & Azizul Karim Hussani, S. M. (2019). Antibiotic residues in milk: Past, present, and future. *Journal of advanced veterinary and animal research, 6*(3), 315–332.

Salehi, M., & Rashidi, L. (2018). A survey on anomaly detection in evolving data: [with application to forest fire risk prediction]. *ACM SIGKDD Explorations Newsletter, 20*(1), 13–23.

SANC. (2013). *Scoping study: Delivering on EU food safety and nutrition in 2050–Scenarios of future change and policy responses*. European Commission.

van der Spiegel, M., van der Fels-Klerx, H. J., & Marvin, H. J. P. (2012). Effects of climate change on food safety hazards in the dairy production chain. *Food Research International, 46*(1), 201–208.

Van Asselt, E., van der Fels-Klerx, H., Marvin, H., Van Bokhorst-van de Veen, H., & Groot, M. N. (2017). Overview of food safety hazards in the European dairy supply chain. *Comprehensive Reviews in Food Science and Food Safety, 16*(1), 59–75.

Van de Brug, F., Luijckx, N. L., Cnossen, H., & Houben, G. (2014). Early signals for emerging food safety risks: From past cases to future identification. *Food Control, 39*, 75–86.

Verhaelen, K., Bauer, A., Günther, F., Müller, B., Nist, M., Ülker Celik, B., Weidner, C., Küchenhoff, H., & Wallner, P. (2018). Anticipation of food safety and fraud issues: ISAR - a new screening tool to monitor food prices and commodity flows. *Food Control, 94*, 93–101.

Warr, W. A. (2012). Scientific workflow systems: Pipeline pilot and KNIME. *Journal of Computer-Aided Molecular Design, 26*(7), 801–804.

Winters, P., Adae, I., & Silipo, R. (2014). Anomaly detection in predictive maintenance. In *Anomaly detection with time series analysis* (pp. 3–9). KNIME.

Zhang, Y. (2020). Food safety risk intelligence early warning based on support vector machine. *Journal Of Intelligent & Fuzzy Systems(Preprint)*, 1–13.