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Emerging risk identification in the food chain – A systematic procedure and data analytical options

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ABSTRACT

Systematic screening for risks emerging in the food chain is essential for the protection of consumer health, however, timely identification of risks is not a trivial task because of the data and information gaps. By creating automated or semi-automated algorithms, a large amount of information can be pre-processed which helps experts to filter for the actual emerging risks that need further assessment. The present study gives an overview on the possible data analytical approaches that can be used for emerging risk screening and presents a practically applicable process management system. By using these methods, 58 emerging risks classified into 10 topics have been identified in 2020 and 2021 with the focus on Hungary and the European Union. The main goal is to aid authorities and industry in preparedness and timely acting to avoid or mitigate future risks. Experiences and limitations of the system and future directions are also presented.

1. Introduction

Based on the definition of Regulation (EU) 2017/625, a hazard can be any agent or condition with the potential to have an adverse effect on human, animal or plant health, animal welfare or the environment, and a risk is understood as the function of the probability of an adverse effect and of the severity of that effect, consequential to a hazard (EU, 2017).

But what are *emerging* risks? According to the definition of European Food Safety Authority (EFSA), an emerging risk is 'a risk resulting from a newly identified hazard to which a significant exposure may occur, or from an unexpected new or increased significant exposure and/or susceptibility to a known hazard' (EFSA, 2007) and an emerging issue as 'an issue that has been very recently identified and merits further investigation to determine whether it meets the requirements of an emerging risk' (EFSA, 2011).

The goal of emerging risk identification in the food chain is complex. Besides protecting human, animal, and plant health, it provides input for strategic planning and analysis, decision making processes, sampling and control plans, risk assessments and risk management measures. By timely identification of emerging risks, there is a possibility to execute the necessary risk mitigation actions and thereby preventing the evolvement of the risk.

Identification of emerging risks in the food chain is a relatively new and evolving scientific area as it requires new methodologies and approaches. In many publications, the basics of theoretical approaches are laid down. For example, Wentholt, Fischer, Rowe, Marvin, and Frewer (2010) published the results of a two-round Delphi survey, in which international experts' views regarding knowledge gaps associated with the identification and mitigation of emerging food risks was investigated. In the study of van Asselt, Meuwissen, van Asseldonk, Teeuw, and van der Fels-Klerx (2010), the selection of critical factors in dynamic production chains for pro-active emerging risk identification is presented. In the study of Marvin et al. (2009), an emerging risk identification system developed according to the knowledge and experience of many experts is presented, however, it is still a general theoretical framework. Based on a so-called 'holistic perspective', an assessment of emerging risk is characterized by the early detection of facts related to that risk derived either from research and/or from monitoring programs or episodic observations. The evidence supporting the identification of an emerging risk should preferably be in the form of an 'indicator' (e.g., measurement and/or observation) and of a trend over time or space (Kleter & Marvin, 2009). Such an indicator-based approach has been

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presented in the publication of Liu et al. (2022), where the authors demonstrated that for the dairy supply chain, the identification and analysis of these indicators, actual food safety incidents can be preceded more than a year ahead. Effects of drivers of change as indicators in different food sectors has been analysed with expert-driven and data science methods such as Bayesian Network approach in the studies of Marvin et al. (2020) and Bouzembrak and Marvin (2019).

There are international activities in the topic of emerging risk identification and foresight such as the respective work of Food and Agricultural Organization (FAO) (Dury et al., 2019; FAO, 2022) and the ongoing activity of a European Union foresight system for the identification of emerging environmental issues (FORENV), which is based on Horizon-Scanning, as developed by the Commission's Joint Research Centre (White et al., 2017). European Food Safety Authority (EFSA) Emerging Risk Exchange Network (EREN) has been working for a long time on European level emerging risk identification with a great success, however, these systems rely yet mainly on networking – gathering expert knowledge and scientific literature research; data analytical methodologies are not exploited (EFSA, 2012b, EFSA, 2015). A more specific field of emerging food safety risks has been targeted by the development of a screening approach to identify potential chemical risks in the food chain by EFSA (Oltmanns et al., 2018; Oltmanns, Bohlen, Escher, Schwarz, & Licht, 2019).

There are publications on retrospective analytical tools for emerging risks occurred in the past, for example van de Brug, Lucas Luijckx, Cnossen, and Houben (2014) analysed 13 historical food safety incidents and characterized the early signals for these. It is much easier to identify the early signs of a risk in retrospect that has already been evolved, however, many similar weak signals that are present, would not cause any events in the future. Elaboration of data analytical methods for food chain safety emerging risk identification is often based on or inspired by case studies for past events and/or often they are too specific and cannot be effectively used for general forecasting purposes. Rortais et al. (2021) used a text mining approach to identify topics in media news that can be related to emerging beeswax adulteration issues. Gavai et al. (2021) presented an algorithmic approach using artificial intelligence to identify unknown stimulants from scientific literature and media reports.

Based on the above, identification of emerging risks in the food chain is a complicated tasks because of the many uncertainties, data and information gaps surrounding an issue before it is escalated. Moreover, as we can see from the definition, not only newly identified hazards, but also increased exposure or susceptibility may lead to emergence of risks, which makes the identification process even more difficult.

The objective of our study is to present a practically applicable, sustainable, and traceable workflow for systematic emerging risk identification and management and to give a brief overview on possible data analytical methodologies for emerging risk identification, to present the results, experiences, and limitations of application of such a system.

2. Materials and methods

2.1. Process management

Emerging risks may arise from different types of hazards. There are well-defined hazards as well as complex, driver-induced scenarios that lead to occurrence of risks. The temporal scale of the occurring damage caused by the risk also may vary greatly – from slowly and evenly spreading risks to rapidly occurring ones. We can talk about emerging risks in terms of spatial spreading as well, known risks breaking into new areas; for example, the well-known African swine fever disease could be considered as an emerging risk in European Union when it has entered the Caucasian area and then the Baltic states. Because of the complex nature of emerging risks, the identification system must be effective regardless these characteristic differences.

In a nutshell, the identification process is basically the collection and structured filtering process of gathered relevant data/information sources (Fig. 1.). From the data and information, emerging issues are selected in PHASE I. From the emerging issues, potential emerging risks are selected (PHASE II) and from them, emerging risks that need further measures are selected in PHASE III.

The identification system has been elaborated based on the method of EFSA (EFSA, 2012a), but has been adjusted to serve somewhat different purposes. EFSA collects information from Member States regarding emerging issues and their main goal is to identify the hazards that need risk assessment and thereby initiate risk assessment studies. In our case, the scope is broader as we consider ourselves as a distribution point of information and after the identification of emerging risks, we reach out to the relevant stakeholders to let them make the necessary steps. The presented framework (Fig. 1.) is successfully used by our team and is considered to be a generally applicable workflow for emerging risk identification, however, it has to be adapted for specific needs of different organizations or researchers.

Risks evolve over time, as new data, information, and knowledge are generated. To capture this evolutionary aspect, different terms are used at different stages of the identification process. By definition, emerging issue is an issue that could be a food or feed safety risk that has very recently been identified and needs further investigation; and the information collected is still too limited to be able to assess whether it meets the requirements of emerging risks. It is identified at the beginning of the emerging risk identification process.

The process is not one-way only; in certain points, more information could be needed to be able to perform the filtering process or in other cases, further measures are not needed at that moment, however, monitoring of the issue is desirable. In these cases, the issues go back to an earlier phase of the process.

2.1.1. Data/information collection

Channelling data and information for emerging risk identification can be done from various sources, and for this, automated methods are the most fit for purpose. However, because of the complexity, interdisciplinarity and the information gaps, the emerging risk identification process as a whole cannot be done only by algorithms. As of today, human expert knowledge is needed for the final judgement regarding the selection and the fate of the issues to complete the information found by the algorithms. The variability of the soundness of information sources is also something to be considered by an expert. In conclusion, because of the huge amount of relevant data and information, automated processes, e.g., machine learning algorithms are needed for information screening and filtering, but an emerging risk identification system greatly relies on expert knowledge that supports the system in many points. Data analytical approaches are useful to solve certain aspects of the identification process or can be used for specific tasks which complete the bigger picture and add information that aid preparedness for the future. Data analytical methodologies for emerging risk identification are detailed in Section 2.2.

Relevant information for collecting potential emerging risk can also be channelled through soft information sources, which means communication with experts in various platforms e.g., conferences, newsletters, organized meetings. The scientific network of European Food Safety Authority, Emerging Risk Exchange Network (EREN) is an extremely useful information source for acquiring soft information regarding emerging risks occurring at European level or in various member states of the EU.

2.1.2. Filtering

Selection of relevant issues in the process is called filtering, which occurs at three levels.

Pre-filtering is the process when emerging issues (PHASE I) are selected with a screening process carried out by the ERI team, from the collected data/information which can be considered potential emerging issues. The outcome of pre-filtering therefore is an emerging issue. Issues considered not relevant are dropped out of our emerging risk

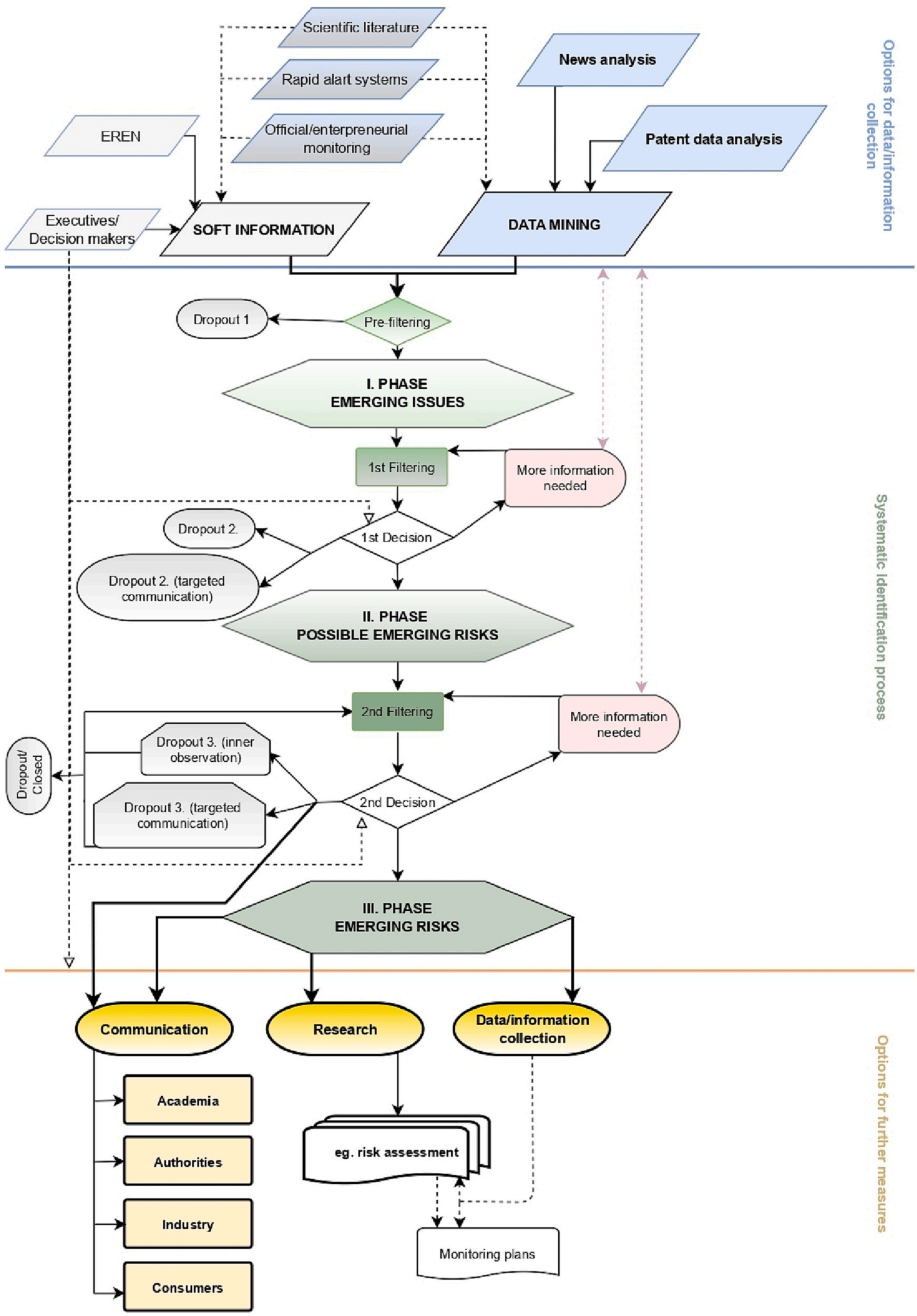

Fig. 1. Flow diagram of systematic emerging risk identification process with possible options for data and information collection methods and further measures after an emerging risk has been identified.
Legend: Different boxes illustrate different steps of the process in sequential order from top to bottom. Boxes in 'Options for data/information collection' and 'Options for further measures' sections illustrate possible options for the work to be done before and after the systematic identification process. Steps for filtering, decisions, phases of emerging issues/risks are the components of the systematic identification process. While issues pass through, there can be a lag in the process when the available information is limited ('More information needed') and they can be dropped out when considered not relevant. Detailed interpretation can be read in Section 2.1. Shapes are to be interpreted as for generic flowcharts. Solid line: specific direction of the process. Dashed line: optional directions of the process. Different colours aim to aid transparency.

identification system ('Dropout 1.' on Fig. 1).

1st filtering is the selection of potential emerging risks (PHASE II) from emerging issues (PHASE I). When an emerging issue meets the definition of emerging risks, it goes further in the process to PHASE II as a possible emerging risk. To help deciding on whether the emerging risk definition criteria are met, Table 1. gives a guidance. Cases 1–3 are the variations for getting emerging risks and case 4 is an example when the issue is not an emerging risk, therefore it is not moved on to PHASE II.

When an issue does not meet the criteria of 1st filtering, the options are the following: more information is needed in order to be able to decide on the fate of the issue (it goes back into PHASE I); the issue is not relevant therefore it is dropped out of the system ('Dropout 2.' in Fig. 1). In certain cases, specific stakeholders need to be informed and targeted communication could take place ('Dropout 2. Targeted communication' on Fig. 1).

2nd filtering is an evaluation with a scoring system that helps to decide whether the PHASE II. possible emerging risks needed further measures or not. Each of the following criterion gets a score from 1 to 4, and if the sum of the scores is ≥11 (defined by practical experience), the possible emerging risk moves to PHASE III as further measures are needed (See Table 2).

1. Soundness: reliability of different information sources varies (e.g., scientific literature versus media news)
2. Imminence: proximity in time (is the risk already present, or it will appear in months, years etc.)
3. Scale: e.g., size of the vulnerable population and/or potentially affected area; trade and consumption patterns etc.
4. Severity: extent of damage caused by the risk. e.g., risk specific morbidity and/or mortality
5. Risk management option: Is it an existing issue in risk management systems? e.g., applied maximum limits or other regulations.

If, based on the scoring, the PHASE II potential emerging risk gets <11 points, it does not move to PHASE III, but it is not dropped out permanently either. PHASE II issues have the relevance to be monitored as they might outgrow themselves into emerging risks that need further measures ('Dropout 3. Inner observation' or 'Dropout 3. Targeted communication' in Fig. 1.). Therefore, they stay in the system and after a pre-defined period they are re-evaluated with the 2nd filtering process considering all new available information. In certain cases, stakeholders need to be informed at this point. It is to be noted that scoring leads the experts in judging the fate of the given issue, however, it might be overridden based on expert opinion as there are no specific metrics in the field of emerging risk identification for e.g., what can be considered significant – it always has to be judged case-by-case by experiences and expertise.

Table 1
Guidance for evaluation of 1st filtering criteria.

	1. Question New risk	2. Question Significant exposure	3. Question Increased exposure	4. Question Increased sensitivity	Result
1.	yes	yes	n.a.[1]	n.a. [1]	PER[2]
2.	no	yes or no	yes	yes or no	PER
3.	no	yes	yes or no	yes	PER
4.	*no*	*yes*	*yes*	*no*	*Not PER*

Legend: Interpretation of the table: the table is intended to facilitate the decision if the identified emerging issue meets the definition of emerging risks – if it is a new hazard or if increased exposure or susceptibility occur. If the result is 'PER' (Possible Emerging Risk), the issue goes forward in the system. If the result is 'Not PER', the issue is dropped out of the system. An example for dropping out an issue can be seen in line 4.

[1] Non-applicable.

[2] PER: Possible Emerging Risk.

2.1.2.1. Expert involvement in the filtering process. Our team for emerging risk identification (ERI team) is comprised of 6–8 experts with different food chain related background knowledge (agricultural engineer, bioengineer, food engineer, microbiologist, veterinarian, risk assessor, chemical contaminant expert, health economy expert, sociologist). The ERI team does the pre-filtering from all possible emerging issues that had been identified (data/information collection, Fig. 1). After that, each selected issue is assigned to one expert from the team who evaluates it more thoroughly (does the 1st and 2nd filtering, Fig. 1). The outcome of the evaluations of the assigned experts regarding each issue are subject of a weekly ERI team discussion, meaning that the final decisions on the issues are made by consensus of the whole expert team. In cases when additional specific knowledge is needed, external experts are reached out and the decision regarding the issue is delayed in the meantime. This is also the case when the assigned expert has to perform a more thorough research or the ERI team has to wait for other information, e.g., scientific reports, information on the exposure increasing ('More information needed' in Fig. 1.).

2.1.3. Further measures

Identified emerging risks need various type of measures to avoid or minimize the damage caused by the occurring risk. It is not the part of emerging risk identification process strictly, therefore not detailed in this document, but some examples are shown on Fig. 1. such as communication for different target audience (e.g., consumers, authorities, academia, industry), research and data/information collection for e.g., food chain safety risk assessment or monitoring plans.

2.2. Data analytical approaches

Data analytical, text and data mining methodologies help us to create automated processes to be able to pre-digest the available information for the experts. Well-defined algorithms adjusted to be fit-for-purpose will result in much less manual (human) effort for identifying emerging risks. Some examples and brief descriptions about the applicable methodologies are listed below.

2.2.1. Analysis of rapid alert systems and monitoring systems for identifying trends

The analysis of food chain related rapid alert systems such as Rapid Alert System for Food and Feed (RASFF) (European Commission, 2017) can be useful in getting an overview of actual food or feed safety issues. Basic statistics, specific searches for food or feed categories, map views of notifications or border rejections are extremely useful for entrepreneurs or food/feed business operators in decision making and timely intervention in the production in case of emergency. However, the issues in these systems are usually well-regulated, therefore they cannot be considered as emerging risks by themselves. But if we look at the trends, e.g., increasing number of mycotoxin cases in a specific area, these might outgrow themselves into emerging risks. In summary, for rapid alert systems, identifying and following trends and patterns are the most relevant in terms of emerging risk identification.

2.2.2. Keyword-based searches for emerging risks

Searching for emerging risks in textual data or in internet search engines by keywords could be an obvious methodology for finding risks, however, food chain is such a broad topic and to find an emerging risk from only a few signs before it evolves might be so complex that a simple search is not considered feasible nor meaningful. Selection of appropriate keywords for this area is a huge task in itself, for example one would find too much and misleading hits for a search string 'emerging AND new AND hazard AND food and FEED'. A well-elaborated, specific, pre-defined set of keywords (and key terms), a so-called ontology, with hierarchical arrangement and defined relations of the keywords and terms would form the basis for this. For the creation of the emerging risk ontology for the whole food chain, machine learning algorithms are

Table 2
Guidance for evaluation of 2nd filtering.

	Score			
	1	2	3	4
Soundness[1]	E.g., *media news without reference*	E.g., *information from an external expert that is not supported by other experts*	E.g., *information gathered by monitoring rapid alert systems*	E.g., *information supported by strong scientific evidence*
Imminence	years	months	weeks	already present
Scale[2]	0–25%	26–50%	51–75%	76–100%
Severity[1]	E.g., *Medical care is not or rarely needed/No quality issues*	E.g., *Medical care is sometimes needed/Slight quality issues*	E.g., *Medical care is often needed/Moderate quality issues*	E.g., *High mortality rate/Quality issues that make the product unsuitable for consumption*
Risk management option	Existing	–	Non-existing	–

Legend: The table contains examples and guiding information for the experts to be able to score the five criteria (soundness, imminence, scale, severity, and risk management option). The sum of the scores will help to decide whether the possible emerging risk should go forward in the system as an emerging risk.
[1] Many factors can affect the criteria of soundness and severity and the type of the issue largely affects the scoring as well, which has to be considered by the expert while scoring. The table shows specific examples.
[2] By considering the size of the population and the area as well.

needed in order to train an algorithm and get the most suitable ontology with an iterative trial-error procedure. There were attempts for creation of ontologies in specific areas of food safety such as GMO ontology (Prins, Top, Kok, & Marvin, 2012) and categories for plant health threats (EFSA, 2012c) for the Medical Information System (MedISys) of the Europe Media Monitor (EMM) (Linge et al., 2009). A text mining tool using an ontology for salmon and oyster related emerging issues is presented in a scientific report of Lucas Luijckx, van de Brug, Leeman, van der Vossen, and Cnossen (2016). Nevertheless, comprehensive food safety emerging risk ontology have not yet been elaborated.

2.2.3. Analyses of patent databases/scientific literature databases

New evidence and findings in scientific literature obviously serve as an input for emerging risk identification systems, but also patented technological innovations may be accompanied by emergence of risks. These two areas are similar in terms of database structure and data analytical approaches; therefore, the applicable methodologies could be also similar.

These knowledge-based databases can be analysed from a network perspective, where citations are the edges of the network and connect the nodes which can be either single documents (patents, publications) or at a higher aggregation level, technological or scientific categories. Network approach is also supported by the fact that scientific/technology systems are highly interdependent (Archibugi & Planta, 1996). The changes in citation patterns in the patent network over time may reveal scientific/technological trends. Network-based computational perspective provides several methodologies in terms or identifying influential or emerging new fields. For example, ranking algorithms are applicable to identify nodes that have certain positional advantages related to their embeddedness in the network. This positional advantage result in influence of scientific or technological developmental directions.

Cho and Shih (2011) applied the so-called structural hole theory as a type of a centrality measure in network analysis, for the identification of emerging technologies in Taiwan, by ranking them based on their ‘structural hole score’. A structural hole is defined as a gap between nodes (individuals) or group of nodes that hold complementary sources to information, as on either side of the structural hole, they have access to different flows of information. Structural holes therefore reflect ‘an opportunity to broker the flow of information between people and control the projects that bring together people from opposite sides of the hole’ (Burt, 2000). Bruck, Réthy, Szente, Tobochnik, and Érdi (2016) has applied another network-based ranking methodology, the algorithm also used by Google, PageRank, for tracing the evolution of new fields of technology.

When looking at the patent/publication categories as clusters that change over time, community detection and clustering methodologies are applicable to identify their temporal behaviour for the prediction of the birth of new categories. Érdi et al. (2013) used a clustering algorithm to study the temporal growth of patent citation network at ‘mesoscopic’ (subclass) level, while Beltz et al. (2019) demonstrated community evolution tracking methodologies (growth, decay, split, birth, merge, and death) with actual examples on United States Patent and Trademark Office (USPTO) patent citation database.

According to Wang and Barabási (2021) the theory that existing technologies are recombined to generate new inventions is confirmed by the analysis of US patents. Each patent is classified by the USPTO using a unified scheme of technology codes (a class and a subclass). Today, 90% of inventions combine at least two codes, showing that invention is increasingly a combinatorial process. This combinatorial view of innovation offers a way to quantify novelty in science. Indeed, scientific papers draw their references from multiple journals, signalling the domains from which they sourced their ideas (Wang & Barabási, 2021). The use of co-citation network analysis of patent data and dissimilarity matrix analysis is demonstrated amongst the results of a project aimed at emerging risk identification determination and metrics (Meijer et al., 2020). Co-citation is defined as the frequency with which two patents are cited together by other patents. The theory behind co-citation analysis is that the more co-citations two patents receive, the higher their co-citation strength, and the more likely they are semantically related. By the temporal evaluation of the co-citations, patterns can be revealed. On the other hand, Bray Curtis dissimilarity method (Bray & Curtis, 1957) is also applicable for capturing temporal changes in the structure of the citation pattern by the analysis of the change of dissimilarity matrices over time. This method is commonly used in numerical ecology, as a statistic to quantify the compositional dissimilarity between two different sites (in this case patent categories) based on the counts of the included units (in this case, patent citations) (Legendre & Legendre, 2012).

2.2.4. Media news analysis – Topic detection

Topic detection is an information processing technique that includes different methodologies that combine several text mining algorithms. The more often used methodologies are (a) clustering algorithms, which, in the pre-processing phase is preceded by keyword extraction algorithms such as Term Frequency-Inverse Document Frequency (TF-IDF) (Salton & Buckley, 1988) and Vector Space Model (Salton, Wong, & Yang, 1975); (b) topic models (AlSumait, Barbará, & Domeniconi, 2008) which use e.g., Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003) to explore the latent semantic knowledge of documents, i.e., treating each document as a probability distribution over topics, then representing news based on this distribution and clustering the news accordingly; and also (c) neural network-based methods (Hashimoto, Kontonatsios, Miwa, & Ananiadou, 2016). In the study of Marvin et al. (2022), network analysis has been used and concluded to be effective for the identification of frauded food products and fraud cases from MedISys-FF food fraud publication collection tool.

By identifying and analysing topics in food chain related media news, food safety events and emerging food safety risks can be detected in a timely manner (Xiao, Wang, Zhang, & Qian, 2019).

A methodology for topic detection in food safety news has been elaborated in DEMETER (Determination and Metrics for Emerging Risks Identification) project (Meijer et al., 2020).

3. Results and discussion

Identifying emerging issues is not a trivial task. Different knowledge levels exist in different organizations, thus different issues will be emerging to a particular food business operator, for an authority, for an academic partner, etc. Therefore, in our conventional way of identifying emerging risks, the experts involved in the process have an extreme importance: their understanding of the knowledge levels and their decisions during the course of the identification process will influence the outcome.

However, manual screening of data, information, and knowledge for identifying emerging risks is a long and resource-demanding process. Data analysis and text mining methods may help in the screening process, to help the experts in filtering out 'noise' from the flow of information. From a didactic perspective, we can have generally two approaches of data assisted screening: 1) imitating the human decision-making process; and 2) applying new approaches and changing the process itself. These methods of course could be used for news, scientific literature, rapid alert systems, monitoring systems or other textual data and information as well.

3.1. Imitating the human decision-making process

This approach is seldom used in its pure form, but the basic idea is to define what is 'emerging', what is 'risk', what is a 'new technology', etc. in a format which is understandable by a machine. So, in other words, ontologies are elaborated on emerging risk identification, then search strings or automated data/information retrieval pipelines are used which parse the knowledge corpus for the defined words or expressions defined by the ontology. A challenge is that if we want to find news on potentially emerging technologies bearing food safety risks, where the words 'emerging' or 'new' are not explicitly mentioned, we won't find them. A more sophisticated ontology is need for that, and the development of such an ontology could also be assisted by various AI methodologies. An example for this would be to train an AI system on a large textual corpus of already identified emerging risks to let the algorithm identify the ontology by itself.

3.2. New approaches changing the identification process itself

Considering the significant resource need to develop an efficient emerging risk ontology, a different approach might be used. This approach suggests that if the human decision-making process can't be fully substituted by machines, then other indicators for emergence might be defined. Emergence in this definition space is a (significant) change in patterns/structures of a system. As an example, patents cite other patents, and this citation network has certain characteristics. There are more dense parts of this network, there are patents or patent groups which have more citations, or they play a central role in the network bridging distant groups, etc. The structure itself tells us which patents and/or patent groups are 'more important'. But when we explore these phenomena in a time-dynamic manner (i.e., exploring the changes of the structure over time), then we could have signals of emergence: new groups are forming, new bridges are developing, etc. This emergence is interpreted as profound changes in the underlying patent universe, and these indicate certain directions which are worth investigating more in details.

These two approaches form just a didactic grouping. From a practical perspective, a certain combination of these is used: first the target groups/individual patents are narrowed down with network analysis, then keywords might be used to find the most relevant patents causing this emergence. Or the other way around: first narrowing down the patent database with specific keywords or filtering options (for a specific topic, patent group, timeframe or other), then perform analysis on this smaller set of data. However, in this case, we have to be careful about interpreting the results taking into account how much information we have lost with the initial filtering.

3.3. Identified ERs – Summary

Currently, from the applicable data analytical methods, the core of our emerging risk identification system is topic detection, this method is continuously applied by the ERI team and supplies the system with around 90% of the possible emerging issues. We also analyse patent databases with structural hole approach and the emergence and divergence of technological categories with numerical ecology analysis and co-citation network analysis. By applying these data analytical methods (media news analysis, Section 2.2.4 and patent network analysis, Section 2.2.3) and the above-described process management system (Section 2.1), in 2020 and 2021, there were 58 emerging risks identified by the ERI team. The list of emerging risks, the measures and the follow-up actions can be seen in the Supplementary material.

In order to give an overview on the identified emerging risks, their classification and briefing is presented hereunder (however, some topics e.g., sustainability and technological innovation might overlap).

- *Microbial safety of ready-to-eat (RTE) fresh greens and mushrooms / raw RTE foods*

Issues related to *Salmonella* spp. (Zwe, Ten, Pang, Wong, & Li, 2021; CDC, 2020b, CDC, 2022) and *Listeria* spp. (CDC, 2020a) on different types of fresh RTE foods such as basil, peaches, leafy greens, cilantro and mushroom occurred in the last six months of 2021. This type of hazard-matrix combination is quite common, nevertheless, the number of issues has increased, which indicates an increasing exposure that is a characteristic of emerging risks.

- *Pet food issues*

In 2021, various problems have occurred regarding pet foods. Some examples are microbial contamination (FDA, 2018),extremely high aflatoxin contamination (FDA, 2020), antibiotic resistance (Finisterra, Duarte, Peixe, Novais, & Freitas, 2021) and unknown hazards (FDA, 2022a, 2022b) in the feed causing the death or other diseases of pets.

- *Micro- and nano plastics*

There are several recent studies investigating the concerns of micro- and nano plastics. The hazards occurring including – but not limited to – accumulation and biomagnification in plants (Sun et al., 2020), animals (Carreras-Colom et al., 2020) and humans (Cox et al., 2019; Oliveri Conti et al., 2020; Ragusa et al., 2021), dissolving chemical contaminants (Li et al., 2020) such as bisphenol A and phthalates (Norström, Olsson, Olsson, & Bergman, 2004), bound chemical contaminants (e.g. PAHs), microbiological risks (Bowley, Baker-Austin, Porter, Hartnell, & Lewis, 2021) and different exposure routs such as the food chain and the environment (water (Kelly, Lannuzel, Rodemann, Meiners, & Auman, 2020; Koelmans et al., 2019; L. J. J. Meijer, van Emmerik, van der Ent, Schmidt, & Lebreton, 2021), soil, air (Brahney et al., 2021)). The area is widely studied but has many information gaps, for example laboratory analysis has a lot of challenges and are not standardised yet.

- *Antimicrobial resistance issues*

New studies regarding different aspects of antimicrobial resistance such as spread (Zrimec, 2020), stimulating agents (Zhao et al., 2021), and prevention technologies shed the light on the importance of this ever-growing issue that needs to be monitored and more understood to mitigate the adverse effects.

- *Chemical contaminant related issues (including pesticide issues)*

Issues came into our sight were related to food additives (Naidenko et al., 2021), dissolving chemicals from food contact materials (Bonwick, Bradley, Lock, & Romero, 2019) and pesticides. There is more and more knowledge gained regarding new chemical contaminants, effects of new and known chemical contaminants and their exposure (Wang et al., 2021).

- *Issues related to sustainability (including alternative protein sources)*

Recycling, reduction of food waste (Vilas-Boas, Pintado, & Oliveira, 2021) and several various alternative protein sources (insects (Gadzama & Ndudim, 2019), microbes (Ciani et al., 2021) and gene engineered sources (Boukid, Rosell, Rosene, Bover-Cid, & Castellari, 2022)) are belonging to this topic driven by climate change and sustainability.

- *Technological innovation (including gene manipulation and nanotechnology related issues)*

Gene manipulation and nanotechnology are extremely popular fields in innovation technologies. With newest technologies, gene manipulation is often used for treating diseases (Raffan et al., 2021), while nanotechnology examined for antimicrobial effects and applicability in the food industry (Ahmed et al., 2022; Aytac et al., 2021). As all new technologies may be accompanied by risks (Nissen, Casciano, & Gianotti, 2021), these issues need to be monitored.

- *Climate change related issues*

Climate change has inevitable effects on the ecosystems and thereby the food chain (Fiorenza et al., 2020; Keesing & Ostfeld, 2021). Issues classified into this topic are usually considered to be drivers such as the topic itself.

- *Emerging microbes*

As an active scientific field, food microbiology always serves with information on new microbe species, strains (Muchaamba, Barmettler, Treier, Houf, & Stephan, 2022), or new exposure routes (FDA, 2021; Carlin et al., 2021) of known microbes in the food chain. Identification of new microbes and food safety outbreaks are driven by innovations and development of diagnostics and microbial evolution. These types of emerging risks are usually included in the national monitoring system after detection.

- *Consumer trends*

Trends coming from catering (e.g., edible flowers (Guiné, Florença, Ferrão, & Correia, 2019)), or new home cooking habits (e.g. home-made fermentation), health-driven food choices are usually accompanied by risks hidden from consumers who are not familiar with potential food safety matters such as non-regulated cultivation or application, microbiological risks or too high concentration of active ingredients. In case of this topic, informing consumers by proper risk communication is essential for mitigating the risks.

The listed topics, in which the specific emerging risks (see in Supplementary material) belong can be considered as drivers of change in terms of food chain safety incidents and emerging risks. Of course, by themselves these are well-known areas, but as identified drivers they might help stakeholders in e.g., decision making or distributing the research and control resources. The specific identified emerging risks have helped the authorities such as National Food Chain Safety Office of Hungary and Emerging Risk Exchange Network (EREN) of EFSA in intervening in order to enhance preparedness, e.g., completing the national monitoring program with a specific hazard-matrix combination based on our findings. Many of the listed emerging risks were subject to EU-level discussion at EREN meetings. The identified emerging risks have also been communicated through our website; therefore, consumers were informed on the possible risks and consequences in matters of their concern.

4. Conclusions and perspectives

Mitigation and prevention of food chain related emerging risks with possible severe consequences requires an identification system that allows for timely identification of potential issues and the tracking of the fate of the issues after the expert evaluations. Continuously developing data analytical and artificial intelligence methodologies provide opportunities for solving specific aspects of issues occurring in the emerging risk universe (Liu et al., 2022; Marvin et al., 2022). However, near real-time identification with high precision and handling the whole process only by machines and algorithms in the food chain area are unlikely as at certain points in the system, human expert knowledge is needed for e.g., validation, interpretation, making final decisions and also because of security and ethical reasons. This statement is also underlined by the fact that gathering expert knowledge for emerging risk identification in the food sector is a topical issue. According to a systematic review conducted by Hadjigeorgiou et al. (2022), there is a significant increase in expert elicitation methods, such as workshops, Delphi method, surveys etc. used for emerging risk identification in the food and feed sector since 2017. While there are promising tools using artificial intelligence and machine learning algorithms developed for risk identification in other sectors, such as in the drug sector for finding adverse effects (Martenot et al., 2022), this method uses the benefits of a classic machine learning-based prediction which is hardly adaptable in such a complex system as the food chain.

In terms of food chain related risks, we can differentiate three different timescales. The shortest timescale is represented by early warning systems. In this case we talk about issues when immediate action is required (e.g., preparation for an incident when there is new information about an ongoing outbreak or incident that happened somewhere else). For this, rapid and structured information flow is required just as in case of rapid alert systems (e.g., RASFF).

In the longest timescale, there are events coming from long timescale studies such as driver-, foresight- and scenario analyses, which serve with information to induce thinking and actions on a strategic level (Marvin et al., 2020).

In our interpretation, the actual emerging risks occur at a medium term. The elaborated emerging risk identification process with the filtering procedures enables a sustainable continuous preparedness system for emerging risks occurring especially at this timescale. Knowledge about continuously identified emerging issues helps authorities to prepare and act in a timely manner and thereby avoid or mitigate possible future risks. It also aids industry and entrepreneurs who can prevent food safety events and non-compliancy issues of their products. When new issues emerge, the knowledge gaps reveal new research directions which direct the focus of research prioritization and initiation for researchers and funding agencies as well. Altogether, the final achievement is the prevention and protection of consumer health and the whole food chain.

Of course, separation of the three timelines is only for better understanding as all of them need different approach in terms of interpretation and analysis. However, the three timelines are closely related and affect each other. One can imagine that long-term drivers such as climate change will inevitably end up in short-term issues and medium-term emerging risks as well. New technological developments also might be accompanied by risks that were not accounted for in advance. Or another example is changing in trends in recent outbreaks (short-term issues) is a strong signal for medium-term risks to emerge.

From preparedness point of view and to have resilient food systems, systematic assessment of short, medium, and long timescale trends and issues is needed, and while different timescale issues affect each other, from analysis and evaluation perspective, these need to be handled separately. Newly evolving area of knowledge management systems will be the key to form and maintain a harmonized system that brings together different timescale emerging issues and drivers of change.

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CRediT authorship contribution statement

Zsuzsa Farkas: Conceptualization, Methodology, Software, Visualization, Writing – original draft. **Erika Országh:** Data curation, Software, Validation, Writing – review & editing. **Tekla Engelhardt:** Data curation, Formal analysis, Validation, Writing – review & editing. **Andrea Zentai:** Data curation, Formal analysis, Validation, Writing – review & editing. **Miklós Süth:** Conceptualization, Funding acquisition. **Szilveszter Csorba:** Data curation, Methodology, Software, Validation, Writing – review & editing. **Ákos Jóźwiak:** Conceptualization, Supervision, Validation, 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.

Data availability

No data was used for the research described in the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ifset.2023.103366.

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